vaex Documentation

Release 3.0.0

Maarten A. Breddels

May 26, 2020

Contents

> **Warning:** It is recommended not to install directly into your operating system's Python using sudo since it may break your system. Instead, you should install Anaconda, which is a Python distribution that makes installing Python packages much easier or use virtualenv or venv.

CHAPTER 1

Short version

- **Anaconda users**: `conda install -c conda-forge vaex`
- **Regular Python users using virtualenv**: `pip install vaex`
- **Regular Python users (not recommended)**: `pip install --user vaex`
- **System install (not recommended)**: `sudo pip install vaex`

CHAPTER 2

Longer version

If you don't want all packages installed, do not install the vaex package. The vaex package is a meta packages that depends on all other vaex packages so it will instal them all, but if you don't need astronomy related parts (`vaex-astro`), or don't care about distributed (`vaex-distributed`), you can leave out those packages. Copy paste the following lines and remove what you do not need:

- **Regular Python users**: `pip install vaex-core vaex-viz vaex-jupyter vaex-arrow vaex-server vaex-ui vaex-hdf5 vaex-astro vaex-distributed`
- **Anaconda users**: `conda install -c conda-forge vaex-core vaex-viz vaex-jupyter vaex-arrow vaex-server vaex-ui vaex-hdf5 vaex-astro vaex-distributed`

When installing `vaex-ui` it does not install PyQt4, PyQt5 or PySide, you have to choose yourself and installing may be tricky. If running pip install PyQt5 fails, you may want to try your favourite package manager (brew, macports) to install it instead. You can check if you have one of these packages by running:

- `python -c "import PyQt4"`
- `python -c "import PyQt5"`
- `python -c "import PySide"`

CHAPTER 3

For developers

If you want to work on vaex for a Pull Request from the source, use the following recipe:

- `git clone --recursive https://github.com/vaexio/vaex` # make sure you get the submodules
- `cd vaex`
- make sure the dev versions of pcre are installed (e.g. `conda install -c conda-forge pcre`)
- install using:
- `pip install -e .` (again, use (ana)conda or virtualenv/venv)
- If you want to do a PR
- `git remote rename origin upstream`
- (now fork on github)
- `git remote add origin https://github.com/yourusername/vaex/`
- ... edit code ... (or do this after the next step)
- `git checkout -b feature_X`
- `git commit -a -m "new: some feature X"`
- `git push origin feature_X`
- `git checkout master`
- Get your code in sync with upstream
- `git checkout master`
- `git fetch upstream`
- `git merge upstream/master`

CHAPTER 4

Tutorials

4.1 Vaex introduction in 11 minutes

Because vaex goes up to 11

If you want to try out this notebook with a live Python kernel, use mybinder:

4.1.1 DataFrame

Central to Vaex is the DataFrame (similar, but more efficient than a Pandas DataFrame), and we often use the variable `df` to represent it. A DataFrame is an efficient representation for a large tabular dataset, and has:

- A number of columns, say `x`, `y` and `z`, which are:
- Backed by a Numpy array;
- Wrapped by an expression system e.g. `df.x`, `df['x']` or `df.col.x` is an Expression;
- Columns/expression can perform lazy computations, e.g. `df.x * np.sin(df.y)` does nothing, until the result is needed.
- A set of virtual columns, columns that are backed by a (lazy) computation, e.g. `df['r'] = df.x/df.y`
- A set of selections, that can be used to explore the dataset, e.g. `df.select(df.x < 0)`
- Filtered DataFrames, that does not copy the data, `df_negative = df[df.x < 0]`

Lets start with an example dataset, which is included in Vaex.

[1]:
```
import vaex
df = vaex.example()
df  # Since this is the last statement in a cell, it will print the DataFrame in a␣
↪nice HTML format.
```

```
[1]: #        id    x                    y                    z                    vx
   ↪                  vy                   vz                   E              L
   ↪            Lz                   FeH
0        0     1.2318683862686157   -0.39692866802215576  -0.598057746887207   301.
 ↪1552734375       174.05947875976562   27.42754554748535    -149431.40625   407.
 ↪38897705078125  333.9555358886719    -1.0053852796554565
1        23    -0.16370061039924622  3.654221296310425    -0.25490644574165344  -195.
 ↪00022888183594  170.47216796875     142.5302276611328    -124247.953125  890.
 ↪2411499023438   684.6676025390625    -1.7086670398712158
2        32    -2.120255947113037    3.326052665710449    1.7078403234481812   -48.
 ↪63423156738281   171.6472930908203    -2.079437255859375   -138500.546875  372.
 ↪2410888671875   -202.17617797851562  -1.8336141109466553
3        8     4.7155890464782715    4.5852508544921875   2.2515437602996826   -232.
 ↪42083740234375  -294.850830078125    62.85865020751953    -60037.0390625  1297.
 ↪63037109375     -324.6875            -1.4786882400512695
4        16    7.21718692779541      11.99471664428711    -1.064562201499939   -1.
 ↪6891745328903198  181.329345703125     -11.333610534667969  -83206.84375    1332.
 ↪7989501953125  1328.948974609375    -1.8570483922958374
...      ...   ...                   ...                  ...                  ...
 ↪                  ...                  ...                  ...            ...
 ↪            ...                  ...
329,995  21    1.9938701391220093    0.789276123046875    0.22205990552902222  -216.
 ↪92990112304688  16.124420166015625   -211.244384765625    -146457.4375    457.
 ↪72247314453125  203.36758422851562   -1.7451677322387695
329,996  25    3.7180912494659424    0.721337616443634    1.6415337324142456   -185.
 ↪92160034179688  -117.25082397460938  -105.4986572265625   -126627.109375  335.
 ↪0025634765625   -301.8370056152344   -0.9822322130203247
329,997  14    0.3688507676124573    13.029608726501465   -3.633934736251831   -53.
 ↪677146911621094  -145.15771484375     76.70909881591797    -84912.2578125  817.
 ↪1375732421875   645.8507080078125    -1.7645612955093384
329,998  18    -0.11259264498949051  1.4529125690460205   2.168952703475952    179.
 ↪30865478515625   205.79710388183594   -68.75872802734375   -133498.46875   724.
 ↪000244140625    -283.6910400390625   -1.8808952569961548
329,999  4     20.796220779418945    -3.331387758255005   12.18841552734375    42.
 ↪69000244140625   69.20479583740234    29.54275131225586    -65519.328125   1843.
 ↪07470703125     1581.4151611328125   -1.1231083869934082
```

Columns

The above preview shows that this dataset contains $> 300,000$ rows, and columns named x ,y, z (positions), vx, vy, vz (velocities), E (energy), L (angular momentum), and an id (subgroup of samples). When we print out a columns, we can see that it is not a Numpy array, but an Expression.

```
[2]: df.x  # df.col.x or df['x'] are equivalent, but df.x may be preferred because it is␣
 ↪more tab completion friendly or programming friendly respectively
```

```
[2]: Expression = x
Length: 330,000 dtype: float32 (column)
---------------------------------------
     0    1.23187
     1  -0.163701
     2   -2.12026
     3    4.71559
     4    7.21719
       ...
329995    1.99387
```

(continues on next page)

(continued from previous page)

```
329996    3.71809
329997   0.368851
329998  -0.112593
329999    20.7962
```

One can use the `.values` method to get an in-memory representation of an expression. The same method can be applied to a DataFrame as well.

[3]:
```
df.x.values
```

[3]:
```
array([ 1.2318684 , -0.16370061, -2.120256  , ...,  0.36885077,
       -0.11259264, 20.79622   ], dtype=float32)
```

Most Numpy functions (ufuncs) can be performed on expressions, and will not result in a direct result, but in a new expression.

[4]:
```
import numpy as np
np.sqrt(df.x**2 + df.y**2 + df.z**2)
```

[4]:
```
Expression = sqrt((((x ** 2) + (y ** 2)) + (z ** 2)))
Length: 330,000 dtype: float32 (expression)
------------------------------------------
     0  1.42574
     1  3.66676
     2  4.29824
     3  6.95203
     4   14.039
      ...
329995  2.15587
329996  4.12785
329997  13.5319
329998  2.61304
329999  24.3339
```

Virtual columns

Sometimes it is convenient to store an expression as a column. We call this a virtual column since it does not take up any memory, and is computed on the fly when needed. A virtual column is treated just as a normal column.

[5]:
```
df['r'] = np.sqrt(df.x**2 + df.y**2 + df.z**2)
df[['x', 'y', 'z', 'r']]
```

[5]:
```
#        x                     y                     z                     r
0        1.2318683862686157    -0.39692866802215576  -0.598057746887207    1.
↪425736665725708
1        -0.16370061039924622  3.654221296310425     -0.25490644574165344  3.
↪666757345199585
2        -2.120255947113037    3.326052665710449     1.7078403234481812    4.
↪298235893249512
3        4.7155890464782715    4.5852508544921875    2.2515437602996826    6.
↪952032566070557
4        7.21718692779541      11.99471664428711     -1.064562201499939    14.
↪03902816772461
...      ...                   ...                   ...                   ...
329,995  1.9938701391220093    0.789276123046875     0.22205990552902222   2.
↪155872344970703
```

(continues on next page)

(continued from previous page)

```
329,996  3.7180912494659424    0.721337616443634     1.6415337324142456    4.
↪127851963043213
329,997  0.3688507676124573    13.029608726501465    -3.633934736251831    13.
↪531896591186523
329,998  -0.11259264498949051  1.4529125690460205    2.168952703475952     2.
↪613041877746582
329,999  20.796220779418945    -3.331387758255005    12.18841552734375     24.
↪333894729614258
```

Selections and filtering

Vaex can be efficient when exploring subsets of the data, for instance to remove outliers or to inspect only a part of the data. Instead of making copies, Vaex internally keeps track which rows are selected.

[6]:
```
df.select(df.x < 0)
df.evaluate(df.x, selection=True)
```

[6]:
```
array([-0.16370061, -2.120256  , -7.7843747 , ..., -8.126636  ,
       -3.9477386 , -0.11259264], dtype=float32)
```

Selections are useful when you frequently modify the portion of the data you want to visualize, or when you want to efficiently compute statistics on several portions of the data effectively.

Alternatively, you can also create filtered datasets. This is similar to using Pandas, except that Vaex does not copy the data.

[7]:
```
df_negative = df[df.x < 0]
df_negative[['x', 'y', 'z', 'r']]
```

[7]:
```
#        x                     y                     z                     r
0        -0.16370061039924622  3.654221296310425     -0.25490644574165344  3.
↪666757345199585
1        -2.120255947113037    3.326052665710449     1.7078403234481812    4.
↪298235893249512
2        -7.784374713897705    5.989774703979492     -0.682695209980011    9.
↪845809936523438
3        -3.5571861267089844   5.413629055023193     0.09171556681394577   6.
↪478376865386963
4        -20.813940048217773   -3.294677495956421    13.486607551574707    25.
↪019264221191406
...      ...                   ...                   ...                   ...
166,274  -2.5926425457000732   -2.871671676635742    -0.18048334121704102  3.
↪8730955123901367
166,275  -0.7566012144088745   2.9830434322357178    -6.940553188323975    7.
↪592250823974609
166,276  -8.126635551452637    1.1619765758514404    -1.6459038257598877   8.
↪372657775878906
166,277  -3.9477386474609375   -3.0684902667999268   -1.5822702646255493   5.
↪244411468505859
166,278  -0.11259264498949051  1.4529125690460205    2.168952703475952     2.
↪613041877746582
```

4.1.2 Statistics on N-d grids

A core feature of Vaex is the extremely efficient calculation of statistics on N-dimensional grids. The is rather useful for making visualisations of large datasets.

[8]:
```
df.count(), df.mean(df.x), df.mean(df.x, selection=True)
```

[8]:
```
(array(330000), array(-0.0632868), array(-5.18457762))
```

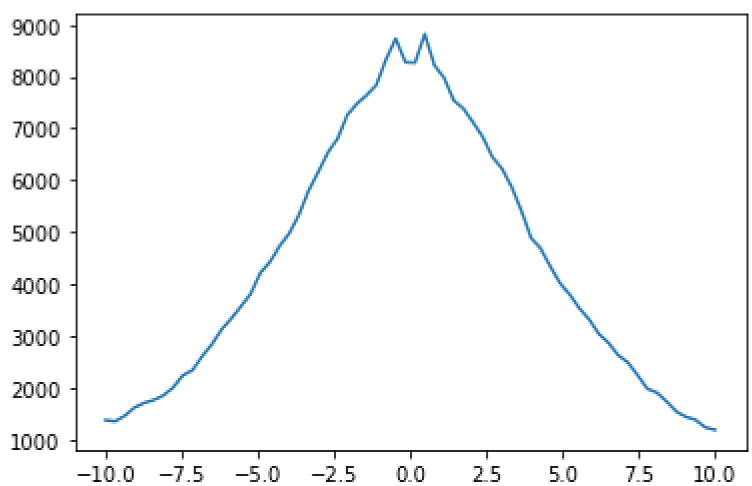
Similar to SQL's groupby, Vaex uses the binby concept, which tells Vaex that a statistic should be calculated on a regular grid (for performance reasons)

[9]:
```
counts_x = df.count(binby=df.x, limits=[-10, 10], shape=64)
counts_x
```

[9]:
```
array([1374, 1350, 1459, 1618, 1706, 1762, 1852, 2007, 2240, 2340, 2610,
       2840, 3126, 3337, 3570, 3812, 4216, 4434, 4730, 4975, 5332, 5800,
       6162, 6540, 6805, 7261, 7478, 7642, 7839, 8336, 8736, 8279, 8269,
       8824, 8217, 7978, 7541, 7383, 7116, 6836, 6447, 6220, 5864, 5408,
       4881, 4681, 4337, 4015, 3799, 3531, 3320, 3040, 2866, 2629, 2488,
       2244, 1981, 1905, 1734, 1540, 1437, 1378, 1233, 1186])
```

This results in a Numpy array with the number counts in 64 bins distributed between x = -10, and x = 10. We can quickly visualize this using Matplotlib.

[10]:
```
import matplotlib.pylab as plt
plt.plot(np.linspace(-10, 10, 64), counts_x)
plt.show()
```

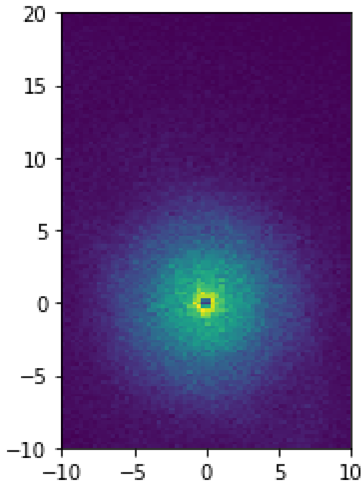


We can do the same in 2D as well (this can be generalized to N-D actually!), and display it with Matplotlib.

[11]:
```
xycounts = df.count(binby=[df.x, df.y], limits=[[-10, 10], [-10, 20]], shape=(64,␣
↪128))
xycounts
```

[11]:
```
array([[ 5,  2,  3, ...,  3,  3,  0],
       [ 8,  4,  2, ...,  5,  3,  2],
       [ 5, 11,  7, ...,  3,  3,  1],
       ...,
       [ 4,  8,  5, ...,  2,  0,  2],
       [10,  6,  7, ...,  1,  1,  2],
       [ 6,  7,  9, ...,  2,  2,  2]])
```

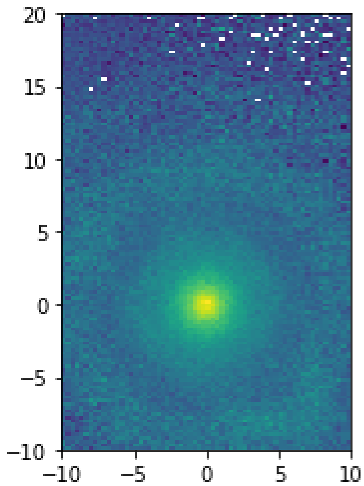
[12]:
```
plt.imshow(xycounts.T, origin='lower', extent=[-10, 10, -10, 20])
plt.show()
```



[13]:
```
v = np.sqrt(df.vx**2 + df.vy**2 + df.vz**2)
xy_mean_v = df.mean(v, binby=[df.x, df.y], limits=[[-10, 10], [-10, 20]], shape=(64,␣
↪128))
xy_mean_v
```

[13]:
```
array([[156.15283203, 226.0004425 , 206.95940653, ...,  90.0340627 ,
        152.08784485,          nan],
       [203.81366634, 133.01436043, 146.95962524, ..., 137.54756927,
         98.68717448, 141.06020737],
       [150.59178772, 188.38820371, 137.46753802, ..., 155.96900177,
        148.91660563, 138.48191833],
       ...,
       [168.93819809, 187.75943136, 137.318647  , ..., 144.83927917,
                 nan, 107.7273407 ],
       [154.80492783, 140.55182203, 180.30700166, ..., 184.01670837,
         95.10913086, 131.18122864],
       [166.06868235, 150.54079764, 125.84606828, ..., 130.56007385,
        121.04217911, 113.34659195]])
```

[14]:
```
plt.imshow(xy_mean_v.T, origin='lower', extent=[-10, 10, -10, 20])
plt.show()
```



Other statistics can be computed, such as:

- *DataFrame.count*
- *DataFrame.mean*
- *DataFrame.std*
- *DataFrame.var*
- *DataFrame.median_approx*
- *DataFrame.percentile_approx*
- *DataFrame.mode*
- *DataFrame.min*
- *DataFrame.max*
- *DataFrame.minmax*
- *DataFrame.mutual_information*
- *DataFrame.correlation*

Or see the full list at the *API docs*.

4.1.3 Getting your data in

Before continuing with this tutorial, you may want to read in your own data. Ultimately, a Vaex DataFrame just wraps a set of Numpy arrays. If you can access your data as a set of Numpy arrays, you can easily construct a DataFrame using *from_arrays*.

[15]:
```
import vaex
import numpy as np
x = np.arange(5)
y = x**2
df = vaex.from_arrays(x=x, y=y)
df
```

[15]:
```
  #    x    y
  0    0    0
  1    1    1
  2    2    4
  3    3    9
  4    4   16
```

Other quick ways to get your data in are:

- *from_arrow_table*: Arrow table support
- *from_csv*: Comma separated files
- *from_ascii*: Space/tab separated files
- *from_pandas*: Converts a pandas DataFrame
- *from_astropy_table*: Converts an astropy table

Exporting, or converting a DataFrame to a different datastructure is also quite easy:

- *DataFrame.to_arrow_table*
- *DataFrame.to_dask_array*
- *DataFrame.to_pandas_df*
- *DataFrame.export*
- *DataFrame.export_hdf5*
- *DataFrame.export_arrow*
- *DataFrame.export_fits*

Nowadays, it is common to put data, especially larger dataset, on the cloud. Vaex can read data straight from S3, in a lazy manner, meaning that only that data that is needed will be downloaded, and cached on disk.

[16]:
```
# Read in the NYC Taxi dataset straight from S3
nyctaxi = vaex.open('s3://vaex/taxi/yellow_taxi_2009_2015_f32.hdf5?anon=true')
nyctaxi.head(5)
```

[16]:
```
  #  vendor_id    pickup_datetime                dropoff_datetime               ␣
↪passenger_count  payment_type     trip_distance    pickup_longitude    pickup_
↪latitude    rate_code    store_and_fwd_flag    dropoff_longitude    dropoff_
↪latitude    fare_amount    surcharge    mta_tax    tip_amount    tolls_amount   ␣
↪total_amount
  0  VTS          2009-01-04 02:52:00.000000000  2009-01-04 03:02:00.000000000  ␣
↪              1  CASH                        2.63            -73.992           40.7216␣
↪             nan                  nan              -73.9938            40.6959    ␣
↪    8.9          0.5          nan            0                    0          9.4
  1  VTS          2009-01-04 03:31:00.000000000  2009-01-04 03:38:00.000000000  ␣
↪              3  Credit                      4.55            -73.9821          40.7363␣
↪             nan                  nan              -73.9558            40.768     ␣
↪   12.1          0.5          nan            2                    0         14.6
  2  VTS          2009-01-03 15:43:00.000000000  2009-01-03 15:57:00.000000000  ␣
↪              5  Credit                     10.35            -74.0026          40.7397␣
↪             nan                  nan              -73.87              40.7702    ␣
↪   23.7          0            nan            4.74                 0         28.44
  3  DDS          2009-01-01 20:52:58.000000000  2009-01-01 21:14:00.000000000  ␣
↪              1  CREDIT                      5               -73.9743          40.791 ␣
↪             nan                  nan              -73.9966            40.7318    ␣
↪   14.9          0.5          nan            3.05                 0         18.45
```

(continues on next page)

(continued from previous page)

```
  4  DDS          2009-01-24 16:18:23.000000000  2009-01-24 16:24:56.000000000 ␣
↪         1  CASH                         0.4             -74.0016            40.7194␣
↪        nan                     nan             -74.0084             40.7203        ␣
↪  3.7          0          nan          0                 0             3.7
```

4.1.4 Plotting

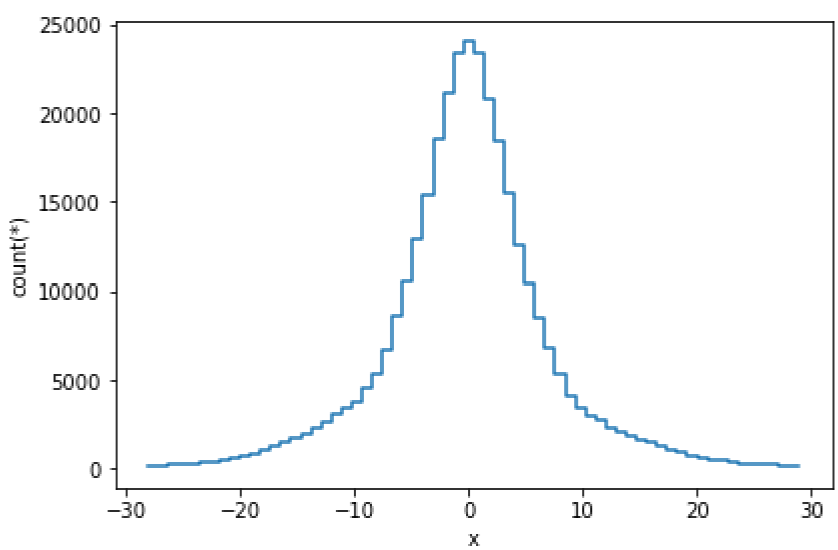
1-D and 2-D

Most visualizations are done in 1 or 2 dimensions, and Vaex nicely wraps Matplotlib to satisfy a variety of frequent use cases.

[17]:
```
import vaex
import numpy as np
df = vaex.example()
```

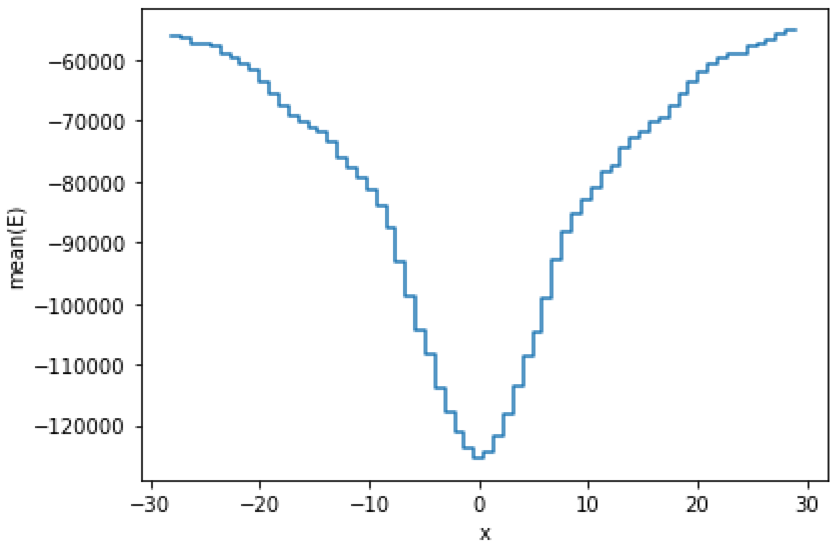
The simplest visualization is a 1-D plot using *DataFrame.plot1d*. When only given one argument, it will show a histogram showing 99.7% of the data.

[18]:
```
df.plot1d(df.x, limits='99.7%');
```



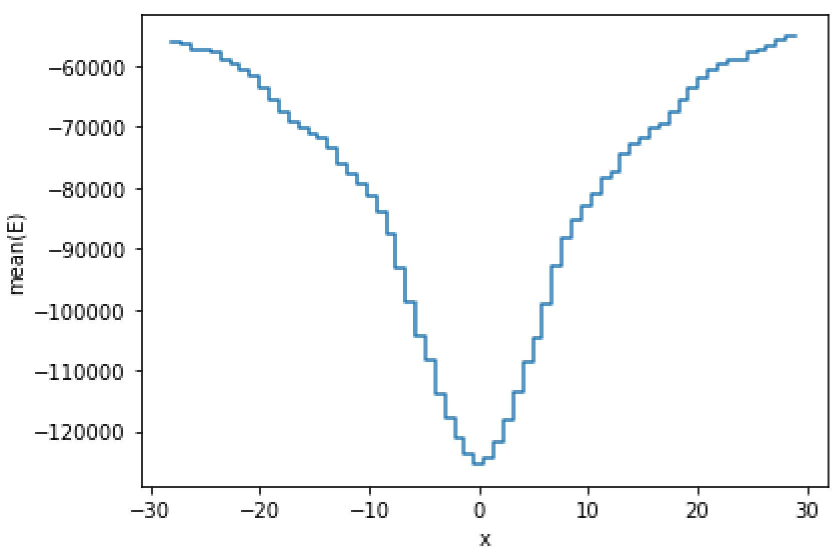
A slighly more complication visualization, is to plot not the counts, but a different statistic for that bin. In most cases, passing the `what='<statistic>(<expression>)` argument will do, where `<statistic>` is any of the statistics mentioned in the list above, or in the *API docs*.

[19]:
```
df.plot1d(df.x, what='mean(E)', limits='99.7%');
```



An equivalent method is to use the `vaex.stat.<statistic>` functions, e.g. *vaex.stat.mean*.

```
[20]: df.plot1d(df.x, what=vaex.stat.mean(df.E), limits='99.7%');
```



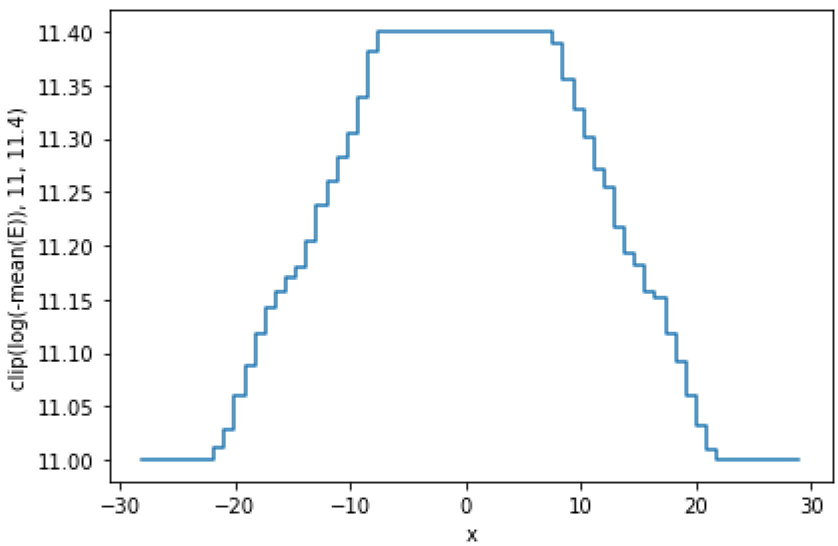
The `vaex.stat.<statistic>` objects are very similar to Vaex expressions, in that they represent an underlying calculation. Typical arithmetic and Numpy functions can be applied to these calulations. However, these objects compute a single statistic, and do not return a column or expression.

```
[21]: np.log(vaex.stat.mean(df.x)/vaex.stat.std(df.x))
```

```
[21]: log((mean(x) / std(x)))
```

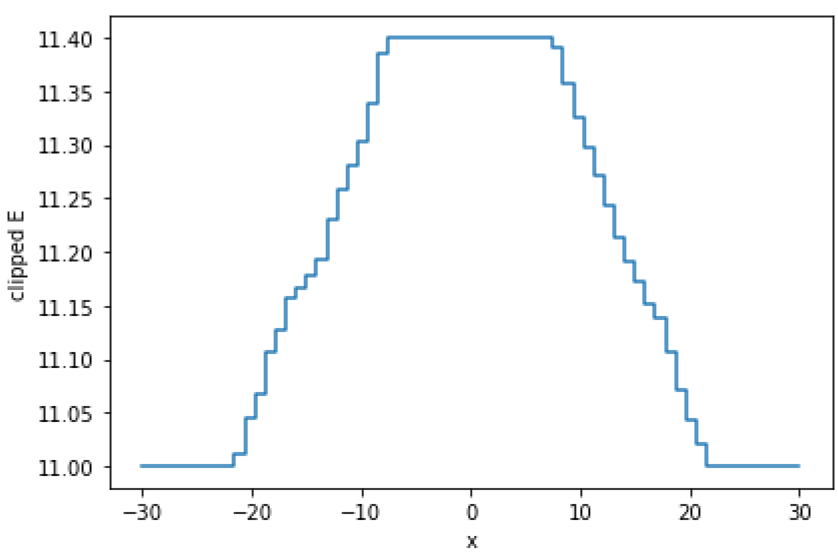
These statistical objects can be passed to the `what` argument. The advantage being that the data will only have to be passed over once.

```
[22]: df.plot1d(df.x, what=np.clip(np.log(-vaex.stat.mean(df.E)), 11, 11.4), limits='99.7%
↪');
```



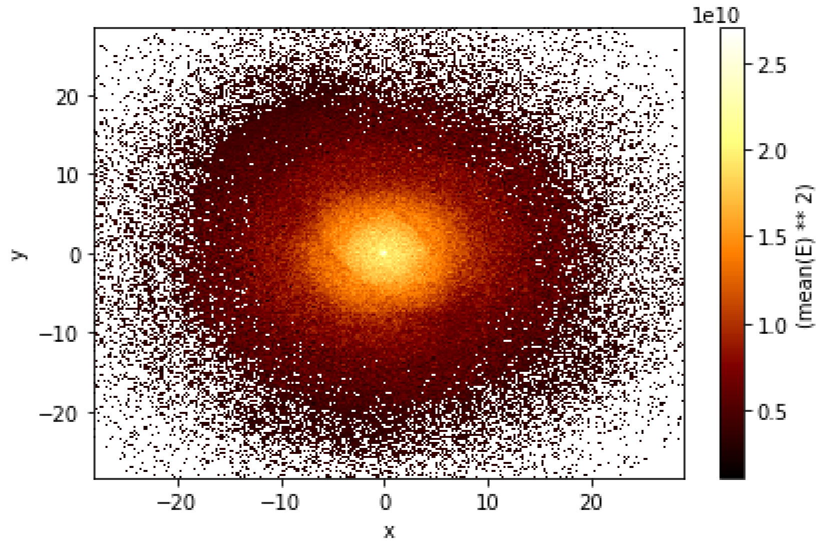
A similar result can be obtained by calculating the statistic ourselves, and passing it to plot1d's grid argument. Care has to be taken that the limits used for calculating the statistics and the plot are the same, otherwise the x axis may not correspond to the real data.

[23]:
```
limits = [-30, 30]
shape  = 64
meanE  = df.mean(df.E, binby=df.x, limits=limits, shape=shape)
grid   = np.clip(np.log(-meanE), 11, 11.4)
df.plot1d(df.x, grid=grid, limits=limits, ylabel='clipped E');
```



The same applies for 2-D plotting.

[24]:
```
df.plot(df.x, df.y, what=vaex.stat.mean(df.E)**2, limits='99.7%');
```



Selections for plotting

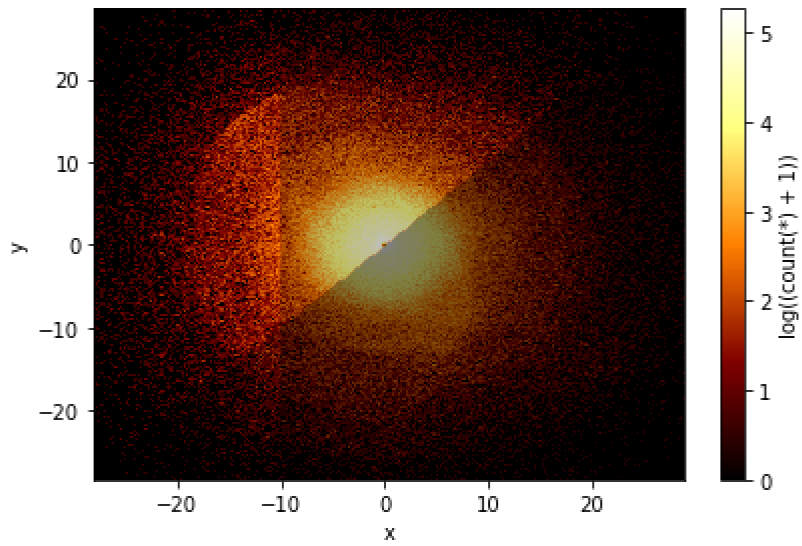
While filtering is useful for narrowing down the contents of a DataFrame (e.g. `df_negative = df[df.x < 0]`) there are a few downsides to this. First, a practical issue is that when you filter 4 different ways, you will need to have 4 different DataFrames polluting your namespace. More importantly, when Vaex executes a bunch of statistical computations, it will do that per DataFrame, meaning that 4 passes over the data will be made, and even though all 4 of those DataFrames point to the same underlying data.

If instead we have 4 (named) selections in our DataFrame, we can calculate statistics in one single pass over the data, which can be significantly faster especially in the cases when your dataset is larger than your memory.

In the plot below we show three selection, which by default are blended together, requiring just one pass over the data.

[25]:
```
df.plot(df.x, df.y, what=np.log(vaex.stat.count()+1), limits='99.7%',
        selection=[None, df.x < df.y, df.x < -10]);
```

```
/Users/jovan/PyLibrary/vaex/packages/vaex-core/vaex/image.py:113: FutureWarning:
↪Using a non-tuple sequence for multidimensional indexing is deprecated; use
↪`arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be interpreted as
↪an array index, `arr[np.array(seq)]`, which will result either in an error or a
↪different result.
  rgba_dest[:, :, c][[mask]] = np.clip(result[[mask]], 0, 1)
```

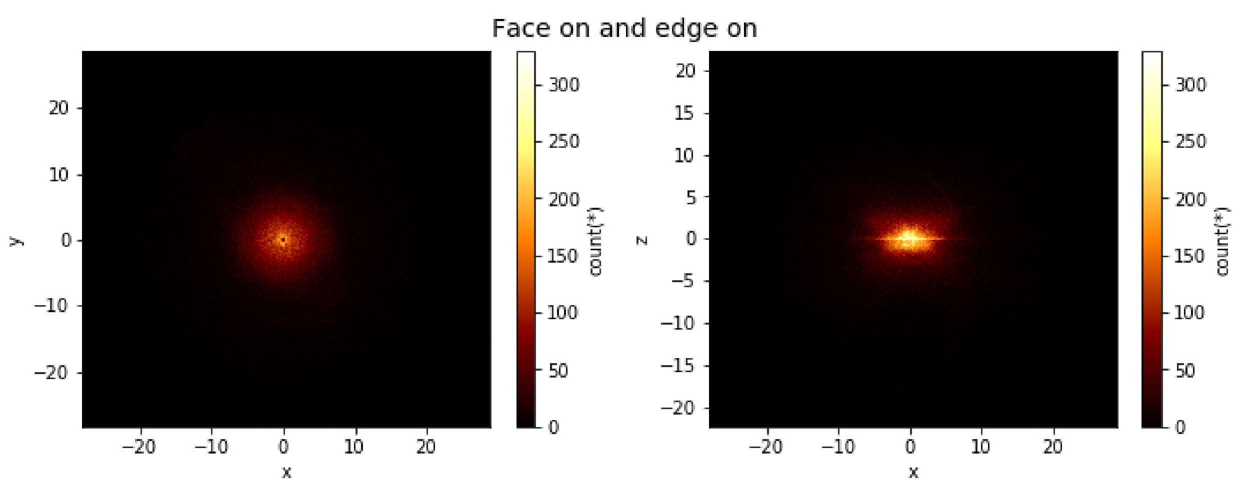


Advanced Plotting

Lets say we would like to see two plots next to eachother. To achieve this we can pass a list of expression pairs.

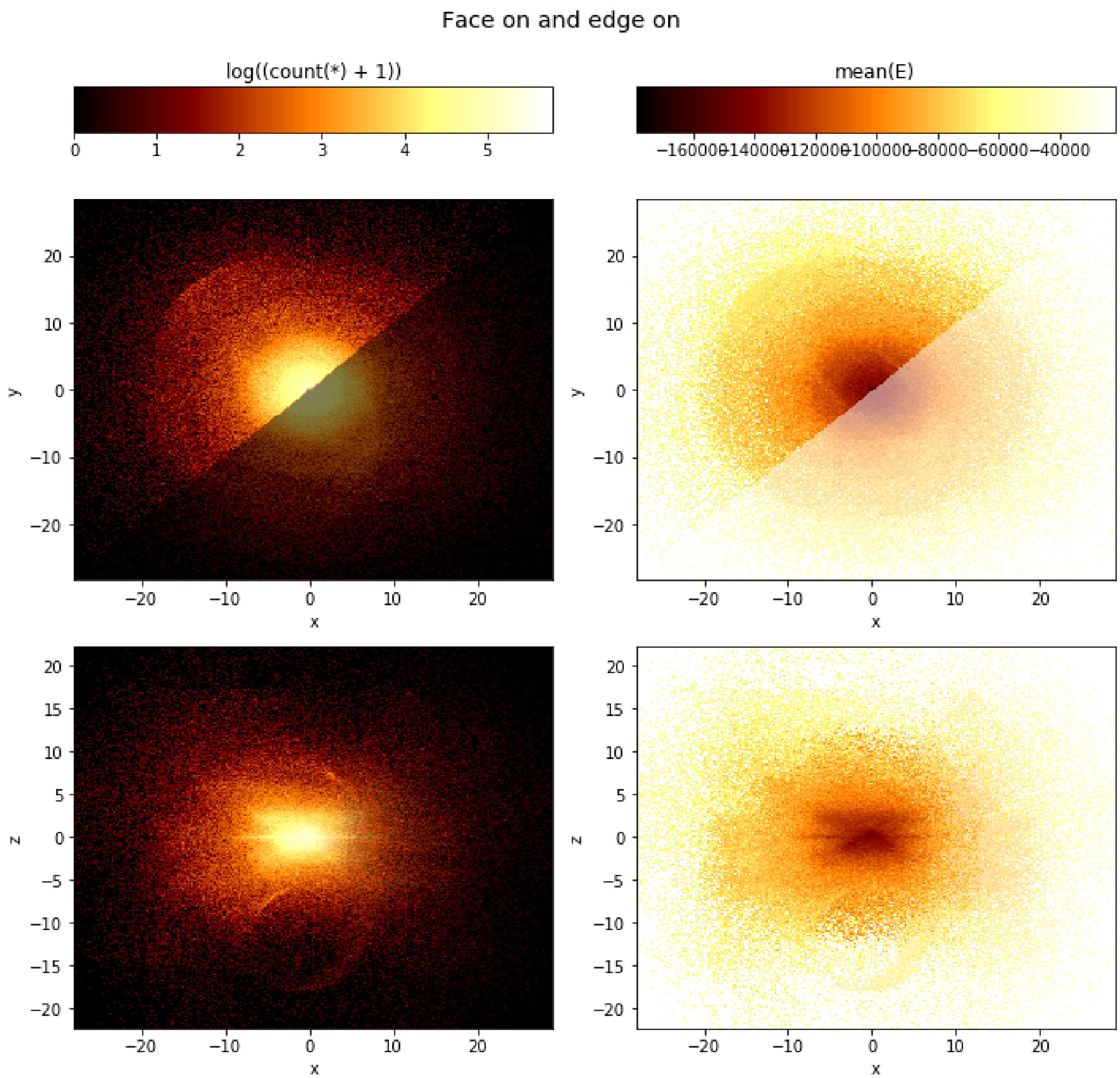
[26]:
```
df.plot([["x", "y"], ["x", "z"]], limits='99.7%',
        title="Face on and edge on", figsize=(10,4));
```

```
/Users/jovan/PyLibrary/vaex/packages/vaex-core/vaex/viz/mpl.py:779:␣
↪MatplotlibDeprecationWarning: Adding an axes using the same arguments as a previous␣
↪axes currently reuses the earlier instance.  In a future version, a new instance␣
↪will always be created and returned.  Meanwhile, this warning can be suppressed,␣
↪and the future behavior ensured, by passing a unique label to each axes instance.
  ax = pylab.subplot(gs[row_offset + row * row_scale:row_offset + (row + 1) * row_
↪scale, column * column_scale:(column + 1) * column_scale])
```



By default, if you have multiple plots, they are shown as columns, multiple selections are overplotted, and multiple 'whats' (statistics) are shown as rows.

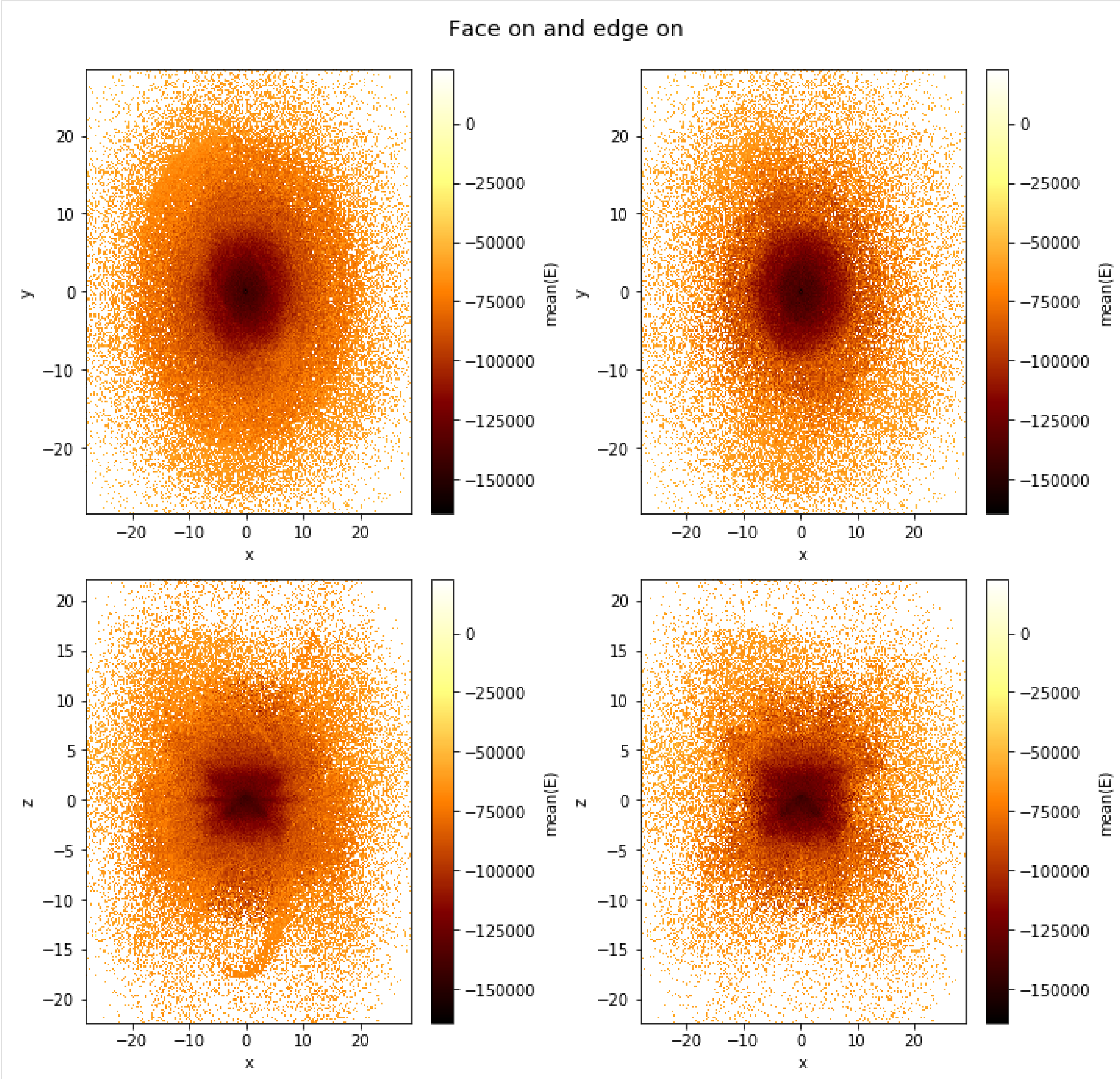
```
[27]: df.plot([["x", "y"], ["x", "z"]],
              limits='99.7%',
              what=[np.log(vaex.stat.count()+1), vaex.stat.mean(df.E)],
              selection=[None, df.x < df.y],
              title="Face on and edge on", figsize=(10,10));
```



Note that the selection has no effect in the bottom rows.

However, this behaviour can be changed using the `visual` argument.

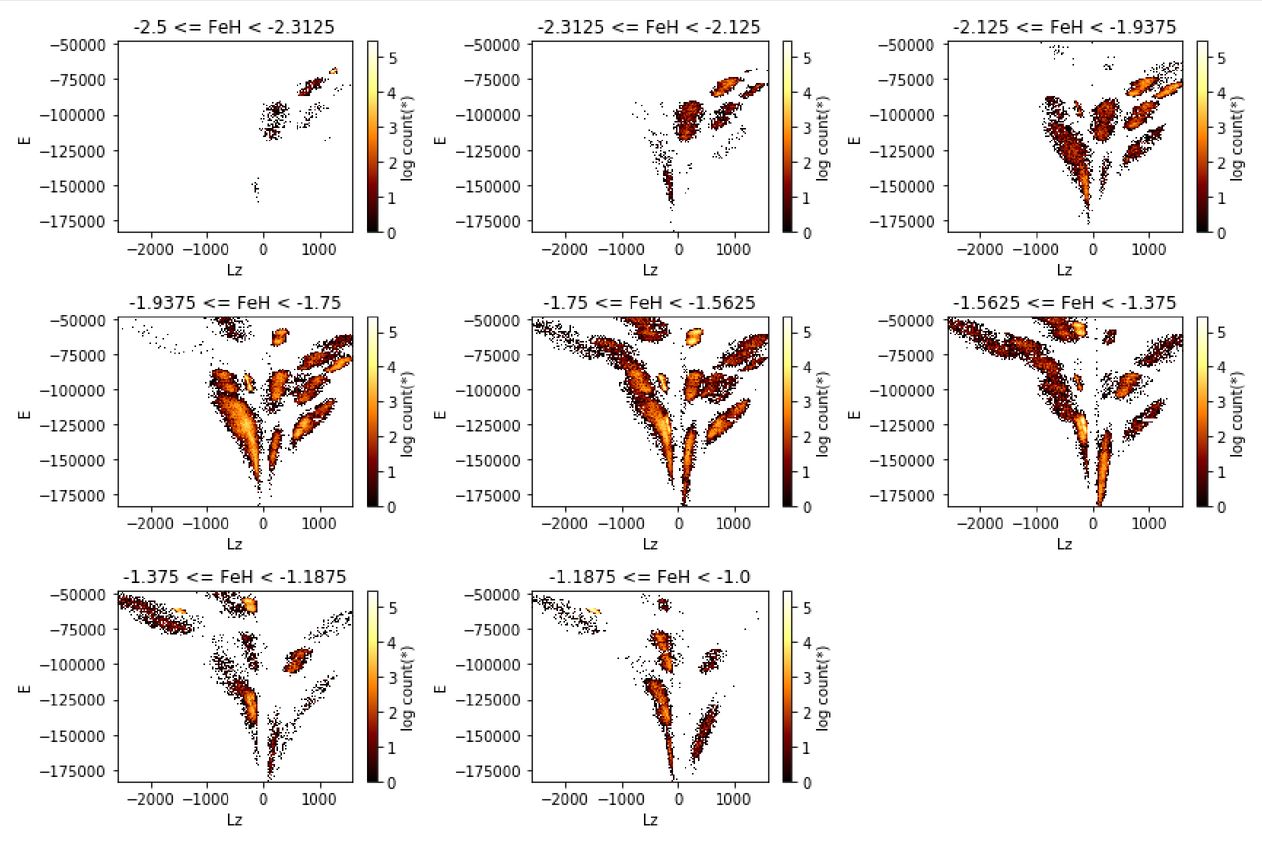
```
[28]: df.plot([["x", "y"], ["x", "z"]],
              limits='99.7%',
              what=vaex.stat.mean(df.E),
              selection=[None, df.Lz < 0],
              visual=dict(column='selection'),
              title="Face on and edge on", figsize=(10,10));
```



Slices in a 3rd dimension

If a 3rd axis (z) is given, you can 'slice' through the data, displaying the z slices as rows. Note that here the rows are wrapped, which can be changed using the `wrap_columns` argument.

[29]:
```
df.plot("Lz", "E",
        limits='99.7%',
        z="FeH:-2.5,-1,8", show=True, visual=dict(row="z"),
        figsize=(12,8), f="log", wrap_columns=3);
```

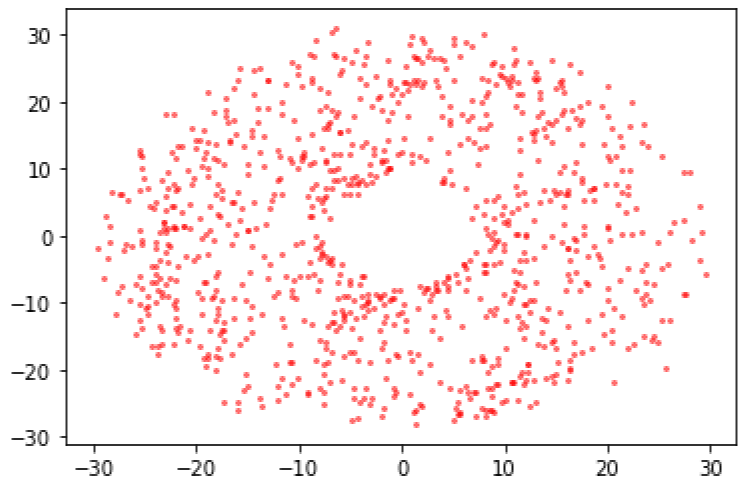


Visualization of smaller datasets

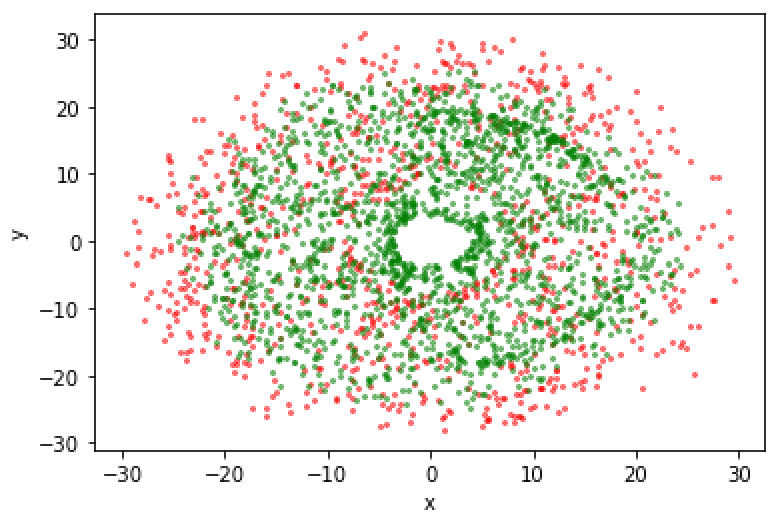
Although Vaex focuses on large datasets, sometimes you end up with a fraction of the data (e.g. due to a selection) and you want to make a scatter plot. You can do so with the following approach:

[30]:
```
import vaex
df = vaex.example()
```

[31]:
```
import matplotlib.pylab as plt
x = df.evaluate("x", selection=df.Lz < -2500)
y = df.evaluate("y", selection=df.Lz < -2500)
plt.scatter(x, y, c="red", alpha=0.5, s=4);
```




```
[32]: df.scatter(df.x, df.y, selection=df.Lz < -2500, c="red", alpha=0.5, s=4)
      df.scatter(df.x, df.y, selection=df.Lz > 1500, c="green", alpha=0.5, s=4);
```



In control

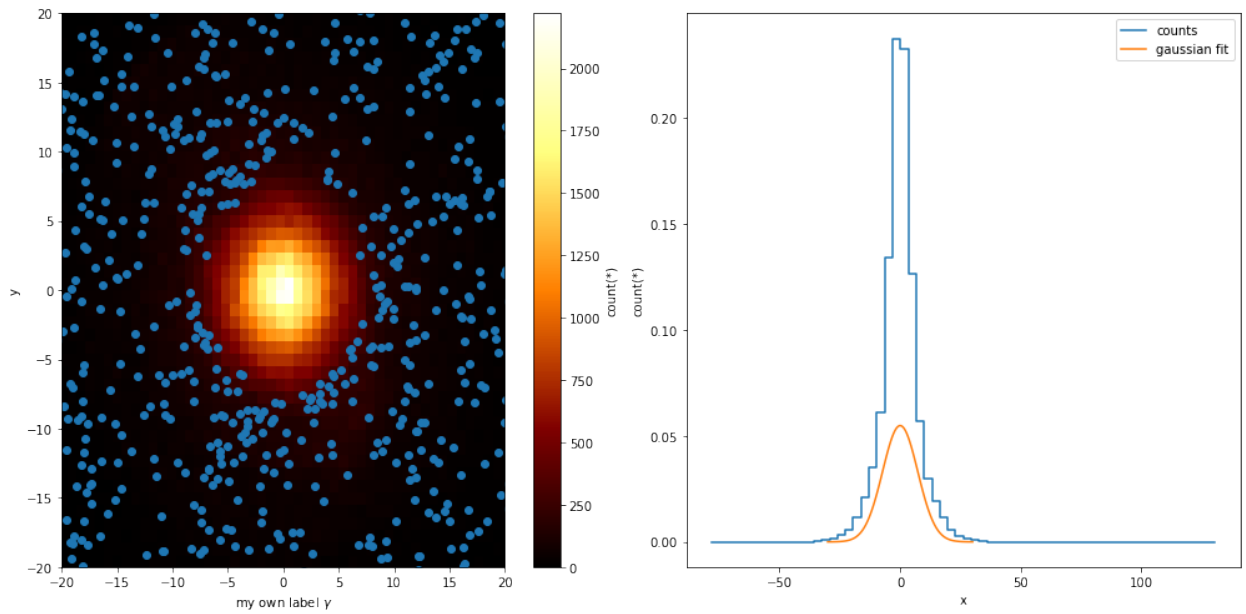
While Vaex provides a wrapper for Matplotlib, there are situations where you want to use the *DataFrame.plot* method, but want to be in control of the plot. Vaex simply uses the current figure and axes objects, so that it is easy to do.

```
[33]: fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(14,7))
      plt.sca(ax1)
      selection = df.Lz < -2500
      x = df[selection].x.evaluate()#selection=selection)
      y = df[selection].y.evaluate()#selection=selection)
      df.plot(df.x, df.y)
      plt.scatter(x, y)
      plt.xlabel('my own label $\gamma$')
      plt.xlim(-20, 20)
      plt.ylim(-20, 20)
```

(continues on next page)

(continued from previous page)

```
plt.sca(ax2)
df.plot1d(df.x, label='counts', n=True)
x = np.linspace(-30, 30, 100)
std = df.std(df.x.expression)
y = np.exp(-(x**2/std**2/2)) / np.sqrt(2*np.pi) / std
plt.plot(x, y, label='gaussian fit')
plt.legend()
plt.show()
```



Healpix (Plotting)

Healpix plotting is supported via the healpy package. Vaex does not need special support for healpix, only for plotting, but some helper functions are introduced to make working with healpix easier.

In the following example we will use the TGAS astronomy dataset.

To understand healpix better, we will start from the beginning. If we want to make a density sky plot, we would like to pass healpy a 1D Numpy array where each value represents the density at a location of the sphere, where the location is determined by the array size (the healpix level) and the offset (the location). The TGAS (and Gaia) data includes the healpix index encoded in the `source_id`. By diving the `source_id` by 34359738368 you get a healpix index level 12, and diving it further will take you to lower levels.

[34]:
```
import vaex
import healpy as hp
tgas = vaex.datasets.tgas.fetch()
```

We will start showing how you could manually do statistics on healpix bins using `vaex.count`. We will do a really course healpix scheme (level 2).

[35]:
```
level = 2
factor = 34359738368 * (4**(12-level))
nmax = hp.nside2npix(2**level)
epsilon = 1e-16
```

(continues on next page)

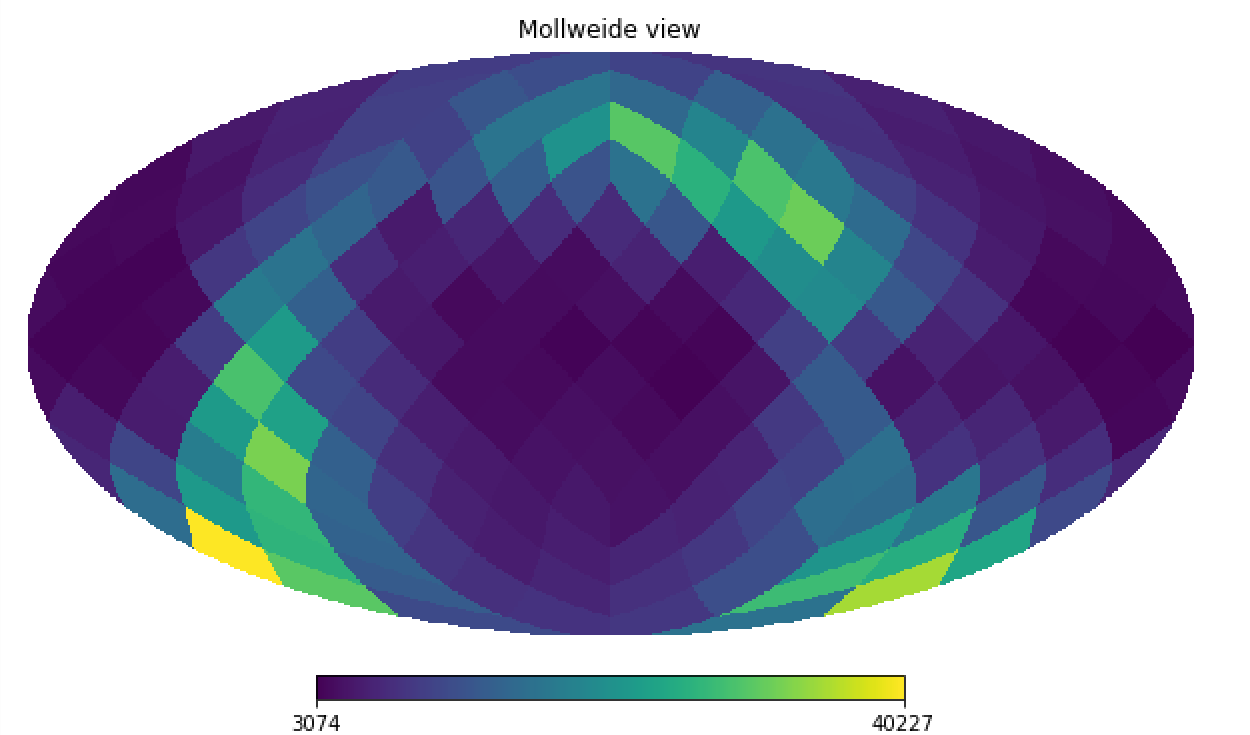
(continued from previous page)

```
counts = tgas.count(binby=tgas.source_id/factor, limits=[-epsilon, nmax-epsilon],␣
↪shape=nmax)
counts
```

```
[35]: array([ 4021,  6171,  5318,  7114,  5755, 13420, 12711, 10193,  7782,
             14187, 12578, 22038, 17313, 13064, 17298, 11887,  3859,  3488,
              9036,  5533,  4007,  3899,  4884,  5664, 10741,  7678, 12092,
             10182,  6652,  6793, 10117,  9614,  3727,  5849,  4028,  5505,
              8462, 10059,  6581,  8282,  4757,  5116,  4578,  5452,  6023,
              8340,  6440,  8623,  7308,  6197, 21271, 23176, 12975, 17138,
             26783, 30575, 31931, 29697, 17986, 16987, 19802, 15632, 14273,
             10594,  4807,  4551,  4028,  4357,  4067,  4206,  3505,  4137,
              3311,  3582,  3586,  4218,  4529,  4360,  6767,  7579, 14462,
             24291, 10638, 11250, 29619,  9678, 23322, 18205,  7625,  9891,
              5423,  5808, 14438, 17251,  7833, 15226,  7123,  3708,  6135,
              4110,  3587,  3222,  3074,  3941,  3846,  3402,  3564,  3425,
              4125,  4026,  3689,  4084, 16617, 13577,  6911,  4837, 13553,
             10074,  9534, 20824,  4976,  6707,  5396,  8366, 13494, 19766,
             11012, 16130,  8521,  8245,  6871,  5977,  8789, 10016,  6517,
              8019,  6122,  5465,  5414,  4934,  5788,  6139,  4310,  4144,
             11437, 30731, 13741, 27285, 40227, 16320, 23039, 10812, 14686,
             27690, 15155, 32701, 18780,  5895, 23348,  6081, 17050, 28498,
             35232, 26223, 22341, 15867, 17688,  8580, 24895, 13027, 11223,
              7880,  8386,  6988,  5815,  4717,  9088,  8283, 12059,  9161,
              6952,  4914,  6652,  4666, 12014, 10703, 16518, 10270,  6724,
              4553,  9282,  4981])
```

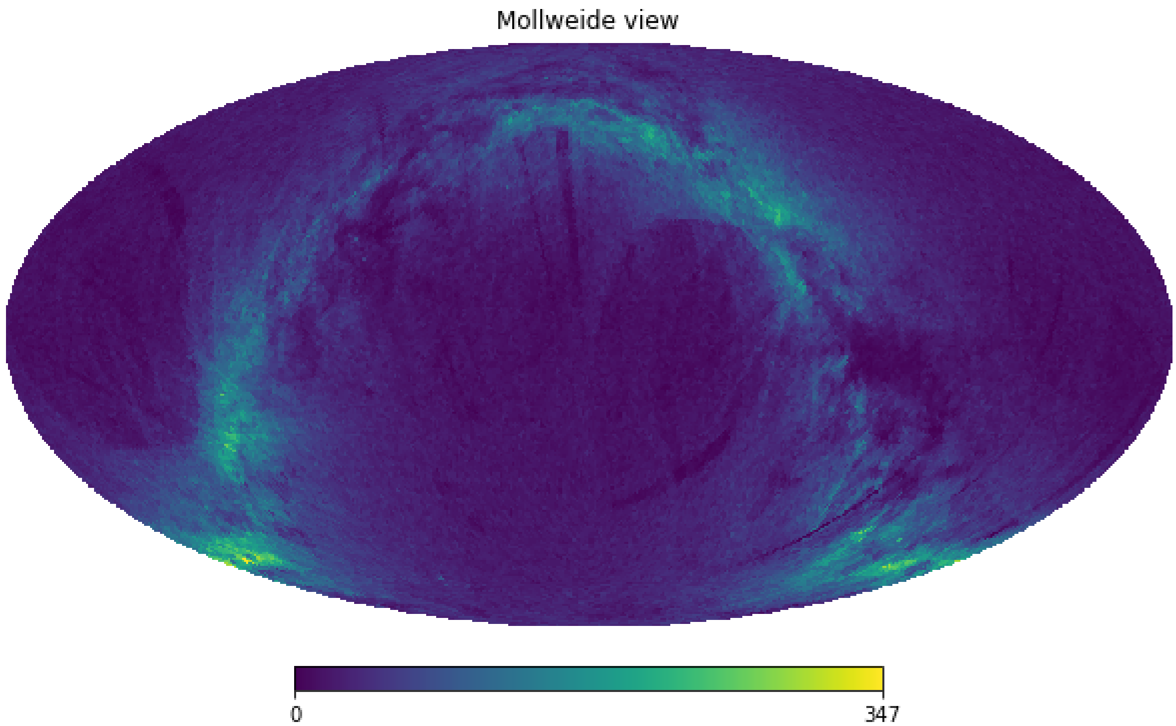
And using healpy's mollview we can visualize this.

```
[36]: hp.mollview(counts, nest=True)
```



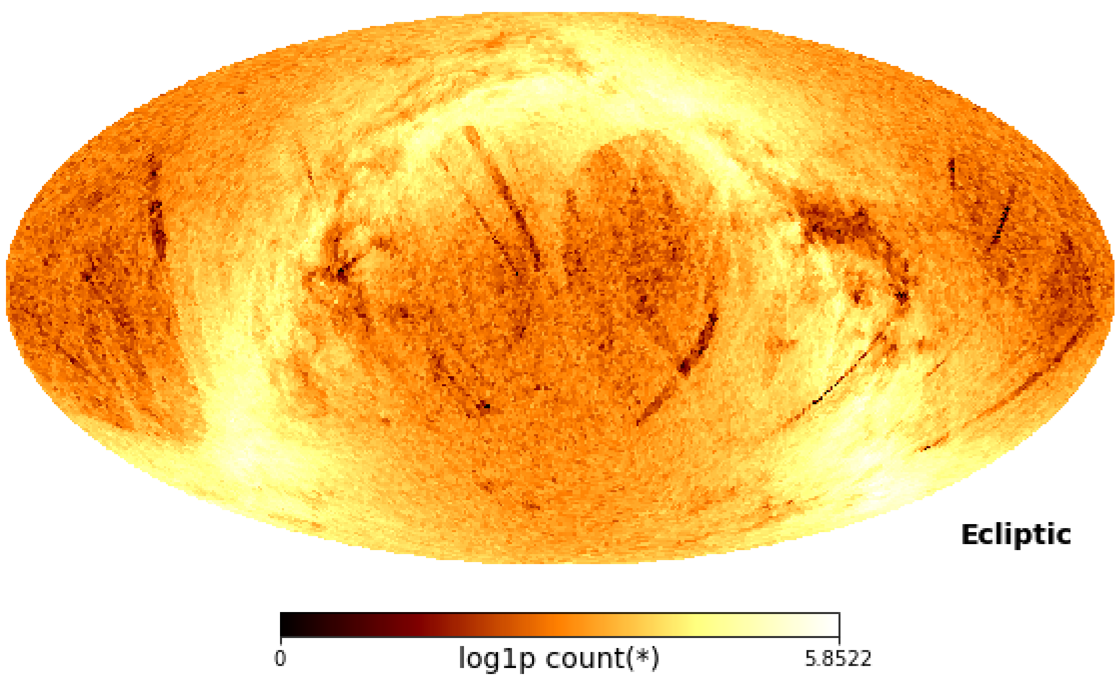
To simplify life, Vaex includes *DataFrame.healpix_count* to take care of this.

[37]:
```
counts = tgas.healpix_count(healpix_level=6)
hp.mollview(counts, nest=True)
```



Or even simpler, use *DataFrame.healpix_plot*

[38]:
```
tgas.healpix_plot(f="log1p", healpix_level=6, figsize=(10,8),
                  healpix_output="ecliptic")
```



4.1.5 xarray suppport

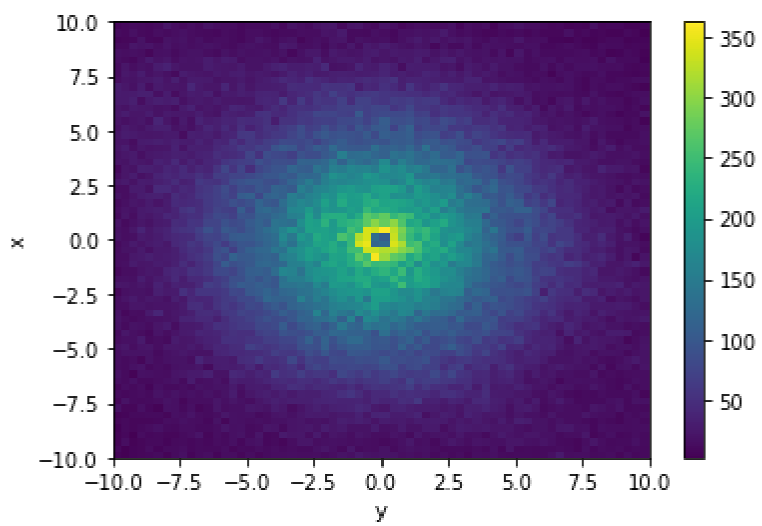
The `df.count` method can also return an xarray data array instead of a numpy array. This is easily done via the `array_type` keyword. Building on top of numpy, xarray adds dimension labels, coordinates and attributes, that makes working with multi-dimensional arrays more convenient.

[39]:
```
xarr = df.count(binby=[df.x, df.y], limits=[-10, 10], shape=64, array_type='xarray')
xarr
```

[39]:
```
<xarray.DataArray (x: 64, y: 64)>
array([[ 6,  3,  7, ..., 15, 10, 11],
       [10,  3,  7, ..., 10, 13, 11],
       [ 5, 15,  5, ..., 12, 18, 12],
       ...,
       [ 7,  8, 10, ...,  6,  7,  7],
       [12, 10, 17, ..., 11,  8,  2],
       [ 7, 10, 13, ...,  6,  5,  7]])
Coordinates:
  * x        (x) float64 -9.844 -9.531 -9.219 -8.906 ... 8.906 9.219 9.531 9.844
  * y        (y) float64 -9.844 -9.531 -9.219 -8.906 ... 8.906 9.219 9.531 9.844
```

In addition, xarray also has a plotting method that can be quite convenient. Since the xarray object has information about the labels of each dimension, the plot axis will be automatially labeled.

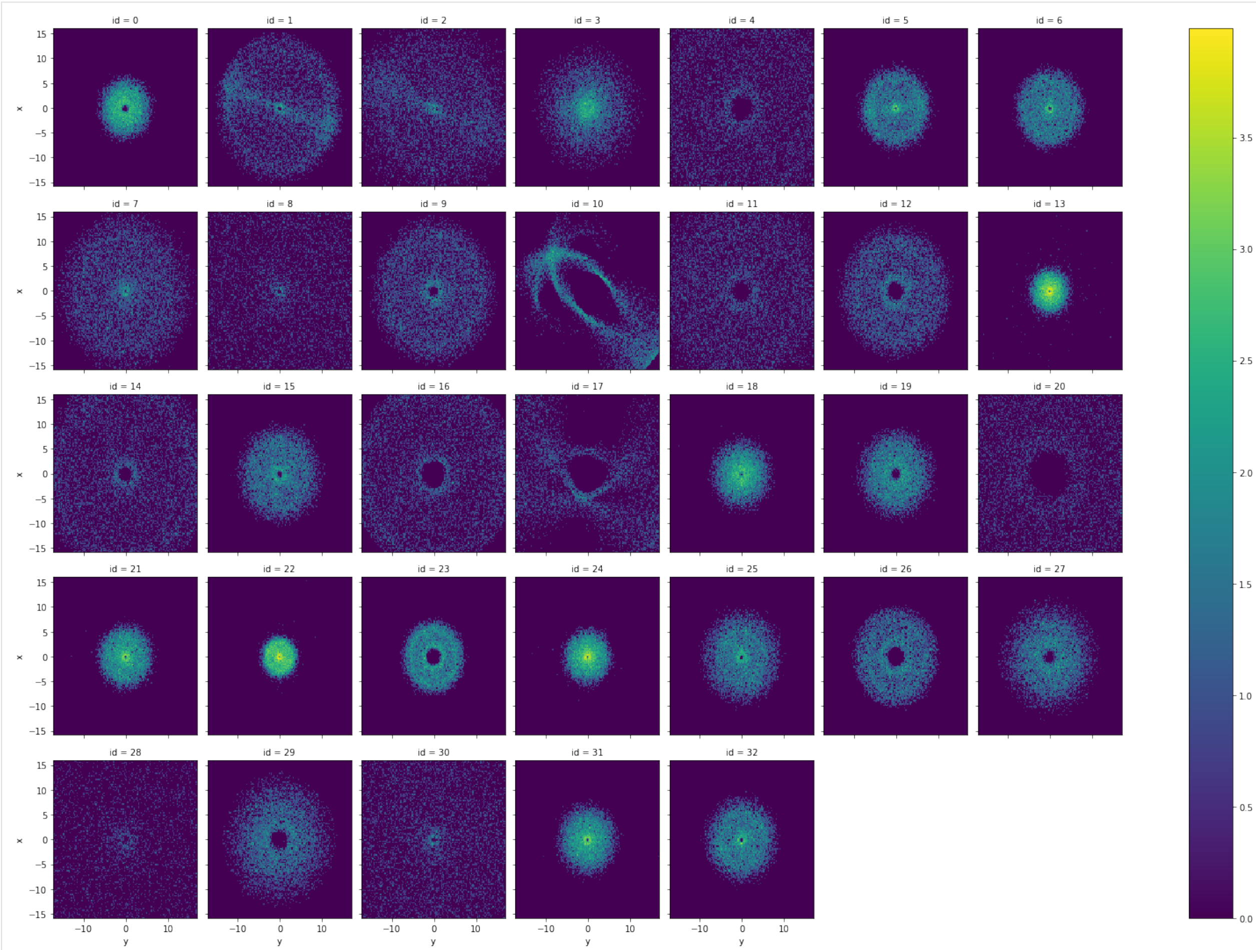
[40]:
```
xarr.plot();
```



Having xarray as output helps us to explore the contents of our data faster. In the following example we show how easy it is to plot the 2D distribution of the positions of the samples (x, y), per id group.

Notice how xarray automatically adds the appropriate titles and axis labels to the figure.

[41]:
```
df.categorize('id', inplace=True)  # treat the id as a categorical column -␣
↪automatically adjusts limits and shape
xarr = df.count(binby=['x', 'y', 'id'], limits='95%', array_type='xarray')
np.log1p(xarr).plot(col='id', col_wrap=7);
```



4.1.6 Interactive widgets

Note: The interactive widgets require a running Python kernel, if you are viewing this documentation online you can get a feeling for what the widgets can do, but computation will not be possible!

Using the `vaex-jupyter` package, we get access to interactive widgets (go see the *Vaex Jupyter tutorial* for a more in depth tutorial)

[42]:
```
import vaex
import vaex.jupyter
import numpy as np
import pylab as plt
df = vaex.example()
```

The simplest way to get a more interactive visualization (or even print out statistics) is to use the `vaex.jupyter.interactive_selection` decorator, which will execute the decorated function each time the selection is changed.

[43]:
```
df.select(df.x > 0)
@vaex.jupyter.interactive_selection(df)
```

(continues on next page)

(continued from previous page)

```
def plot(*args, **kwargs):
    print("Mean x for the selection is:", df.mean(df.x, selection=True))
    df.plot(df.x, df.y, what=np.log(vaex.stat.count()+1), selection=[None, True],␣
↪limits='99.7%')
    plt.show()
```

```
Output()
```

After changing the selection programmatically, the visualization will update, as well as the print output.

[44]:
```
df.select(df.x > df.y)
```

However, to get truly interactive visualization, we need to use widgets, such as the bqplot library. Again, if we make a selection here, the above visualization will also update, so lets select a square region.

See more interactive widgets in the *Vaex Jupyter tutorial*

4.1.7 Joining

Joining in Vaex is similar to Pandas, except the data will no be copied. Internally an index array is kept for each row on the left DataFrame, pointing to the right DataFrame, requiring about 8GB for a billion row 10^9 dataset. Lets start with 2 small DataFrames, `df1` and `df2`:

[47]:
```
a = np.array(['a', 'b', 'c'])
x = np.arange(1,4)
df1 = vaex.from_arrays(a=a, x=x)
df1
```

[47]:

#	a	x
0	a	1
1	b	2
2	c	3

[48]:
```
b = np.array(['a', 'b', 'd'])
y = x**2
df2 = vaex.from_arrays(b=b, y=y)
df2
```

[48]:

#	b	y
0	a	1
1	b	4
2	d	9

The default join, is a 'left' join, where all rows for the left DataFrame (`df1`) are kept, and matching rows of the right DataFrame (`df2`) are added. We see that for the columns b and y, some values are missing, as expected.

[49]:
```
df1.join(df2, left_on='a', right_on='b')
```

[49]:

#	a	x	b	y
0	a	1	a	1
1	b	2	b	4
2	c	3	--	--

A 'right' join, is basically the same, but now the roles of the left and right label swapped, so now we have some values from columns x and a missing.

[50]:
```
df1.join(df2, left_on='a', right_on='b', how='right')
```

[50]:

#	b	y	a	x
0	a	1	a	1
1	b	4	b	2
2	d	9	--	--

We can also do 'inner' join, in which the output DataFrame has only the rows common between `df1` and `df2`.

[51]:
```
df1.join(df2, left_on='a', right_on='b', how='inner')
```

[51]:

#	a	x	b	y
0	a	1	a	1
1	b	2	b	4

Other joins (e.g. outer) are currently not supported. Feel free to open an issue on GitHub for this.

4.1.8 Group-by

With Vaex one can also do fast group-by aggregations. The output is Vaex DataFrame. Let us see few examples.

[52]:
```
import vaex
animal = ['dog', 'dog', 'cat', 'guinea pig', 'guinea pig', 'dog']
age = [2, 1, 5, 1, 3, 7]
cuteness = [9, 10, 5, 8, 4, 8]
df_pets = vaex.from_arrays(animal=animal, age=age, cuteness=cuteness)
df_pets
```

[52]:

#	animal	age	cuteness
0	dog	2	9
1	dog	1	10
2	cat	5	5
3	guinea pig	1	8
4	guinea pig	3	4
5	dog	7	8

The syntax for doing group-by operations is virtually identical to that of Pandas. Note that when multiple aggregations are passed to a single column or expression, the output colums are appropriately named.

[53]:
```
df_pets.groupby(by='animal').agg({'age': 'mean',
                                  'cuteness': ['mean', 'std']})
```

[53]:

#	animal	age	cuteness_mean	cuteness_std
0	dog	3.33333	9	0.816497
1	cat	5	5	0
2	guinea pig	2	6	2

Vaex supports a number of aggregation functions:

- vaex.agg.count: Number of elements in a group
- vaex.agg.first: The first element in a group
- vaex.agg.max: The largest value in a group
- vaex.agg.min: The smallest value in a group
- vaex.agg.sum: The sum of a group
- vaex.agg.mean: The mean value of a group

- vaex.agg.std: The standard deviation of a group
- vaex.agg.var: The variance of a group
- vaex.agg.nunique: Number of unique elements in a group

In addition, we can specify the aggregation operations inside the groupby-method. Also we can name the resulting aggregate columns as we wish.

[54]:
```
df_pets.groupby(by='animal',
                agg={'mean_age': vaex.agg.mean('age'),
                     'cuteness_unique_values': vaex.agg.nunique('cuteness'),
                     'cuteness_unique_min': vaex.agg.min('cuteness')})
```

[54]:

#	animal	mean_age	cuteness_unique_values	cuteness_unique_min
0	dog	3.33333	3	8
1	cat	5	1	5
2	guinea pig	2	2	4

A powerful feature of the aggregation functions in Vaex is that they support selections. This gives us the flexibility to make selections while aggregating. For example, let's calculate the mean cuteness of the pets in this example DataFrame, but separated by age.

[55]:
```
df_pets.groupby(by='animal',
                agg={'mean_cuteness_old': vaex.agg.mean('cuteness', selection='age>=5
↪'),
                     'mean_cuteness_young': vaex.agg.mean('cuteness', selection='~
↪(age>=5)')})
```

[55]:

#	animal	mean_cuteness_old	mean_cuteness_young
0	dog	8	9.5
1	cat	5	nan
2	guinea pig	nan	6

Note that in the last example, the grouped DataFrame contains NaNs for the groups in which there are no samples.

4.1.9 String processing

String processing is similar to Pandas, except all operations are performed lazily, multithreaded, and faster (in C++). Check the *API docs* for more examples.

[56]:
```
import vaex
text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
df = vaex.from_arrays(text=text)
df
```

[56]:

#	text
0	Something
1	very pretty
2	is coming
3	our
4	way.

[57]:
```
df.text.str.upper()
```

[57]:
```
Expression = str_upper(text)
Length: 5 dtype: str (expression)
---------------------------------
0    SOMETHING
```

(continues on next page)

(continued from previous page)

```
1  VERY PRETTY
2    IS COMING
3          OUR
4         WAY.
```

[58]:
```
df.text.str.title().str.replace('et', 'ET')
```

[58]:
```
Expression = str_replace(str_title(text), 'et', 'ET')
Length: 5 dtype: str (expression)
---------------------------------
0    SomEThing
1  Very PrETty
2    Is Coming
3          Our
4         Way.
```

[59]:
```
df.text.str.contains('e')
```

[59]:
```
Expression = str_contains(text, 'e')
Length: 5 dtype: bool (expression)
----------------------------------
0   True
1   True
2  False
3  False
4  False
```

[60]:
```
df.text.str.count('e')
```

[60]:
```
Expression = str_count(text, 'e')
Length: 5 dtype: int64 (expression)
-----------------------------------
0  1
1  2
2  0
3  0
4  0
```

4.1.10 Propagation of uncertainties

In science one often deals with measurement uncertainties (sometimes refererred to as measurement errors). When transformations are made with quantities that have uncertainties associated with them, the uncertainties on these transformed quantities can be calculated automatically by Vaex. Note that propagation of uncertainties requires derivatives and matrix multiplications of lengthy equations, which is not complex, but tedious. Vaex can automatically calculate all dependencies, derivatives and compute the full covariance matrix.

As an example, let us use the TGAS astronomy dataset once again. Even though the TGAS dataset already contains galactic sky coordiantes (l and b), let's add them again by performing a coordinate system rotation from RA. and Dec. We can apply a similar transformation and convert from the Sperical galactic to Cartesian coordinates.

[61]:
```
# convert parallas to distance
tgas.add_virtual_columns_distance_from_parallax(tgas.parallax)
# 'overwrite' the real columns 'l' and 'b' with virtual columns
tgas.add_virtual_columns_eq2gal('ra', 'dec', 'l', 'b')
```

(continues on next page)

(continued from previous page)

```
# and combined with the galactic sky coordinates gives galactic cartesian coordinates␣
↪of the stars
tgas.add_virtual_columns_spherical_to_cartesian(tgas.l, tgas.b, tgas.distance, 'x', 'y
↪', 'z')
```

[61]:

```
#          astrometric_delta_q    astrometric_excess_noise    astrometric_excess_
↪noise_sig    astrometric_n_bad_obs_ac    astrometric_n_bad_obs_al    astrometric_n_
↪good_obs_ac    astrometric_n_good_obs_al    astrometric_n_obs_ac    astrometric_n_
↪obs_al    astrometric_primary_flag    astrometric_priors_used    astrometric_
↪relegation_factor    astrometric_weight_ac    astrometric_weight_al    b            ␣
↪        dec                    dec_error                dec_parallax_corr      dec_pmdec_
↪corr         dec_pmra_corr          duplicated_source    ecl_lat              ecl_
↪lon              hip           l                     matched_observations    parallax ␣
↪          parallax_error        parallax_pmdec_corr    parallax_pmra_corr       phot_
↪g_mean_flux    phot_g_mean_flux_error    phot_g_mean_mag      phot_g_n_obs    phot_
↪variable_flag    pmdec                pmdec_error           pmra                  ␣
↪pmra_error            pmra_pmdec_corr       ra                  ra_dec_corr          ␣
↪  ra_error              ra_parallax_corr      ra_pmdec_corr            ra_pmra_corr     ␣
↪       random_index     ref_epoch    scan_direction_mean_k1    scan_direction_mean_
↪k2    scan_direction_mean_k3    scan_direction_mean_k4    scan_direction_strength_
↪k1    scan_direction_strength_k2    scan_direction_strength_k3    scan_direction_
↪strength_k4    solution_id          source_id            tycho2_id       distance     ␣
↪          x                    y                     z
0          1.9190566539764404     0.7171010000916003         412.6059727233687          ␣
↪        1                         0                           78                     ␣
↪         79                         79                         79                     ␣
↪  84                          3                          2.9360971450805664          ␣
↪      1.2669624084082898e-05   1.818157434463501        -16.121042828114014  0.
↪23539164875137225   0.21880220693566088  -0.4073381721973419   0.06065881997346878 ␣
↪ -0.09945132583379745   70                   -16.121052173353853  42.64182504417002␣
↪ 13989         42.641804308626725   9                    6.35295075173405    0.
↪3079103606852086   -0.10195717215538025   -0.0015767893055453897  10312332.
↪172993332  10577.365273118843        7.991377829505826   77              b'NOT_
↪AVAILABLE'      -7.641989988351149   0.08740179334554747  43.75231341609215    0.
↪07054220642640081  0.21467718482017517   45.03433035439128   -0.41497212648391724  ␣
↪0.30598928200282727  0.17996619641780853  -0.08575969189405441    0.
↪15920649468898773    243619          2015.0       -113.76032257080078       21.
↪39291763305664         -41.67839813232422        26.201841354370117        0.
↪3823484778404236            0.5382660627365112            0.3923785090446472        ␣
↪    0.9163063168525696            1635378410781933568  7627862074752         b''      ␣
↪        0.15740717016058217  0.11123604040005637  0.10243667003803988   -0.
↪04370685490397632
1          nan                        0.2534628812968044         47.316290890180255        ␣
↪        2                         0                           55                     ␣
↪         57                         57                         57                     ␣
↪  84                          5                          2.6523141860961914          ␣
↪      3.1600175134371966e-05   12.861557006835938        -16.19302376369384   0.
↪2000676896877873    1.1977893944215496   0.8376259803771973    -0.9756439924240112 ␣
↪ 0.9725773334503174      70                   -16.19303311057312   42.
↪761180489478576  -2147483648  42.76115974936648    8                         3.
↪90032893506844    0.3234880030045522   -0.8537789583206177    0.8397389650344849     ␣
↪  949564.6488279914   1140.173576223928         10.580958718900256  62               ␣
↪b'NOT_AVAILABLE'      -55.10917285969142   2.522928801165149    10.03626300124532   ␣
↪ 4.611413518289133    -0.9963987469673157   45.1650067708984    -0.9959233403205872␣
↪   2.583882288511597    -0.8609106540679932  0.9734798669815063      -0.
↪9724165201187134    487238          2015.0       -156.432861328125        22.
↪76607322692871         -36.23965835571289        22.890602111816406        0.
↪7110026478767395            0.9659702777862549            0.6461148858070374        ␣
↪    0.8671600818634033            1635378410781933568  9277129363072         b'55-28-
↪1'      0.25638863199686845  0.1807701962996959   0.16716755815017084   -0.
↪07500169577305491
```

(continues on next page)

(continued from previous page)

```
2          nan                     0.3989006354041912          221.18496561724646    ␣
↪        4                          1                           57                  ␣
↪         60                          61                       61                   ␣
↪  84                           5                          3.9934017658233643       ␣
↪      2.5633918994572014e-05   5.767529487609863        -16.12335382439265   0.
↪24882543945301736   0.1803264123376257   -0.3918911516664124  -0.19325552880764008␣
↪ 0.08942046016454697    70                    -16.123363170402296  42.69750168007008␣
↪  -2147483648  42.69748094193635    7                         3.1553132200367373  0.
↪2734838183180671   -0.11855248361825943   -0.0418587327003479     817837.6000768564␣
↪  1827.3836759985832        10.743102380434273  60                b'NOT_AVAILABLE'  ␣
↪  -1.602867102186794   1.0352589283446592   2.9322836829569003   1.908644426623371 ␣
↪  -0.9142706990242004   45.08615483797584   -0.1774432212114334    0.
↪2138361631952843   0.30772241950035095  -0.1848166137933731     0.04686680808663368␣
↪   1948952         2015.0       -117.00751495361328         19.772153854370117     ␣
↪-43.108219146728516       26.7157039642334          0.4825277626514435           0.
↪4287584722042084           0.5241528153419495            0.9030616879463196        ␣
↪    1635378410781933568  13297218905216        b'55-1191-1'    0.31692574722846595 ␣
↪0.22376103019475546  0.2064625216744117    -0.08801225918215205
3          nan                     0.4224923646481251          179.98201436339852    ␣
↪        1                          0                           51                  ␣
↪         52                          52                       52                   ␣
↪  84                           5                          4.215157985687256        ␣
↪      2.8672602638835087e-05   5.3608622550964355       -16.118206879297034  0.
↪24821079122833972   0.20095844850181172  -0.33721715211868286  -0.22350119054317474␣
↪ 0.13181143999099731    70                    -16.11821622503516   42.67779093546686␣
↪  -2147483648  42.67777019818556    7                         2.292366835156796   0.
↪2809724206784257   -0.10920235514640808   -0.049440864473581314   602053.4754362862␣
↪  905.8772856344845         11.075682394435745  61                b'NOT_AVAILABLE'  ␣
↪  -18.414912114825732  1.1298513589995536   3.661982345981763    2.065051873379775 ␣
↪  -0.9261773228645325   45.06654155758114   -0.36570677161216736   0.
↪2760390513575931   0.2028782218694687   -0.058928851038217545   -0.
↪050908856093883514  102321          2015.0       -132.42112731933594       22.
↪56928253173828         -38.95445251464844        25.878559112548828        0.
↪4946548640727997           0.6384561061859131            0.5090736746788025        ␣
↪    0.8989177942276001           1635378410781933568  13469017597184       b'55-
↪624-1'      0.43623035574565916  0.30810014040531863  0.2840853806346911    -0.
↪12110624783986161
4          nan                     0.3175001122010629          119.74837853832186    ␣
↪        2                          3                           85                  ␣
↪         84                          87                       87                   ␣
↪  84                           5                          3.2356362342834473       ␣
↪      2.22787512029754e-05     8.080779075622559        -16.055471830750374  0.
↪33504360351532875   0.1701298562030361   -0.43870800733566284  -0.27934885025024414␣
↪ 0.12179157137870789    70                    -16.0554811777948    42.77336987816832␣
↪  -2147483648  42.77334913546197    11                        1.582076960273368   0.
↪2615394689640736   -0.329196035861969     0.10031197965145111     1388122.242048847␣
↪  2826.428866453177         10.168700781271088  96                b'NOT_AVAILABLE'  ␣
↪  -2.379387386351838   0.7106320061478508   0.34080233369502516  1.2204755227890713␣
↪  -0.8336043357849121   45.13603822322069   -0.049052558839321136  0.
↪17069695283376776  0.4714251756668091   -0.1563923954963684     -0.
↪15207625925540924   409284          2015.0       -106.85968017578125       4.
↪452099323272705          -47.8953971862793          26.755468368530273        0.
↪5206537842750549           0.23930974304676056           0.653376579284668         ␣
↪    0.8633849024772644           1635378410781933568  15736760328576       b'55-
↪849-1'      0.6320805024726543   0.44587838095402044  0.41250283253756015   -0.
↪17481316927621393
...        ...                     ...                         ...                   ␣
↪        ...                        ...                         ...                 ␣
↪         ...                         ...                      ...                  ␣
↪   ...                        ...                         ...                      ␣
↪       ...                      ...                      ...                  ...  ␣
↪            ...                     ...                      ...                ...␣
↪               ...                    ...                      ...            ␣
↪...        ...                     ...                      ...                ... ␣
```

(continues on next page)

(continued from previous page)

```
2,057,045  25.898868560791016     0.6508009723190962         172.3136755413185     ␣
↪         0                           0                          54                ␣
↪          54                          54                      54                  ␣
↪  84                          3                          6.386378765106201        ␣
↪       1.8042501324089244e-05   2.2653496265411377       16.006806970347426   -0.
↪42319686025158043  0.24974147639642075  0.00821441039443016   0.2133195698261261 ␣
↪-0.000805279181804508  70                     16.006807041815204   317.0782357688112 ␣
↪ 103561       -42.92178788756781   8                          5.0743069397419776  0.
↪2840892420661878   -0.0308084636926651    -0.03397708386182785    4114975.455725508␣
↪  3447.5776608146016         8.988851940956916   69              b'NOT_AVAILABLE'   ␣
↪  -4.440524133201202   0.04743297901782237  21.970772995655643   0.
↪07846893118669047  0.3920176327228546    314.74170043792924  0.08548042178153992   ␣
↪0.2773321068969684   0.2473779171705246   -0.0006040430744178593  0.
↪11652233451604843    1595738          2015.0       -18.078920364379883       -17.
↪731922149658203       38.27400588989258        27.63787269592285          0.
↪29217642545700073           0.11402469873428345          0.0404343381524086      ␣
↪    0.937016487121582            1635378410781933568  6917488998546378368  b''    ␣
↪        0.19707124773395138  0.13871698568448773  -0.12900211309069443  0.
↪054342703136315784
2,057,046  nan                    0.17407523451856974        28.886549102578012    ␣
↪         0                           2                          54                ␣
↪          52                          54                      54                  ␣
↪  84                          5                          1.9612410068511963       ␣
↪       2.415467497485224e-05    24.774322509765625       16.12926993546893    -0.
↪32497534368232894  0.14823365569199975  0.8842677474021912    -0.9121489524841309 ␣
↪-0.8994856476783752    70                     16.129270018016896   317.0105462544942 ␣
↪ -2147483648  -42.98947742356782   7                          1.6983480817439922  0.
↪7410137777358506   -0.9793509840965271    -0.9959075450897217     1202425.
↪5197785893  871.2480333575235         10.324624601435723  59             b'NOT_
↪AVAILABLE'      -10.401225111268962  1.4016954983272711   -1.2835612990841874  2.
↪7416807292293637   0.980453610420227     314.64381789311193  0.8981446623802185    ␣
↪0.3590974400544809   0.9818224906921387   -0.9802247881889343     -0.
↪9827051162719727    2019553          2015.0       -87.07184600830078        -31.
↪574886322021484       -36.37055206298828       29.130958557128906         0.
↪22651544213294983           0.07730517536401749          0.2675701975822449      ␣
↪    0.9523505568504333           1635378410781933568  6917493705830041600  b'5179-
↪753-1'   0.5888074481016426   0.4137467499267554   -0.38568304807850484  0.
↪16357391078619246
2,057,047  nan                    0.47235246463190794        92.12190417660749     ␣
↪         2                           0                          34                ␣
↪          36                          36                      36                  ␣
↪  84                          5                          4.68601131439209         ␣
↪       2.138371200999245e-05    3.9279115200042725       15.92496896432183    -0.
↪34317732044320387  0.20902981533215972  -0.2000708132982254   0.31042322516441345 ␣
↪-0.3574342727661133    70                     15.924968943694909   317.6408327998631 ␣
↪ -2147483648  -42.359190842094414  6                          6.036938108863445   0.
↪39688014089787665  -0.7275367975234985    -0.25934046506881714    3268640.
↪5253614695  4918.5087736624755        9.238852161621992   51             b'NOT_
↪AVAILABLE'      -27.852344752672245  1.2778575351686428   15.713555906870294   0.
↪9411842746983148   -0.1186852976679802   315.2828795933192   -0.47665935754776     ␣
↪0.4722647631556871   0.704002320766449    -0.77033931016922        0.
↪12704335153102875    788948           2015.0       -21.23501205444336        20.
↪132535934448242        33.55913162231445        26.732301712036133         0.
↪41511622071266174           0.5105549693107605           0.15976844727993011     ␣
↪    0.9333845376968384           1635378410781933568  6917504975824469248  b'5192-
↪877-1'   0.1654688621402263   0.11770477437507047  -0.10732559074953243  0.
↪045449912782963474
```

(continues on next page)

(continued from previous page)

```
2,057,048  nan                    0.3086465263182493          76.66564461310193     ␣
↪        1                           2                           52                 ␣
↪         51                           53                      53                   ␣
↪  84                          5                          3.154139280319214         ␣
↪       1.9043474821955897e-05   9.627826690673828        16.193728871838935   -0.
↪22811360043544882  0.131650037775767    0.3082593083381653    -0.5279345512390137  ␣
↪-0.4065483510494232    70                   16.193728933791913   317.1363617703344 ␣
↪ -2147483648  -42.86366191921117   7                        1.484142306295484   0.
↪34860128377301614  -0.7272516489028931    -0.9375584125518799     4009408.
↪3172682906  1929.9834553649182        9.017069346445364   60               b'NOT_
↪AVAILABLE'      1.8471079057572073   0.7307171627866237   11.352888915160555   1.
↪219847308406543    0.7511345148086548    314.7406481637209   0.41397571563720703   ␣
↪0.19205296641778563  0.7539510726928711   -0.7239754796028137     -0.
↪7911394238471985    868066          2015.0       -89.73970794677734        -25.
↪196216583251953       -35.13546371459961        29.041872024536133        0.
↪21430812776088715           0.06784655898809433           0.2636755108833313       ␣
↪    0.9523414969444275            1635378410781933568  6917517998165066624  b'5179-
↪1401-1'  0.6737898352187435   0.4742760432178817   -0.44016428945980135  0.
↪18791055094922077
2,057,049  nan                    0.4329850465924866          60.789771079095715    ␣
↪        0                           0                           26                 ␣
↪         26                           26                      26                   ␣
↪  84                          5                          4.3140177726745605        ␣
↪       2.7940122890868224e-05   4.742301940917969        16.135962442685898   -0.
↪22130081624351935  0.2686748166142929   -0.46605369448661804  0.30018869042396545  ␣
↪-0.3290684223175049    70                   16.13596246842634    317.3575812619557 ␣
↪ -2147483648  -42.642442417388324  5                        2.680111343641743   0.
↪4507741964825321   -0.689416229724884     -0.1735922396183014     2074338.153903563␣
↪  4136.498086035368          9.732571175024953   31                b'NOT_AVAILABLE'   ␣
↪  3.15173423618292     1.4388911228835037    2.897878776243949    1.0354817855168323␣
↪  -0.21837876737117767  314.960730599014    -0.4467950165271759    0.
↪49182050944792216  0.7087226510047913   -0.8360105156898499      0.2156151533126831 ␣
↪   1736132         2015.0       -63.01319885253906        18.303699493408203       ␣
↪-49.05630111694336        28.76698875427246         0.3929939866065979           0.
↪32352808117866516           0.24211134016513824           0.9409775733947754       ␣
↪    1635378410781933568  6917521537218608640  b'5179-1719-1'  0.3731188267130712  ␣
↪0.2636519673685346   -0.24280110216486334  0.10369630532457579
```

Since RA. and Dec. are in degrees, while ra_error and dec_error are in miliarcseconds, we need put them on the same scale

[62]:
```
tgas['ra_error'] = tgas.ra_error / 1000 / 3600
tgas['dec_error'] = tgas.dec_error / 1000 / 3600
```

We now let Vaex sort out what the covariance matrix is for the Cartesian coordinates x, y, and z. Then take 50 samples from the dataset for visualization.

[63]:
```
tgas.propagate_uncertainties([tgas.x, tgas.y, tgas.z])
tgas_50 = tgas.sample(50, random_state=42)
```

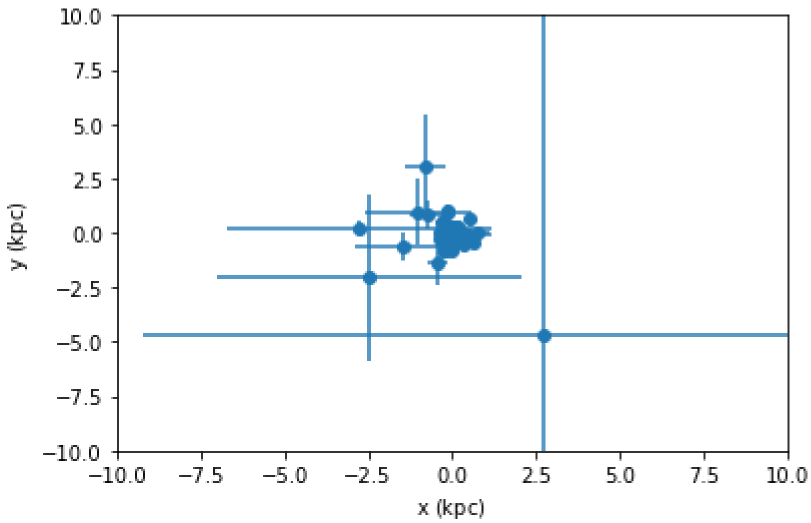
For this small subset of the dataset we can visualize the uncertainties, with and without the covariance.

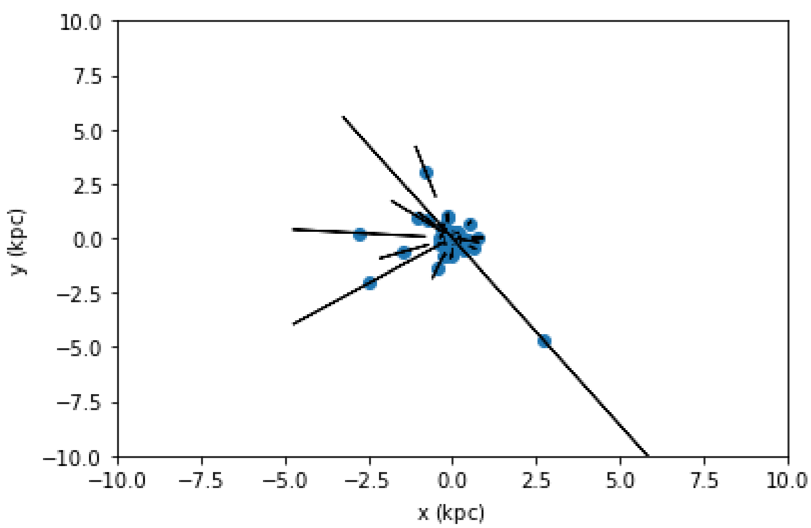
[64]:
```
tgas_50.scatter(tgas_50.x, tgas_50.y, xerr=tgas_50.x_uncertainty, yerr=tgas_50.y_
↪uncertainty)
plt.xlim(-10, 10)
plt.ylim(-10, 10)
```

(continues on next page)

(continued from previous page)

```
plt.show()
tgas_50.scatter(tgas_50.x, tgas_50.y, xerr=tgas_50.x_uncertainty, yerr=tgas_50.y_
↪uncertainty, cov=tgas_50.y_x_covariance)
plt.xlim(-10, 10)
plt.ylim(-10, 10)
plt.show()
```





From the second plot, we see that showing error ellipses (so narrow that they appear as lines) instead of error bars reveal that the distance information dominates the uncertainty in this case.

4.1.11 Just-In-Time compilation

Let us start with a function that calculates the angular distance between two points on a surface of a sphere. The input of the function is a pair of 2 angular coordinates, in radians.

[65]:
```
import vaex
import numpy as np
```

(continues on next page)

(continued from previous page)

```
# From http://pythonhosted.org/pythran/MANUAL.html
def arc_distance(theta_1, phi_1, theta_2, phi_2):
    """
    Calculates the pairwise arc distance
    between all points in vector a and b.
    """
    temp = (np.sin((theta_2-2-theta_1)/2)**2
            + np.cos(theta_1)*np.cos(theta_2) * np.sin((phi_2-phi_1)/2)**2)
    distance_matrix = 2 * np.arctan2(np.sqrt(temp), np.sqrt(1-temp))
    return distance_matrix
```

Let us use the New York Taxi dataset of 2015, *as can be downloaded in hdf5 format*

[66]:
```
# nytaxi = vaex.open('s3://vaex/taxi/yellow_taxi_2009_2015_f32.hdf5?anon=true')
nytaxi = vaex.open('/Users/jovan/Work/vaex-work/vaex-taxi/data/yellow_taxi_2009_2015_
↪f32.hdf5')
# lets use just 20% of the data, since we want to make sure it fits
# into memory (so we don't measure just hdd/ssd speed)
nytaxi.set_active_fraction(0.2)
```

Although the function above expects Numpy arrays, Vaex can pass in columns or expression, which will delay the execution untill it is needed, and add the resulting expression as a virtual column.

[67]:
```
nytaxi['arc_distance'] = arc_distance(nytaxi.pickup_longitude * np.pi/180,
                                      nytaxi.pickup_latitude * np.pi/180,
                                      nytaxi.dropoff_longitude * np.pi/180,
                                      nytaxi.dropoff_latitude * np.pi/180)
```

When we calculate the mean angular distance of a taxi trip, we encounter some invalid data, that will give warnings, which we can safely ignore for this demonstration.

[68]:
```
%%time
nytaxi.mean(nytaxi.arc_distance)
```

```
/Users/jovan/PyLibrary/vaex/packages/vaex-core/vaex/functions.py:121: RuntimeWarning:␣
↪invalid value encountered in sqrt
  return function(*args, **kwargs)
/Users/jovan/PyLibrary/vaex/packages/vaex-core/vaex/functions.py:121: RuntimeWarning:␣
↪invalid value encountered in sin
  return function(*args, **kwargs)
/Users/jovan/PyLibrary/vaex/packages/vaex-core/vaex/functions.py:121: RuntimeWarning:␣
↪invalid value encountered in cos
  return function(*args, **kwargs)
```

```
CPU times: user 44.5 s, sys: 5.03 s, total: 49.5 s
Wall time: 6.14 s
```

[68]:
```
array(1.99993285)
```

This computation uses quite some heavy mathematical operations, and since it's (internally) using Numpy arrays, also uses quite some temporary arrays. We can optimize this calculation by doing a Just-In-Time compilation, based on numba, pythran, or if you happen to have an NVIDIA graphics card cuda. Choose whichever gives the best performance or is easiest to install.

[69]:
```
nytaxi['arc_distance_jit'] = nytaxi.arc_distance.jit_numba()
# nytaxi['arc_distance_jit'] = nytaxi.arc_distance.jit_pythran()
# nytaxi['arc_distance_jit'] = nytaxi.arc_distance.jit_cuda()
```

[70]:
```
%%time
nytaxi.mean(nytaxi.arc_distance_jit)
```

```
/Users/jovan/PyLibrary/vaex/packages/vaex-core/vaex/expression.py:1038:␣
↪RuntimeWarning: invalid value encountered in f
  return self.f(*args, **kwargs)
```

```
CPU times: user 25.7 s, sys: 330 ms, total: 26 s
Wall time: 2.31 s
```

[70]:
```
array(1.9999328)
```

We can get a significant speedup ($\sim 3x$) in this case.

4.1.12 Parallel computations

As mentioned in the sections on selections, Vaex can do computations in parallel. Often this is taken care of, for instance, when passing multiple selections to a method, or multiple arguments to one of the statistical functions. However, sometimes it is difficult or impossible to express a computation in one expression, and we need to resort to doing so called 'delayed' computation, similar as in joblib and dask.

[71]:
```
import vaex
df = vaex.example()
limits = [-10, 10]
delayed_count = df.count(df.E, binby=df.x, limits=limits,
                         shape=4, delay=True)
delayed_count
```

[71]:
```
<vaex.promise.Promise at 0x7ffbd64072d0>
```

Note that now the returned value is now a promise (TODO: a more Pythonic way would be to return a Future). This may be subject to change, and the best way to work with this is to use the *delayed* decorator. And call *DataFrame.execute* when the result is needed.

In addition to the above delayed computation, we schedule more computation, such that both the count and mean are executed in parallel such that we only do a single pass over the data. We schedule the execution of two extra functions using the `vaex.delayed` decorator, and run the whole pipeline using `df.execute()`.

[72]:
```
delayed_sum = df.sum(df.E, binby=df.x, limits=limits,
                         shape=4, delay=True)

@vaex.delayed
def calculate_mean(sums, counts):
    print('calculating mean')
    return sums/counts

print('before calling mean')
# since calculate_mean is decorated with vaex.delayed
# this now also returns a 'delayed' object (a promise)
delayed_mean = calculate_mean(delayed_sum, delayed_count)

# if we'd like to perform operations on that, we can again
# use the same decorator
@vaex.delayed
def print_mean(means):
    print('means', means)
print_mean(delayed_mean)
```

(continues on next page)

(continued from previous page)

```
print('before calling execute')
df.execute()

# Using the .get on the promise will also return the result
# However, this will only work after execute, and may be
# subject to change
means = delayed_mean.get()
print('same means', means)
```

```
before calling mean
before calling execute
calculating mean
means [ -94323.68051598 -118749.23850834 -119119.46292653  -95021.66183457]
same means [ -94323.68051598 -118749.23850834 -119119.46292653  -95021.66183457]
```

4.1.13 Extending Vaex

Vaex can be extended using several mechanisms.

Adding functions

Use the vaex.register_function decorator API to add new functions.

[73]:
```
import vaex
import numpy as np
@vaex.register_function()
def add_one(ar):
    return ar+1
```

The function can be invoked using the `df.func` accessor, to return a new expression. Each argument that is an expresssion, will be replaced by a Numpy array on evaluations in any Vaex context.

[74]:
```
df = vaex.from_arrays(x=np.arange(4))
df.func.add_one(df.x)
```

[74]:
```
Expression = add_one(x)
Length: 4 dtype: int64 (expression)
-----------------------------------
0  1
1  2
2  3
3  4
```

By default (passing `on_expression=True`), the function is also available as a method on Expressions, where the expression itself is automatically set as the first argument (since this is a quite common use case).

[75]:
```
df.x.add_one()
```

[75]:
```
Expression = add_one(x)
Length: 4 dtype: int64 (expression)
-----------------------------------
0  1
1  2
```

(continues on next page)

(continued from previous page)

```
2   3
3   4
```

In case the first argument is not an expression, pass `on_expression=True`, and use `df.func.<funcname>`, to build a new expression using the function:

[76]:
```
@vaex.register_function(on_expression=False)
def addmul(a, b, x, y):
    return a*x + b * y
```

[77]:
```
df = vaex.from_arrays(x=np.arange(4))
df['y'] = df.x**2
df.func.addmul(2, 3, df.x, df.y)
```

[77]:
```
Expression = addmul(2, 3, x, y)
Length: 4 dtype: int64 (expression)
-----------------------------------
0    0
1    5
2   16
3   33
```

These expressions can be added as virtual columns, as expected.

[78]:
```
df = vaex.from_arrays(x=np.arange(4))
df['y'] = df.x**2
df['z'] = df.func.addmul(2, 3, df.x, df.y)
df['w'] = df.x.add_one()
df
```

[78]:

#	x	y	z	w
0	0	0	0	1
1	1	1	5	2
2	2	4	16	3
3	3	9	33	4

Adding DataFrame accessors

When adding methods that operate on Dataframes, it makes sense to group them together in a single namespace.

[79]:
```
@vaex.register_dataframe_accessor('scale', override=True)
class ScalingOps(object):
    def __init__(self, df):
        self.df = df

    def mul(self, a):
        df = self.df.copy()
        for col in df.get_column_names(strings=False):
            if df[col].dtype:
                df[col] = df[col] * a
        return df

    def add(self, a):
        df = self.df.copy()
        for col in df.get_column_names(strings=False):
```

(continues on next page)

(continued from previous page)

```
            if df[col].dtype:
                df[col] = df[col] + a
        return df
```

[80]:
```
df.scale.add(1)
```

[80]:

#	x	y	z	w
0	1	1	1	2
1	2	2	6	3
2	3	5	17	4
3	4	10	34	5

[81]:
```
df.scale.mul(2)
```

[81]:

#	x	y	z	w
0	0	0	0	2
1	2	2	10	4
2	4	8	32	6
3	6	18	66	8

<style> pre white-space: pre-wrap !important; .table-striped > tbody > tr:nth-of-type(odd) background-color: f9f9f9; .table-striped > tbody > tr:nth-of-type(even) background-color: white; .table-striped td, .table-striped th, .table-striped tr border: 1px solid black; border-collapse: collapse; margin: 1em 2em; .rendered$_h tmltd, .rendered_h tmlthtext - align : left; vertical - align : middle; padding : 4px; < /style >$

4.2 Machine Learning with vaex.ml

If you want to try out this notebook with a live Python kernel, use mybinder:

The `vaex.ml` package brings some machine learning algorithms to `vaex`. If you installed the individual subpackages (`vaex-core`, `vaex-hdf5`, …) instead of the `vaex` metapackage, you may need to install it by running `pip install vaex-ml`, or `conda install -c conda-forge vaex-ml`.

The API of `vaex.ml` stays close to that of scikit-learn, while providing better performance and the ability to efficiently perform operations on data that is larger than the available RAM. This page is an overview and a brief introduction to the capabilities offered by `vaex.ml`.

[1]:
```
import vaex
import vaex.ml

import numpy as np
import pylab as plt
```

We will use the well known Iris flower and Titanic passenger list datasets, two classical datasets for machine learning demonstrations.

[2]:
```
df = vaex.ml.datasets.load_iris()
df
```

[2]:

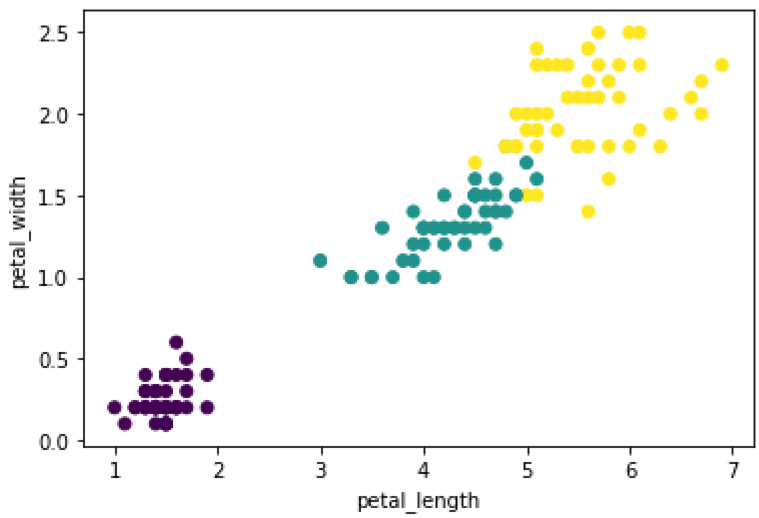
#	sepal_length	sepal_width	petal_length	petal_width	class_
0	5.9	3.0	4.2	1.5	1
1	6.1	3.0	4.6	1.4	1
2	6.6	2.9	4.6	1.3	1

(continues on next page)

(continued from previous page)

```
3    6.7           3.3          5.7           2.1          2
4    5.5           4.2          1.4           0.2          0
...  ...           ...          ...           ...          ...
145  5.2           3.4          1.4           0.2          0
146  5.1           3.8          1.6           0.2          0
147  5.8           2.6          4.0           1.2          1
148  5.7           3.8          1.7           0.3          0
149  6.2           2.9          4.3           1.3          1
```

[3]:
```
df.scatter(df.petal_length, df.petal_width, c_expr=df.class_);
```



4.2.1 Preprocessing: Scaling of numerical features

`vaex.ml` packs the common numerical scalers:

- `vaex.ml.StandardScaler` - Scale features by removing their mean and dividing by their variance;
- `vaex.ml.MinMaxScaler` - Scale features to a given range;
- `vaex.ml.RobustScaler` - Scale features by removing their median and scaling them according to a given percentile range;
- `vaex.ml.MaxAbsScaler` - Scale features by their maximum absolute value.

The usage is quite similar to that of `scikit-learn`, in the sense that each transformer implements the `.fit` and `.transform` methods.

[4]:
```
features = ['petal_length', 'petal_width', 'sepal_length', 'sepal_width']
scaler = vaex.ml.StandardScaler(features=features, prefix='scaled_')
scaler.fit(df)
df_trans = scaler.transform(df)
df_trans
```

[4]:
```
#    sepal_length     sepal_width     petal_length     petal_width     class_     scaled_
↪petal_length      scaled_petal_width       scaled_sepal_length      scaled_sepal_width
0    5.9              3.0             4.2              1.5             1          0.
↪25096730693923325     0.39617188299171285     0.06866179325140277     -0.
↪12495760117130607
```

(continues on next page)

(continued from previous page)

```
1    6.1             3.0            4.6            1.4            1         0.
↪4784301228962429    0.26469891297233916    0.3109975341387059    -0.
↪12495760117130607
2    6.6             2.9            4.6            1.3            1         0.
↪4784301228962429    0.13322594295296575    0.9168368863569659    -0.
↪3563605663033572
3    6.7             3.3            5.7            2.1            2         1.
↪1039528667780207    1.1850097031079545     1.0380047568006185    0.
↪5692512942248463
4    5.5             4.2            1.4            0.2            0         -1.
↪341272404759837     -1.3129767272601438    -0.4160096885232057    2.6518779804133055
...  ...             ...            ...            ...            ...       ...     ␣
↪               ...                 ...                 ...
145  5.2             3.4            1.4            0.2            0         -1.
↪341272404759837     -1.3129767272601438    -0.7795132998541615    0.8006542593568975
146  5.1             3.8            1.6            0.2            0         -1.
↪2275409967813318    -1.3129767272601438    -0.9006811702978141    1.726266119885101
147  5.8             2.6            4.0            1.2            1         0.
↪13723589896072813    0.0017529729335920385  -0.052506077192249874  -1.
↪0505694616995096
148  5.7             3.8            1.7            0.3            0         -1.
↪1706752927920796    -1.18150375724077      -0.17367394763590144   1.726266119885101
149  6.2             2.9            4.3            1.3            1         0.
↪30783301092848553    0.13322594295296575    0.4321654045823586    -0.
↪3563605663033572
```

The output of the `.transform` method of any `vaex.ml` transformer is a *shallow copy* of a DataFrame that contains the resulting features of the transformations in addition to the original columns. A shallow copy means that this new DataFrame just references the original one, and no extra memory is used. In addition, the resulting features, in this case the scaled numerical features are *virtual columns,* which do not take any memory but are computed on the fly when needed. This approach is ideal for working with very large datasets.

Preprocessing: Encoding of categorical features

`vaex.ml` contains several categorical encoders:

- `vaex.ml.LabelEncoder` - Encoding features with as many integers as categories, startinfg from 0;
- `vaex.ml.OneHotEncoder` - Encoding features according to the one-hot scheme;
- `vaex.ml.FrequencyEncoder` - Encode features by the frequency of their respective categories;
- `vaex.ml.BayesianTargetEncoder` - Encode categories with the mean of their target value;
- `vaex.ml.WeightOfEvidenceEncoder` - Encode categories their weight of evidence value.

The following is a quick example using the Titanic dataset.

```
[5]: df =  vaex.ml.datasets.load_titanic()
df.head(5)
```

```
[5]:  #    pclass  survived    name                                              sex      ␣
↪  age     sibsp     parch     ticket     fare   cabin     embarked     boat       body ␣
↪home_dest
  0         1   True        Allen, Miss. Elisabeth Walton                     female ␣
↪29               0         0      24160  211.338   B5        S            2          nan ␣
↪St Louis, MO
  1         1   True        Allison, Master. Hudson Trevor                    male    ␣
↪0.9167          1          2      113781   151.55    C22 C26   S           11         nan ␣
↪Montreal, PQ / Chesterville, ON
```

(continues on next page)

(continued from previous page)

```
 2          1  False       Allison, Miss. Helen Loraine                        female  ␣
↪2           1         2     113781  151.55   C22 C26  S            None       nan ␣
↪Montreal, PQ / Chesterville, ON
 3          1  False       Allison, Mr. Hudson Joshua Creighton                male   ␣
↪30           1         2     113781  151.55   C22 C26  S            None       135 ␣
↪Montreal, PQ / Chesterville, ON
 4          1  False       Allison, Mrs. Hudson J C (Bessie Waldo Daniels)  female ␣
↪25           1         2     113781  151.55   C22 C26  S            None       nan ␣
↪Montreal, PQ / Chesterville, ON
```

[6]:
```
label_encoder = vaex.ml.LabelEncoder(features=['embarked'])
one_hot_encoder = vaex.ml.OneHotEncoder(features=['pclass'])
freq_encoder = vaex.ml.FrequencyEncoder(features=['home_dest'])

df = label_encoder.fit_transform(df)
df = one_hot_encoder.fit_transform(df)
df = freq_encoder.fit_transform(df)

df.head(5)
```

[6]:
```
 #    pclass  survived    name                                             sex     ␣
↪  age    sibsp    parch    ticket     fare  cabin    embarked    boat      body ␣
↪home_dest                          label_encoded_embarked    pclass_1    pclass_2  ␣
↪ pclass_3    frequency_encoded_home_dest
 0          1  True        Allen, Miss. Elisabeth Walton                       female ␣
↪29           0         0      24160  211.338  B5       S            2          nan ␣
↪St Louis, MO                                                  1           1           0  ␣
↪        0                    0.00305577
 1          1  True        Allison, Master. Hudson Trevor                      male    ␣
↪0.9167        1         2     113781  151.55   C22 C26  S           11         nan ␣
↪Montreal, PQ / Chesterville, ON                              1           1           0  ␣
↪        0                    0.00305577
 2          1  False       Allison, Miss. Helen Loraine                        female  ␣
↪2           1         2     113781  151.55   C22 C26  S            None       nan ␣
↪Montreal, PQ / Chesterville, ON                              1           1           0  ␣
↪        0                    0.00305577
 3          1  False       Allison, Mr. Hudson Joshua Creighton                male   ␣
↪30           1         2     113781  151.55   C22 C26  S            None       135 ␣
↪Montreal, PQ / Chesterville, ON                              1           1           0  ␣
↪        0                    0.00305577
 4          1  False       Allison, Mrs. Hudson J C (Bessie Waldo Daniels)  female ␣
↪25           1         2     113781  151.55   C22 C26  S            None       nan ␣
↪Montreal, PQ / Chesterville, ON                              1           1           0  ␣
↪        0                    0.00305577
```

Notice that the transformed features are all included in the resulting DataFrame and are appropriately named. This is excellent for the construction of various diagnostic plots, and engineering of more complex features. The fact that the resulting (encoded) features take no memory, allows one to try out or combine a variety of preprocessing steps without spending any extra memory.

4.2.2 Dimensionality reduction

Principal Component Analysis

The PCA implemented in `vaex.ml` can scale to a very large number of samples, even if that data we want to transform does not fit into RAM. To demonstrate this, let us do a PCA transformation on the Iris dataset. For this example, we have replicated this dataset thousands of times, such that it contains over **1 billion** samples.

[7]:
```
df = vaex.ml.datasets.load_iris_1e9()
n_samples = len(df)
print(f'Number of samples in DataFrame: {n_samples:,}')
```

```
Number of samples in DataFrame: 1,005,000,000
```

[8]:
```
features = ['petal_length', 'petal_width', 'sepal_length', 'sepal_width']
pca = vaex.ml.PCA(features=features, n_components=4, progress=True)
pca.fit(df)
```

```
[########################################] 100.00% elapsed time  :    25.39s =  0.4m␣
↪=  0.0h
[########################################] 100.00% elapsed time  :    21.16s =  0.4m␣
↪=  0.0h
```

The PCA transformer implemented in `vaex.ml` can be fit in well under a minute, even when the data comprises 4 columns and 1 billion rows.

[9]:
```
df_trans = pca.transform(df)
df_trans
```

[9]:
```
#              sepal_length    sepal_width     petal_length    petal_width     class_  ␣
↪ PCA_0                 PCA_1                  PCA_2                  PCA_3
0              5.9             3.0             4.2             1.5             1       ␣
↪ -0.5110980606779778   0.10228410712350186   0.1323278893222748    -0.
↪05010053509219568
1              6.1             3.0             4.6             1.4             1       ␣
↪ -0.8901604458458314   0.03381244392899576   -0.009768027251340669  0.
↪15344820595853972
2              6.6             2.9             4.6             1.3             1       ␣
↪ -1.0432977815146882   -0.22895691422385436  -0.4148145621997159    0.
↪03752355212469092
3              6.7             3.3             5.7             2.1             2       ␣
↪ -2.275853649499827    -0.33338651939283853  0.28467815929803336    0.
↪062230280587310186
4              5.5             4.2             1.4             0.2             0       ␣
↪ 2.5971594761444177    -1.1000219272349778   0.1635819259153647     0.
↪09895807663018358
...            ...             ...             ...             ...             ...     ␣
↪ ...                   ...                    ...                    ...
1,004,999,995  5.2             3.4             1.4             0.2             0       ␣
↪ 2.639821267772449     -0.31929007064114523  -0.13925337154239886   -0.
↪06514104661032082
1,004,999,996  5.1             3.8             1.6             0.2             0       ␣
↪ 2.537573370562511     -0.5103675440827672   0.17191840827679977    0.
↪19216594922046545
1,004,999,997  5.8             2.6             4.0             1.2             1       ␣
↪ -0.2288790500828927   0.402257616677128     -0.22736271123587368   -0.
↪018620454169007566
1,004,999,998  5.7             3.8             1.7             0.3             0       ␣
↪ 2.199077960400875     -0.8792440918495404   -0.1145214537809282    -0.
↪025326936252885096
```

(continues on next page)

(continued from previous page)

```
1,004,999,999  6.2            2.9            4.3            1.3            1
↪ -0.6416902785957136  -0.019071179119340448  -0.20417287643043353   0.
↪02050967499165212
```

Recall that the transformed DataFrame, which includes the PCA components, takes no extra memory.

4.2.3 Clustering

K-Means

`vaex.ml` implements a fast and scalable K-Means clustering algorithm. The usage is similar to that of `scikit-learn`.

[10]:

```
import vaex.ml.cluster

df = vaex.ml.datasets.load_iris()

features = ['petal_length', 'petal_width', 'sepal_length', 'sepal_width']
kmeans = vaex.ml.cluster.KMeans(features=features, n_clusters=3, max_iter=100,
↪verbose=True, random_state=42)
kmeans.fit(df)

df_trans = kmeans.transform(df)
df_trans
```

```
Iteration    0, inertia  519.0500000000001
Iteration    1, inertia  156.70447116074328
Iteration    2, inertia  88.70688235734133
Iteration    3, inertia  80.23054939305554
Iteration    4, inertia  79.28654263977778
Iteration    5, inertia  78.94084142614601
Iteration    6, inertia  78.94084142614601
```

[10]:

```
#    sepal_length    sepal_width    petal_length    petal_width    class_
↪prediction_kmeans
0    5.9             3.0            4.2             1.5            1         0
1    6.1             3.0            4.6             1.4            1         0
2    6.6             2.9            4.6             1.3            1         0
3    6.7             3.3            5.7             2.1            2         1
4    5.5             4.2            1.4             0.2            0         2
...  ...             ...            ...             ...            ...       ...
145  5.2             3.4            1.4             0.2            0         2
146  5.1             3.8            1.6             0.2            0         2
147  5.8             2.6            4.0             1.2            1         0
148  5.7             3.8            1.7             0.3            0         2
149  6.2             2.9            4.3             1.3            1         0
```

K-Means is an unsupervised algorithm, meaning that the predicted cluster labels in the transformed dataset do not necessarily correspond to the class label. We can map the predicted cluster identifiers to match the class labels, making it easier to construct diagnostic plots.

[11]:

```
df_trans['predicted_kmean_map'] = df_trans.prediction_kmeans.map(mapper={0: 1, 1: 2,
↪2: 0})
df_trans
```

[11]:
```
#    sepal_length    sepal_width    petal_length    petal_width    class_   ␣
↪prediction_kmeans    predicted_kmean_map
0    5.9             3.0            4.2             1.5            1          0       ␣
↪               1
1    6.1             3.0            4.6             1.4            1          0       ␣
↪               1
2    6.6             2.9            4.6             1.3            1          0       ␣
↪               1
3    6.7             3.3            5.7             2.1            2          1       ␣
↪               2
4    5.5             4.2            1.4             0.2            0          2       ␣
↪               0
...  ...             ...            ...             ...            ...        ...     ␣
↪               ...
145  5.2             3.4            1.4             0.2            0          2       ␣
↪               0
146  5.1             3.8            1.6             0.2            0          2       ␣
↪               0
147  5.8             2.6            4.0             1.2            1          0       ␣
↪               1
148  5.7             3.8            1.7             0.3            0          2       ␣
↪               0
149  6.2             2.9            4.3             1.3            1          0       ␣
↪               1
```

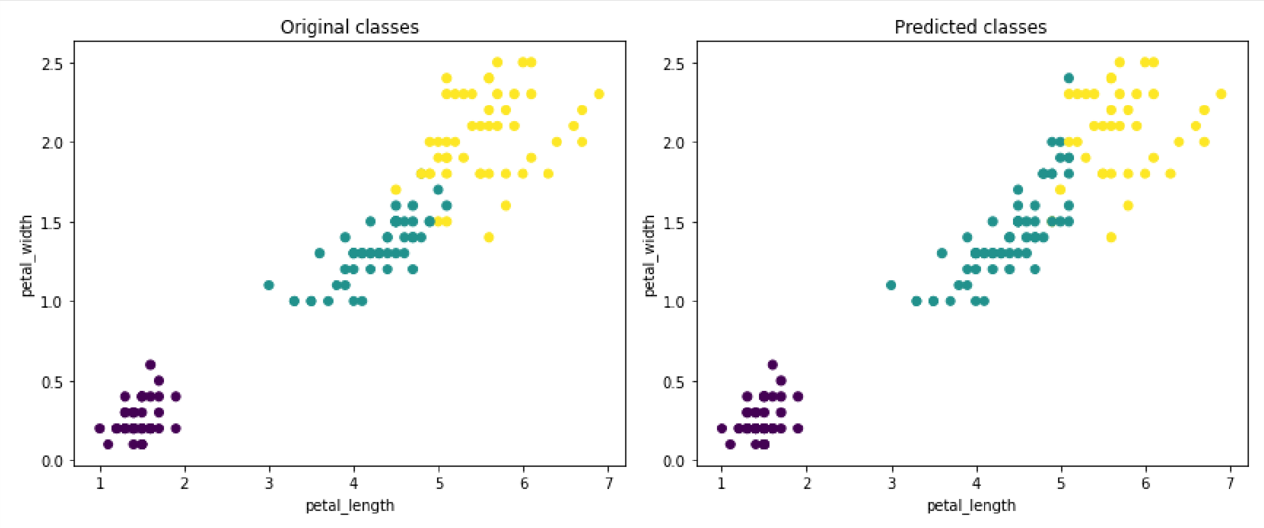
Now we can construct simple scatter plots, and see that in the case of the Iris dataset, K-Means does a pretty good job splitting the data into 3 classes.

[12]:
```
fig = plt.figure(figsize=(12, 5))

plt.subplot(121)
df_trans.scatter(df_trans.petal_length, df_trans.petal_width, c_expr=df_trans.class_)
plt.title('Original classes')

plt.subplot(122)
df_trans.scatter(df_trans.petal_length, df_trans.petal_width, c_expr=df_trans.
↪predicted_kmean_map)
plt.title('Predicted classes')

plt.tight_layout()
plt.show()
```



As with any algorithm implemented in `vaex.ml`, K-Means can be used on billions of samples. Fitting takes **under 2 minutes** when applied on the oversampled Iris dataset, numbering over **1 billion** samples.

```
[13]: df = vaex.ml.datasets.load_iris_1e9()
      n_samples = len(df)
      print(f'Number of samples in DataFrame: {n_samples:,}')
```

```
Number of samples in DataFrame: 1,005,000,000
```

```
[14]: %%time

      features = ['petal_length', 'petal_width', 'sepal_length', 'sepal_width']
      kmeans = vaex.ml.cluster.KMeans(features=features, n_clusters=3, max_iter=100,␣
      ↪verbose=True, random_state=31)
      kmeans.fit(df)
```

```
Iteration    0, inertia  838974000.003719
Iteration    1, inertia  535903134.00030565
Iteration    2, inertia  530190921.4848897
Iteration    3, inertia  528931941.0337245
Iteration    4, inertia  528931941.03372455
CPU times: user 4min 7s, sys: 1min 33s, total: 5min 41s
Wall time: 1min 23s
```

4.2.4 Supervised learning

While `vaex.ml` does not yet implement any supervised machine learning models, it does provide wrappers to several popular libraries such as scikit-learn, XGBoost, LightGBM and CatBoost.

The main benefit of these wrappers is that they turn the models into `vaex.ml` transformers. This means the models become part of the DataFrame *state* and thus can be serialized, and their predictions can be returned as *virtual columns*. This is especially useful for creating various diagnostic plots and evaluating performance metrics at no memory cost, as well as building ensembles.

Scikit-Learn example

The `vaex.ml.sklearn` module provides convenient wrappers to the `scikit-learn` estimators. In fact, these wrappers can be used with any library that follows the API convention established by `scikit-learn`, i.e. implements the `.fit` and `.transform` methods.

Here is an example:

[15]:
```
from vaex.ml.sklearn import Predictor
from sklearn.ensemble import GradientBoostingClassifier

df = vaex.ml.datasets.load_iris()

features = ['petal_length', 'petal_width', 'sepal_length', 'sepal_width']
target = 'class_'

model = GradientBoostingClassifier(random_state=42)
vaex_model = Predictor(features=features, target=target, model=model, prediction_name=
↪'prediction')

vaex_model.fit(df=df)

df = vaex_model.transform(df)
df
```

[15]:
```
#    sepal_length    sepal_width    petal_length    petal_width    class_    ␣
↪prediction
0    5.9             3.0            4.2             1.5            1         1
1    6.1             3.0            4.6             1.4            1         1
2    6.6             2.9            4.6             1.3            1         1
3    6.7             3.3            5.7             2.1            2         2
4    5.5             4.2            1.4             0.2            0         0
...  ...             ...            ...             ...            ...       ...
145  5.2             3.4            1.4             0.2            0         0
146  5.1             3.8            1.6             0.2            0         0
147  5.8             2.6            4.0             1.2            1         1
148  5.7             3.8            1.7             0.3            0         0
149  6.2             2.9            4.3             1.3            1         1
```

One can still train a predictive model on datasets that are too big to fit into memory by leveraging the on-line learners provided by `scikit-learn`. The `vaex.ml.sklearn.IncrementalPredictor` conveniently wraps these learners and provides control on how the data is passed to them from a `vaex` DataFrame.

Let us train a model on the oversampled Iris dataset which comprises over 1 billion samples.

[16]:
```
from vaex.ml.sklearn import IncrementalPredictor
from sklearn.linear_model import SGDClassifier

df = vaex.ml.datasets.load_iris_1e9()

features = ['petal_length', 'petal_width', 'sepal_length', 'sepal_width']
target = 'class_'

model = SGDClassifier(learning_rate='constant', eta0=0.0001, random_state=42)
vaex_model = IncrementalPredictor(features=features, target=target, model=model,
                                  batch_size=11_000_000, partial_fit_kwargs={'classes
↪':[0, 1, 2]})

vaex_model.fit(df=df, progress=True)
```

(continues on next page)

(continued from previous page)

```
df = vaex_model.transform(df)
df
```

```
[########################################] 100.00% elapsed time  :   747.59s =  12.5m␣
↪=  0.2h
```

[16]:

```
#              sepal_length    sepal_width    petal_length    petal_width    class_  ␣
↪ prediction
0              5.9             3.0            4.2             1.5            1       ␣
↪ 1
1              6.1             3.0            4.6             1.4            1       ␣
↪ 1
2              6.6             2.9            4.6             1.3            1       ␣
↪ 1
3              6.7             3.3            5.7             2.1            2       ␣
↪ 2
4              5.5             4.2            1.4             0.2            0       ␣
↪ 0
...            ...             ...            ...             ...            ...     ␣
↪ ...
1,004,999,995  5.2             3.4            1.4             0.2            0       ␣
↪ 0
1,004,999,996  5.1             3.8            1.6             0.2            0       ␣
↪ 0
1,004,999,997  5.8             2.6            4.0             1.2            1       ␣
↪ 1
1,004,999,998  5.7             3.8            1.7             0.3            0       ␣
↪ 0
1,004,999,999  6.2             2.9            4.3             1.3            1       ␣
↪ 1
```

XGBoost example

Libraries such as XGBoost provide more options such as validation during training and early stopping for example. We provide wrappers that keeps close to the native API of these libraries, in addition to the scikit-learn API.

While the following example showcases the XGBoost wrapper, vaex.ml implements similar wrappers for LightGBM and CatBoost.

[17]:

```python
from vaex.ml.xgboost import XGBoostModel

df = vaex.ml.datasets.load_iris_1e5()
df_train, df_test = df.ml.train_test_split(test_size=0.2, verbose=False)

features = ['petal_length', 'petal_width', 'sepal_length', 'sepal_width']
target = 'class_'

params = {'learning_rate': 0.1,
          'max_depth': 3,
          'num_class': 3,
          'objective': 'multi:softmax',
          'subsample': 1,
          'random_state': 42,
          'n_jobs': -1}
```

(continues on next page)

(continued from previous page)

```
booster = XGBoostModel(features=features, target=target, num_boost_round=500,␣
↪params=params)
booster.fit(df=df_train, evals=[(df_train, 'train'), (df_test, 'test')], early_
↪stopping_rounds=5)

df_test = booster.transform(df_train)
df_test
```

```
[17]: #       sepal_length    sepal_width    petal_length    petal_width    class_    ␣
↪xgboost_prediction
0       5.9             3.0            4.2             1.5            1         1.0
1       6.1             3.0            4.6             1.4            1         1.0
2       6.6             2.9            4.6             1.3            1         1.0
3       6.7             3.3            5.7             2.1            2         2.0
4       5.5             4.2            1.4             0.2            0         0.0
...     ...             ...            ...             ...            ...       ...
80,395  5.2             3.4            1.4             0.2            0         0.0
80,396  5.1             3.8            1.6             0.2            0         0.0
80,397  5.8             2.6            4.0             1.2            1         1.0
80,398  5.7             3.8            1.7             0.3            0         0.0
80,399  6.2             2.9            4.3             1.3            1         1.0
```

4.2.5 State transfer - pipelines made easy

Each `vaex` DataFrame consists of two parts: *data* and *state*. The *data* is immutable, and any operation such as filtering, adding new columns, or applying transformers or predictive models just modifies the *state*. This is extremely powerful concept and can completely redefine how we imagine machine learning pipelines.

As an example, let us once again create a model based on the Iris dataset. Here, we will create a couple of new features, do a PCA transformation, and finally train a predictive model.

```
[18]: # Load data and split it in train and test sets
df = vaex.ml.datasets.load_iris()
df_train, df_test = df.ml.train_test_split(test_size=0.2, verbose=False)

# Create new features
df_train['petal_ratio'] = df_train.petal_length / df_train.petal_width
df_train['sepal_ratio'] = df_train.sepal_length / df_train.sepal_width

# Do a PCA transformation
features = ['petal_length', 'petal_width', 'sepal_length', 'sepal_width', 'petal_ratio
↪', 'sepal_ratio']
pca = vaex.ml.PCA(features=features, n_components=6)
df_train = pca.fit_transform(df_train)

# Display the training DataFrame at this stage
df_train
```

```
[18]: #    sepal_length    sepal_width    petal_length    petal_width    class_    petal_
↪ratio          sepal_ratio          PCA_0                    PCA_1                    PCA_2    ␣
↪                PCA_3                   PCA_4                    PCA_5
0    5.4             3.0            4.5             1.5            1         3.0      ␣
↪           1.8                 -1.510547480171215    0.3611524321126822    -0.
↪4005106138591812      0.5491844107628985     0.21135370342329635      -0.
↪009542243224854377
```

(continues on next page)

(continued from previous page)

```
1    4.8              3.4             1.6             0.2             0          8.0     ␣
↪           1.411764705882353   4.447550641536847    0.2799644730487585   -0.
↪04904458661276928    0.18719360579644695   0.10928493945448532     0.
↪005228919010020094
2    6.9              3.1             4.9             1.5             1          3.
↪266666666666667   2.2258064516129035   -1.777649528149752   -0.6082889770845891  0.
↪48007833550651513     -0.37762011866831335  0.05174472701894024     -0.
↪04673816474220924
3    4.4              3.2             1.3             0.2             0          6.5     ␣
↪           1.375              3.400548263702555    1.437036928591846    -0.
↪3662652846960042     0.23420836198441913   0.05750021481634099     -0.
↪023055011653267066
4    5.6              2.8             4.9             2.0             2          2.45    ␣
↪           2.0                -2.3245098766222094  0.14710673877401348  -0.
↪5150809942258257     0.5471824391426298    -0.12154714382375817    0.
↪0044686197532133876
...  ...              ...             ...             ...             ...        ...     ␣
↪           ...                ...                  ...                  ...    ␣
↪             ...                 ...                  ...
115  5.2              3.4             1.4             0.2             0          6.
↪999999999999999   1.5294117647058825   3.623794583238953    0.8255759252729563   0.
↪23453320686724874     -0.17599408825208826  -0.04687036865354327    -0.
↪02424621891240747
116  5.1              3.8             1.6             0.2             0          8.0     ␣
↪           1.3421052631578947  4.42115266246093     0.22287505533663704  0.
↪4450642830179705      0.2184424557783562    0.14504752606375293     0.
↪07229123907677276
117  5.8              2.6             4.0             1.2             1          3.
↪3333333333333335  2.230769230769231   -1.069062832993727   0.3874258314654399   -0.
↪4471767749236783     -0.2956609879568117   -0.0010695982441835394  -0.
↪0065225306610744715
118  5.7              3.8             1.7             0.3             0          5.
↪666666666666667   1.5000000000000002   2.2846521048417037   1.1920826609681359   0.
↪8273738848637026      -0.21048946462725737  0.03381892388998425     0.
↪018792165273013528
119  6.2              2.9             4.3             1.3             1          3.
↪3076923076923075  2.137931034482759   -1.2988229958748452  0.06960434514054464  -0.
↪0012167985718341268  -0.24072255219180883  0.05282732890885841     -0.
↪032459999314411514
```

At this point, we are ready to train a predictive model. In this example, let's use `LightGBM` with its `scikit-learn` API.

[19]:
```
import lightgbm

features = df_train.get_column_names(regex='^PCA')

booster = lightgbm.LGBMClassifier()

vaex_model = Predictor(model=booster, features=features, target='class_')

vaex_model.fit(df=df_train)
df_train = vaex_model.transform(df_train)

df_train
```

[19]:
```
#    sepal_length    sepal_width    petal_length    petal_width    class_    petal_
↪ratio          sepal_ratio          PCA_0               PCA_1               PCA_2    ␣
↪                 PCA_3                PCA_4                  PCA_5                ␣
↪   prediction
```

(continues on next page)

(continued from previous page)

```
0    5.4             3.0            4.5             1.5            1         3.0        ␣
↪          1.8                 -1.510547480171215   0.3611524321126822   -0.
↪4005106138591812     0.5491844107628985    0.21135370342329635     -0.
↪009542243224854377   1
1    4.8             3.4            1.6             0.2            0         8.0        ␣
↪          1.411764705882353   4.447550641536847    0.2799644730487585   -0.
↪04904458661276928    0.18719360579644695   0.10928493945448532     0.
↪005228919010020094    0
2    6.9             3.1            4.9             1.5            1         3.
↪266666666666667   2.2258064516129035  -1.777649528149752   -0.6082889770845891  0.
↪48007833550651513     -0.37762011866831335  0.05174472701894024     -0.
↪04673816474220924    1
3    4.4             3.2            1.3             0.2            0         6.5        ␣
↪          1.375               3.400548263702555    1.437036928591846    -0.
↪3662652846960042     0.23420836198441913   0.05750021481634099     -0.
↪023055011653267066   0
4    5.6             2.8            4.9             2.0            2         2.45       ␣
↪          2.0                 -2.3245098766222094  0.14710673877401348  -0.
↪5150809942258257     0.5471824391426298    -0.12154714382375817    0.
↪0044686197532133876   2
...  ...             ...            ...             ...            ...       ...        ␣
↪          ...                 ...                  ...                  ...        ␣
↪            ...                    ...                    ...                     ␣
↪...
115  5.2             3.4            1.4             0.2            0         6.
↪999999999999999   1.5294117647058825  3.623794583238953    0.8255759252729563   0.
↪23453320686724874     -0.17599408825208826  -0.04687036865354327    -0.
↪02424621891240747     0
116  5.1             3.8            1.6             0.2            0         8.0        ␣
↪          1.3421052631578947  4.42115266246093     0.22287505533663704  0.
↪4450642830179705      0.2184424557783562    0.14504752606375293     0.
↪07229123907677276     0
117  5.8             2.6            4.0             1.2            1         3.
↪3333333333333335  2.230769230769231   -1.069062832993727   0.3874258314654399   -0.
↪4471767749236783     -0.2956609879568117   -0.0010695982441835394  -0.
↪0065225306610744715  1
118  5.7             3.8            1.7             0.3            0         5.
↪666666666666667   1.5000000000000002  2.2846521048417037   1.1920826609681359   0.
↪8273738848637026      -0.21048946462725737  0.03381892388998425     0.
↪018792165273013528    0
119  6.2             2.9            4.3             1.3            1         3.
↪3076923076923075  2.137931034482759   -1.2988229958748452  0.06960434514054464  -0.
↪0012167985718341268  -0.24072255219180883  0.05282732890885841     -0.
↪032459999314411514   1
```

The final `df_train` DataFrame contains all the features we created, including the predictions right at the end. Now, we would like to apply the same transformations to the test set. All we need to do, is to simply extract the *state* from `df_train` and apply it to `df_test`. This will propagate all the changes that were made to the training set on the test set.

[20]:
```
state = df_train.state_get()

df_test.state_set(state)
df_test
```

[20]:
```
#    sepal_length    sepal_width    petal_length    petal_width    class_    petal_
↪ratio          sepal_ratio         PCA_0                 PCA_1                 PCA_2 ␣
↪                PCA_3                  PCA_4                  PCA_5
↪prediction
```

(continues on next page)

(continued from previous page)

```
0    5.9              3.0            4.2              1.5            1          2.
↪8000000000000003  1.9666666666666668  -1.642627940409072   0.49931302910747727   -0.
↪06308800806664466  0.10842057110641677   -0.03924298664189224  -0.
↪027394439700272822  1
1    6.1              3.0            4.6              1.4            1          3.
↪2857142857142856  2.033333333333333   -1.445047446393471   -0.1019091578746504   -0.
↪01899012239493801  0.020980767646090408  0.1614215276667148    -0.02716639637934938␣
↪  1
2    6.6              2.9            4.6              1.3            1          3.
↪538461538461538   2.2758620689655173  -1.330564613235537   -0.41978474749131267  0.
↪1759590589290671    -0.4631301992308477   0.08304243689815374   -0.
↪033351733677429274  1
3    6.7              3.3            5.7              2.1            2          2.
↪7142857142857144  2.0303030303030303  -2.6719170661531013  -0.9149428897499291   0.
↪4156162725009377    0.34633692661436644   0.03742964707590906   -0.
↪013254286196245774  2
4    5.5              4.2            1.4              0.2            0          6.
↪999999999999999   1.3095238095238095  3.6322930267831404   0.8198526437905096    1.
↪046277579362938     0.09738737839850209   0.09412658096734221   0.1329137026697501 ␣
↪   0
...  ...              ...            ...              ...            ...        ...    ␣
↪            ...                  ...                  ...                ...    ␣
↪            ...                  ...                  ...                ...
25   5.5              2.5            4.0              1.3            1          3.
↪0769230769230766  2.2                 -1.2523120088600896  0.5975071562677784    -0.
↪7019801415469216   -0.11489031841855571  -0.03615945782087869  0.005496321827264977␣
↪  1
26   5.8              2.7            3.9              1.2            1          3.25   ␣
↪            2.148148148148    -1.0792352165904657  0.5236883751378523    -0.
↪34037717939532286  -0.23743695029955128  -0.00936891422024664  -0.02184110533380834␣
↪  1
27   4.4              2.9            1.4              0.2            0          6.
↪999999999999999   1.517241379310345   3.7422969192506095   1.048460304741977     -0.
↪636475521315278    0.07623157913054074   0.004215355833312173  -0.06354157393133958␣
↪  0
28   4.5              2.3            1.3              0.3            0          4.
↪333333333333334   1.956521739130435   1.4537380535696471   2.4197864889383505    -1.
↪0301500321688102   -0.5150263062576134   -0.2631218962099228   -0.06608059456656257␣
↪  0
29   6.9              3.2            5.7              2.3            2          2.
↪4782608695652177  2.15625             -2.963110301521378   -0.924626055589704    0.
↪44833006106219797   0.20994670504662372   -0.2012725506779131   -0.
↪018900414287719353  2
```

And just like that `df_test` contains all the columns, transformations and the prediction we modelled on the training set. The state can be easily serialized to disk in a form of a JSON file. This makes deployment of a machine learning model as trivial as simply copying a JSON file from one environment to another.

[21]:
```
df_train.state_write('./iris_model.json')

df_test.state_load('./iris_model.json')
df_test
```

[21]:
```
#    sepal_length     sepal_width    petal_length     petal_width    class_     petal_
↪ratio           sepal_ratio        PCA_0                PCA_1                PCA_2 ␣
↪                 PCA_3              PCA_4                PCA_5                    ␣
↪prediction
```

(continues on next page)

(continued from previous page)

```
0    5.9              3.0            4.2              1.5            1          2.
↪8000000000000003  1.9666666666666668  -1.642627940409072   0.49931302910747727   -0.
↪06308800806664466  0.10842057110641677   -0.03924298664189224  -0.
↪027394439700272822  1
1    6.1              3.0            4.6              1.4            1          3.
↪2857142857142856  2.033333333333333   -1.445047446393471   -0.1019091578746504   -0.
↪01899012239493801  0.020980767646090408  0.1614215276667148    -0.02716639637934938␣
↪  1
2    6.6              2.9            4.6              1.3            1          3.
↪538461538461538   2.2758620689655173  -1.330564613235537   -0.41978474749131267  0.
↪1759590589290671    -0.4631301992308477   0.08304243689815374   -0.
↪033351733677429274  1
3    6.7              3.3            5.7              2.1            2          2.
↪7142857142857144  2.0303030303030303  -2.6719170661531013  -0.9149428897499291   0.
↪4156162725009377    0.34633692661436644   0.03742964707590906   -0.
↪013254286196245774  2
4    5.5              4.2            1.4              0.2            0          6.
↪999999999999999   1.3095238095238095  3.6322930267831404   0.8198526437905096    1.
↪046277579362938     0.09738737839850209   0.09412658096734221   0.1329137026697501 ␣
↪   0
...  ...              ...            ...              ...            ...        ...    ␣
↪           ...                  ...                  ...                 ...      ␣
↪           ...                  ...                  ...                 ...
25   5.5              2.5            4.0              1.3            1          3.
↪0769230769230766  2.2                 -1.2523120088600896  0.5975071562677784    -0.
↪7019801415469216   -0.11489031841855571  -0.03615945782087869  0.005496321827264977␣
↪  1
26   5.8              2.7            3.9              1.2            1          3.25   ␣
↪           2.148148148148148   -1.0792352165904657  0.5236883751378523    -0.
↪34037717939532286  -0.23743695029955128  -0.00936891422024664  -0.02184110533380834␣
↪  1
27   4.4              2.9            1.4              0.2            0          6.
↪999999999999999   1.517241379310345   3.7422969192506095   1.048460304741977     -0.
↪636475521315278    0.07623157913054074   0.004215355833312173  -0.06354157393133958␣
↪  0
28   4.5              2.3            1.3              0.3            0          4.
↪333333333333334   1.956521739130435   1.4537380535696471   2.4197864889383505    -1.
↪0301500321688102   -0.5150263062576134   -0.2631218962099228   -0.06608059456656257␣
↪  0
29   6.9              3.2            5.7              2.3            2          2.
↪4782608695652177  2.15625             -2.963110301521378   -0.924626055589704    0.
↪44833006106219797   0.20994670504662372   -0.2012725506779131   -0.
↪018900414287719353  2
```

Warning: This notebook needs a running kernel to be fully interactive, please run it locally or on mybinder.

4.3 Jupyter integration: interactivity

Vaex can process about 1 billion rows per second, and in combination with the Jupyter notebook, this allows for interactive exporation of large datasets.

4.3.1 Introduction

The `vaex-jupyter` package contains the building blocks to interactively define an N-dimensional grid, which is then used for visualizations.

We start by defining the building blocks (`vaex.jupyter.model.Axis`, `vaex.jupyter.model.DataArray` and `vaex.jupyter.view.DataArray`) used to define and visualize our N-dimensional grid.

Let us first import the relevant packages, and open the example DataFrame:

[1]:
```
import vaex
import vaex.jupyter.model as vjm

import numpy as np
import matplotlib.pyplot as plt

df = vaex.example()
df
```

[1]:
```
#        id    x                    y                     z                   vx  ␣
↪               vy                  vz                  E               L       ␣
↪          Lz                   FeH
0        0     1.2318683862686157   -0.3969286680221557 6  -0.598057746887207   301.
↪1552734375       174.05947875976562   27.42754554748535    -149431.40625   407.
↪38897705078125  333.9555358886719    -1.0053852796554565
1        23    -0.16370061039924622  3.654221296310425    -0.25490644574165344  -195.
↪00022888183594  170.47216796875      142.5302276611328    -124247.953125  890.
↪2411499023438   684.6676025390625    -1.7086670398712158
2        32    -2.120255947113037    3.326052665710449    1.7078403234481812    -48.
↪63423156738281   171.6472930908203    -2.079437255859375   -138500.546875  372.
↪2410888671875   -202.17617797851562  -1.8336141109466553
3        8     4.7155890464782715    4.5852508544921875   2.2515437602996826    -232.
↪42083740234375  -294.850830078125    62.85865020751953    -60037.0390625  1297.
↪63037109375     -324.6875            -1.4786882400512695
4        16    7.21718692779541      11.99471664428711    -1.064562201499939    -1.
↪6891745328903198  181.329345703125     -11.333610534667969  -83206.84375    1332.
↪7989501953125  1328.948974609375    -1.8570483922958374
...      ...   ...                   ...                  ...                   ... ␣
↪                 ...                  ...                  ...             ...     ␣
↪           ...                  ...
329,995  21    1.9938701391220093    0.789276123046875    0.22205990552902222   -216.
↪92990112304688  16.124420166015625   -211.244384765625    -146457.4375    457.
↪72247314453125  203.36758422851562   -1.7451677322387695
329,996  25    3.7180912494659424    0.721337616443634    1.6415337324142456    -185.
↪92160034179688  -117.25082397460938  -105.4986572265625   -126627.109375  335.
↪0025634765625   -301.8370056152344   -0.9822322130203247
329,997  14    0.3688507676124573    13.029608726501465   -3.633934736251831    -53.
↪677146911621094  -145.15771484375     76.70909881591797    -84912.2578125  817.
↪1375732421875   645.8507080078125    -1.7645612955093384
329,998  18    -0.11259264498949051  1.4529125690460205   2.168952703475952     179.
↪30865478515625   205.79710388183594   -68.75872802734375   -133498.46875   724.
↪000244140625    -283.6910400390625   -1.8808952569961548
329,999  4     20.796220779418945    -3.331387758255005   12.18841552734375     42.
↪69000244140625   69.20479583740234    29.54275131225586    -65519.328125   1843.
↪07470703125     1581.4151611328125   -1.1231083869934082
```

We want to build a 2 dimensinoal grid with the number counts in each bin. To do this, we first define two axis objects:

```
[2]: E_axis = vjm.Axis(df=df, expression=df.E, shape=140)
     Lz_axis = vjm.Axis(df=df, expression=df.Lz, shape=100)
     Lz_axis
```

```
[2]: Axis(bin_centers=None, exception=None, expression=Lz, max=None, min=None, shape=100,␣
     ↪shape_default=64, slice=None, status=Status.NO_LIMITS)
```

When we inspect the `Lz_axis` object we see that the `min`, `max`, and `bin centers` are all `None`. This is because Vaex calculates them in the background, so the kernel stays interactive, meaning you can continue working in the notebook. We can ask Vaex to wait until all background calculations are done. Note that for billions of rows, this can take over a second.

```
[3]: await vaex.jupyter.gather()  # wait until Vaex is done with all background computation
     Lz_axis  # now min and max are computed, and bin_centers is set
```

```
[3]: Axis(bin_centers=[-2877.11808899 -2830.27174744 -2783.42540588 -2736.57906433
      -2689.73272278 -2642.88638123 -2596.04003967 -2549.19369812
      -2502.34735657 -2455.50101501 -2408.65467346 -2361.80833191
      -2314.96199036 -2268.1156488  -2221.26930725 -2174.4229657
      -2127.57662415 -2080.73028259 -2033.88394104 -1987.03759949
      -1940.19125793 -1893.34491638 -1846.49857483 -1799.65223328
      -1752.80589172 -1705.95955017 -1659.11320862 -1612.26686707
      -1565.42052551 -1518.57418396 -1471.72784241 -1424.88150085
      -1378.0351593  -1331.18881775 -1284.3424762  -1237.49613464
      -1190.64979309 -1143.80345154 -1096.95710999 -1050.11076843
      -1003.26442688  -956.41808533  -909.57174377  -862.72540222
       -815.87906067  -769.03271912  -722.18637756  -675.34003601
       -628.49369446  -581.64735291  -534.80101135  -487.9546698
       -441.10832825  -394.26198669  -347.41564514  -300.56930359
       -253.72296204  -206.87662048  -160.03027893  -113.18393738
        -66.33759583   -19.49125427    27.35508728    74.20142883
        121.04777039   167.89411194   214.74045349   261.58679504
        308.4331366    355.27947815   402.1258197    448.97216125
        495.81850281   542.66484436   589.51118591   636.35752747
        683.20386902   730.05021057   776.89655212   823.74289368
        870.58923523   917.43557678   964.28191833  1011.12825989
       1057.97460144  1104.82094299  1151.66728455  1198.5136261
       1245.35996765  1292.2063092   1339.05265076  1385.89899231
       1432.74533386  1479.59167542  1526.43801697  1573.28435852
       1620.13070007  1666.97704163  1713.82338318  1760.66972473], exception=None,␣
     ↪expression=Lz, max=1784.0928955078125, min=-2900.541259765625, shape=100, shape_
     ↪default=64, slice=None, status=Status.READY)
```

Note that the Axis is a traitlets HasTrait object, similar to all ipywidget objects. This means that we can link all of its properties to an ipywidget and thus creating interactivity. We can also use observe to listen to any changes to our model.

4.3.2 An interactive xarray DataArray display

Now that we have defined our two axes, we can create a vaex.jupyter.model.DataArray (model) together with a vaex.jupyter.view.DataArray (view).

A convenient way to do this, is to use the widget accessor `data_array` method, which creates both, links them together and will return a view for us.

The returned view is an ipywidget object, which becomes a visual element in the Jupyter notebook when displayed.

```
[4]: data_array_widget = df.widget.data_array(axes=[Lz_axis, E_axis], selection=[None,
     ↪'default'])
     data_array_widget  # being the last expression in the cell, Jupyter  will 'display'␣
     ↪the widget
```

```
DataArray(children=[Container(children=[ProgressCircularNoAnimation(color='#9ECBF5',␣
↪size=30, text='', value=1...
```

Note: If you see this notebook on readthedocs, you will see the selection coordinate already has ''[None, 'default']'', because cells below have already been executed and have updated this widget. If you run this notebook yourself (say on mybinder), you will see after executing the above cell, the selection will have ''[None]'' as its only value.

From the specification of the axes and the selections, Vaex computes a 3d histogram, the first dimension being the selections. Interally this is simply a numpy array, but we wrap it in an xarray DataArray object. An xarray DataArray object can be seen as a labeled Nd array, i.e. a numpy array with extra metadata to make it fully self-describing.

Notice that in the above code cell, we specified the `selection` argument with a list containing two elements in this case, `None` and `'default'`. The `None` selection simply shows all the data, while the `default` refers to any selection made without explicitly naming it. Even though the later has not been defined at this point, we can still pre-emptively include it, in case we want to modify it later.

The most important properties of the `data_array` are printed out below:

```
[5]: # NOTE: since the computations are done in the background, data_array_widget.model.
     ↪grid is initially None.
     # We can ask vaex-jupyter to wait till all executions are done using:
     await vaex.jupyter.gather()
     # get a reference to the xarray DataArray object
     data_array = data_array_widget.model.grid
     print(f"type:", type(data_array))
     print("dims:", data_array.dims)
     print("data:", data_array.data)
     print("coords:", data_array.coords)
     print("Lz's data:", data_array.coords['Lz'].data)
     print("Lz's attrs:", data_array.coords['Lz'].attrs)
     print("And displaying the xarray DataArray:")
     display(data_array)  # this is what the vaex.jupyter.view.DataArray uses
```

```
type: <class 'xarray.core.dataarray.DataArray'>
dims: ('selection', 'Lz', 'E')
data: [[[0 0 0 ... 0 0 0]
  [0 0 0 ... 0 0 0]
  [0 0 0 ... 0 0 0]
  ...
  [0 0 0 ... 0 0 0]
  [0 0 0 ... 0 0 0]
  [0 0 0 ... 0 0 0]]]
coords: Coordinates:
  * selection  (selection) object None
  * Lz         (Lz) float64 -2.877e+03 -2.83e+03 ... 1.714e+03 1.761e+03
  * E          (E) float64 -2.414e+05 -2.394e+05 ... 3.296e+04 3.495e+04
Lz's data: [-2877.11808899 -2830.27174744 -2783.42540588 -2736.57906433
 -2689.73272278 -2642.88638123 -2596.04003967 -2549.19369812
 -2502.34735657 -2455.50101501 -2408.65467346 -2361.80833191
 -2314.96199036 -2268.1156488  -2221.26930725 -2174.4229657
 -2127.57662415 -2080.73028259 -2033.88394104 -1987.03759949
 -1940.19125793 -1893.34491638 -1846.49857483 -1799.65223328
 -1752.80589172 -1705.95955017 -1659.11320862 -1612.26686707
 -1565.42052551 -1518.57418396 -1471.72784241 -1424.88150085
```

(continues on next page)

(continued from previous page)

```
 -1378.0351593  -1331.18881775 -1284.3424762  -1237.49613464
 -1190.64979309 -1143.80345154 -1096.95710999 -1050.11076843
 -1003.26442688  -956.41808533  -909.57174377  -862.72540222
  -815.87906067  -769.03271912  -722.18637756  -675.34003601
  -628.49369446  -581.64735291  -534.80101135  -487.9546698
  -441.10832825  -394.26198669  -347.41564514  -300.56930359
  -253.72296204  -206.87662048  -160.03027893  -113.18393738
   -66.33759583   -19.49125427    27.35508728    74.20142883
   121.04777039   167.89411194   214.74045349   261.58679504
   308.4331366    355.27947815   402.1258197    448.97216125
   495.81850281   542.66484436   589.51118591   636.35752747
   683.20386902   730.05021057   776.89655212   823.74289368
   870.58923523   917.43557678   964.28191833  1011.12825989
  1057.97460144  1104.82094299  1151.66728455  1198.5136261
  1245.35996765  1292.2063092   1339.05265076  1385.89899231
  1432.74533386  1479.59167542  1526.43801697  1573.28435852
  1620.13070007  1666.97704163  1713.82338318  1760.66972473]
Lz's attrs: {'min': -2900.541259765625, 'max': 1784.0928955078125}
And displaying the xarray DataArray:
```

```
<xarray.DataArray (selection: 1, Lz: 100, E: 140)>
array([[[0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0],
        ...,
        [0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0]]])
Coordinates:
  * selection  (selection) object None
  * Lz         (Lz) float64 -2.877e+03 -2.83e+03 ... 1.714e+03 1.761e+03
  * E          (E) float64 -2.414e+05 -2.394e+05 ... 3.296e+04 3.495e+04
```

Note that `data_array.coords['Lz'].data` is the same as `Lz_axis.bin_centers` and `data_array.coords['Lz'].attrs` contains the same `min/max` as the `Lz_axis`.

Also, we see that displaying the xarray.DataArray object (`data_array_view.model.grid`) gives us the same output as the `data_array_view` above. There is a big difference however. If we change a selection:

[6]:
```
df.select(df.x > 0)
```

and scroll back we see that the `data_array_view` widget has updated itself, and now contains two selections! This is a very powerful feature, that allows us to make interactive visualizations.

4.3.3 Interactive plots

To make interactive plots we can pass a custom `display_function` to the `data_array_widget`. This will override the default notebook behaviour which is a call to `display(data_array_widget)`. In the following example we create a function that displays a matplotlib figure:

[7]:
```
# NOTE: da is short for 'data array'
def plot2d(da):
    plt.figure(figsize=(8, 8))
    ar = da.data[1]  # take the numpy data, and select take the selection
    print(f'imshow of a numpy array of shape: {ar.shape}')
    plt.imshow(np.log1p(ar.T), origin='lower')
```

(continues on next page)

(continued from previous page)

```
df.widget.data_array(axes=[Lz_axis, E_axis], display_function=plot2d, selection=[None,
↪ True])
```

```
DataArray(children=[Container(children=[ProgressCircularNoAnimation(color='#9ECBF5',␣
↪size=30, text='', value=1...
```

In the above figure, we choose index 1 along the selection axis, which referes to the `'default'` selection. Choosing an index of 0 would correspond to the `None` selection, and all the data would be displayed. If we now change the selection, the figure will update itself:

```
[8]: df.select(df.id < 10)
```

As xarray's DataArray is fully self describing, we can improve the plot by using the dimension names for labeling, and setting the extent of the figure's axes.

Note that we don't need any information from the Axis objects created above, and in fact, we should not use them, since they may not be in sync with the xarray DataArray object. Later on, we will create a widget that will edit the Axis' expression.

Our improved visualization with proper axes and labeling:

```
[9]: def plot2d_with_labels(da):
         plt.figure(figsize=(8, 8))
         grid = da.data  # take the numpy data
         dim_x = da.dims[0]
         dim_y = da.dims[1]
         plt.title(f'{dim_y} vs {dim_x} - shape: {grid.shape}')
         extent = [
             da.coords[dim_x].attrs['min'], da.coords[dim_x].attrs['max'],
             da.coords[dim_y].attrs['min'], da.coords[dim_y].attrs['max']
         ]
         plt.imshow(np.log1p(grid.T), origin='lower', extent=extent, aspect='auto')
         plt.xlabel(da.dims[0])
         plt.ylabel(da.dims[1])

     da_plot_view_nicer = df.widget.data_array(axes=[Lz_axis, E_axis], display_
     ↪function=plot2d_with_labels)
     da_plot_view_nicer
```

```
DataArray(children=[Container(children=[ProgressCircularNoAnimation(color='#9ECBF5',␣
↪size=30, text='', value=1...
```

We can also create more sophisticated plots, for example one where we show all of the selections. Note that we can pre-emptively expect a selection and define it later:

```
[10]: def plot2d_with_selections(da):
          grid = da.data
          # Create 1 row and #selections of columns of matplotlib axes
          fig, axgrid = plt.subplots(1, grid.shape[0], sharey=True, squeeze=False)
          for selection_index, ax in enumerate(axgrid[0]):
              ax.imshow(np.log1p(grid[selection_index].T), origin='lower')

      df.widget.data_array(axes=[Lz_axis, E_axis], display_function=plot2d_with_selections,
                           selection=[None, 'default', 'rest'])
```

```
DataArray(children=[Container(children=[ProgressCircularNoAnimation(color='#9ECBF5',␣
↪size=30, text='', value=1...
```

Modifying a selection will update the figure.

```
[11]: df.select(df.id < 10)  # select 10 objects
      df.select(df.id >= 10, name='rest')  # and the rest
```

Another advantage of using xarray is its excellent plotting capabilities. It handles a lot of the boring stuff like axis labeling, and also provides a nice interface for slicing the data even more.

Let us introduce another axis, FeH (fun fact: FeH is a property of stars that tells us how much iron relative to hydrogen is contained in them, an idicator of their origin):

```
[12]: FeH_axis = vjm.Axis(df=df, expression='FeH', min=-3, max=1, shape=5)
      da_view = df.widget.data_array(axes=[E_axis, Lz_axis, FeH_axis], selection=[None,
      ↪'default'])
      da_view
```

```
DataArray(children=[Container(children=[ProgressCircularNoAnimation(color='#9ECBF5',␣
↪size=30, text='', value=1...
```

We can see that we now have a 4 dimensional grid, which we would like to visualize.

And xarray's plot make our life much easier:

```
[13]: def plot_with_xarray(da):
          da_log = np.log1p(da)  # Note that an xarray DataArray is like a numpy array
          da_log.plot(x='Lz', y='E', col='FeH', row='selection', cmap='viridis')

      plot_view = df.widget.data_array([E_axis, Lz_axis, FeH_axis], display_function=plot_
      ↪with_xarray,
                                       selection=[None, 'default', 'rest'])
      plot_view
```

```
DataArray(children=[Container(children=[ProgressCircularNoAnimation(color='#9ECBF5',␣
↪size=30, text='', value=1...
```

We only have to tell xarray which axis it should map to which 'aesthetic', speaking in Grammar of Graphics terms.

4.3.4 Selection widgets

Although we can change the selection in the notebook (e.g. `df.select(df.id > 20)`), if we create a dashboard (using Voila) we cannot execute arbitrary code. Vaex-jupyter also comes with many widgets, and one of them is a `selection_expression` widget:

```
[14]: selection_widget = df.widget.selection_expression()
      selection_widget
```

```
ExpressionSelectionTextArea(label='Filter by custom expression', placeholder='Enter a␣
↪custom (boolean) express...
```

The `counter_selection` creates a widget which keeps track of the number of rows in a selection. In this case we ask it to be 'lazy', which means that it will not cause extra passes over the data, but will ride along if some user action triggers a calculation.

```
[15]: await vaex.jupyter.gather()
      w = df.widget.counter_selection('default', lazy=True)
      w
```

```
Counter(characters=[' ', ' ', ' ', ' ', ' ', ' ', '&
↪nbsp;', ' ', '9', '9', ...
```

4.3.5 Axis control widgets

Let us create new axis objects using the same expressions as before, but give them more general names (x_axis and y_axis), because we want to change the expressions interactively.

[16]:
```
x_axis = vjm.Axis(df=df, expression=df.Lz)
y_axis = vjm.Axis(df=df, expression=df.E)

da_xy_view = df.widget.data_array(axes=[x_axis, y_axis], display_function=plot2d_with_
↪labels, shape=180)
da_xy_view
```

```
DataArray(children=[Container(children=[ProgressCircularNoAnimation(color='#9ECBF5',␣
↪size=30, text='', value=1...
```

Again, we can change the expressions of the axes programmatically:

[17]:
```
# wait for the previous plot to finish
await vaex.jupyter.gather()
# Change both the x and y axis
x_axis.expression = np.log(df.x**2)
y_axis.expression = df.y
# Note that both assignment will create 1 computation in the background (minimal␣
↪amount of passes over the data)
await vaex.jupyter.gather()
# vaex computed the new min/max, and the xarray DataArray
# x_axis.min, x_axis.max, da_xy_view.model.grid
```

But, if we want to create a dashboard with Voila, we need to have a widget that controls them:

[18]:
```
x_widget = df.widget.expression(x_axis.expression, label='X axis')
x_widget
```

```
Expression(label='X axis', placeholder='Enter a custom expression', prepend_icon=
↪'functions', success_messages...
```

This widget will allow us to edit an expression, which will be validated by Vaex. How do we 'link' the value of the widget to the axis expression? Because both the Axis as well as the `x_widget` are HasTrait objects, we can link their traits together:

[19]:
```
from ipywidgets import link
link((x_widget, 'value'), (x_axis, 'expression'))
```

[19]:
```
<traitlets.traitlets.link at 0x122bed450>
```

Since this operation is so common, we can also directly pass the Axis object, and Vaex will set up the linking for us:

[20]:
```
y_widget = df.widget.expression(y_axis, label='X axis')
# vaex now does this for us, much shorter
# link((y_widget, 'value'), (y_axis, 'expression'))
y_widget
```

```
Expression(label='X axis', placeholder='Enter a custom expression', prepend_icon=
↪'functions', success_messages...
```

[21]:
```
await vaex.jupyter.gather()  # lets wait again till all calculations are finished
```

4.3.6 A nice container

If you are familiar with the ipyvuetify components, you can combine them to create very pretty widgets. Vaex-jupyter comes with a nice container:

[22]:
```
from vaex.jupyter.widgets import ContainerCard

ContainerCard(title='My plot',
              subtitle="using vaex-jupyter",
              main=da_xy_view,
              controls=[x_widget, y_widget], show_controls=True)
```

```
ContainerCard(controls=[Expression(label='X axis', placeholder='Enter a custom␣
↪expression', prepend_icon='func...
```

We can directly assign a Vaex expression to the `x_axis.expression`, or to `x_widget.value` since they are linked.

[23]:
```
y_axis.expression = df.vx
```

4.3.7 Interactive plots

So far we have been using interactive widgets to control the axes in the view. The figure itself however was not interactive, and we could not have panned or zoomed for example.

Vaex has a few builtin visualizations, most notably a heatmap and histogram using bqplot:

[24]:
```
df = vaex.example()  # we create the dataframe again, to leave all the plots above
↪'alone'
heatmap_xy = df.widget.heatmap(df.x, df.y, selection=[None, True])
heatmap_xy
```

```
Heatmap(children=[ToolsToolbar(interact_value=None, supports_normalize=False,␣
↪template='<template>\n  <v-toolb...
```

Note that we passed expressions, and not axis objects. Vaex recognizes this and will create the axis objects for you. You can access them from the model:

[25]:
```
heatmap_xy.model.x
```

[25]:
```
Axis(bin_centers=[-77.7255446  -76.91058156 -76.09561852 -75.28065547 -74.46569243
 -73.65072939 -72.83576635 -72.0208033  -71.20584026 -70.39087722
 -69.57591417 -68.76095113 -67.94598809 -67.13102505 -66.316062
 -65.50109896 -64.68613592 -63.87117288 -63.05620983 -62.24124679
 -61.42628375 -60.6113207  -59.79635766 -58.98139462 -58.16643158
 -57.35146853 -56.53650549 -55.72154245 -54.90657941 -54.09161636
 -53.27665332 -52.46169028 -51.64672723 -50.83176419 -50.01680115
 -49.20183811 -48.38687506 -47.57191202 -46.75694898 -45.94198593
 -45.12702289 -44.31205985 -43.49709681 -42.68213376 -41.86717072
 -41.05220768 -40.23724464 -39.42228159 -38.60731855 -37.79235551
 -36.97739246 -36.16242942 -35.34746638 -34.53250334 -33.71754029
 -32.90257725 -32.08761421 -31.27265117 -30.45768812 -29.64272508
 -28.82776204 -28.01279899 -27.19783595 -26.38287291 -25.56790987
 -24.75294682 -23.93798378 -23.12302074 -22.3080577  -21.49309465
 -20.67813161 -19.86316857 -19.04820552 -18.23324248 -17.41827944
 -16.6033164  -15.78835335 -14.97339031 -14.15842727 -13.34346423
 -12.52850118 -11.71353814 -10.8985751  -10.08361205  -9.26864901
```

(continues on next page)

(continued from previous page)

```
 -8.45368597  -7.63872293  -6.82375988  -6.00879684  -5.1938338
 -4.37887076  -3.56390771  -2.74894467  -1.93398163  -1.11901858
 -0.30405554   0.5109075    1.32587054   2.14083359   2.95579663
  3.77075967   4.58572271   5.40068576   6.2156488    7.03061184
  7.84557489   8.66053793   9.47550097  10.29046401  11.10542706
 11.9203901   12.73535314  13.55031618  14.36527923  15.18024227
 15.99520531  16.81016836  17.6251314   18.44009444  19.25505748
 20.07002053  20.88498357  21.69994661  22.51490965  23.3298727
 24.14483574  24.95979878  25.77476183  26.58972487  27.40468791
 28.21965095  29.034614    29.84957704  30.66454008  31.47950312
 32.29446617  33.10942921  33.92439225  34.7393553   35.55431834
 36.36928138  37.18424442  37.99920747  38.81417051  39.62913355
 40.4440966   41.25905964  42.07402268  42.88898572  43.70394877
 44.51891181  45.33387485  46.14883789  46.96380094  47.77876398
 48.59372702  49.40869007  50.22365311  51.03861615  51.85357919
 52.66854224  53.48350528  54.29846832  55.11343136  55.92839441
 56.74335745  57.55832049  58.37328354  59.18824658  60.00320962
 60.81817266  61.63313571  62.44809875  63.26306179  64.07802483
 64.89298788  65.70795092  66.52291396  67.33787701  68.15284005
 68.96780309  69.78276613  70.59772918  71.41269222  72.22765526
 73.0426183   73.85758135  74.67254439  75.48750743  76.30247048
 77.11743352  77.93239656  78.7473596   79.56232265  80.37728569
 81.19224873  82.00721177  82.82217482  83.63713786  84.4521009
 85.26706395  86.08202699  86.89699003  87.71195307  88.52691612
 89.34187916  90.1568422   90.97180524  91.78676829  92.60173133
 93.41669437  94.23165742  95.04662046  95.8615835   96.67654654
 97.49150959  98.30647263  99.12143567  99.93639871 100.75136176
101.5663248  102.38128784 103.19625089 104.01121393 104.82617697
105.64114001 106.45610306 107.2710661  108.08602914 108.90099218
109.71595523 110.53091827 111.34588131 112.16084436 112.9758074
113.79077044 114.60573348 115.42069653 116.23565957 117.05062261
117.86558565 118.6805487  119.49551174 120.31047478 121.12543783
121.94040087 122.75536391 123.57032695 124.38529    125.20025304
126.01521608 126.83017913 127.64514217 128.46010521 129.27506825
130.0900313 ], exception=None, expression=x, max=130.4975128173828, min=-78.
↪13302612304688, shape=None, shape_default=256, slice=None, status=Status.READY)
```

The heatmap itself is again a widget. Thus we can combine it with other widgets to create a more sophisticated interface.

[26]:
```
x_widget = df.widget.expression(heatmap_xy.model.x, label='X axis')
y_widget = df.widget.expression(heatmap_xy.model.y, label='X axis')

ContainerCard(title='My plot',
              subtitle="using vaex-jupyter and bqplot",
              main=heatmap_xy,
              controls=[x_widget, y_widget, selection_widget],
              show_controls=True,
              card_props={'style': 'min-width: 800px;'})
```

```
ContainerCard(card_props={'style': 'min-width: 800px;'}, controls=[Expression(label=
↪'X axis', placeholder='Ent...
```

By switching the tool in the toolbar (click pan_tool, or changing it programmmatically in the next cell), we can zoom in. The plot's axis bounds are directly synched to the axis object (the x_min is linked to the x_axis min, etc). Thus a zoom action causes the axis objects to be changed, which will trigger a recomputation.

```
[27]: heatmap_xy.tool = 'pan-zoom'  # we can also do this programmatically.
```

Since we can access the Axis objects, we can also programmatically change the heatmap. Note that both the expression widget, the plot axis label and the heatmap it self is updated. Everything is linked together!

```
[28]: heatmap_xy.model.x.expression = np.log10(df.x**2)
      await vaex.jupyter.gather()  # and we wait before we continue
```

Another visualization based on bqplot is the interactive histogram. In the example below, we show all the data, but the selection interaction will affect/set the 'default' selection.

```
[29]: histogram_Lz = df.widget.histogram(df.Lz, selection_interact='default')
      histogram_Lz.tool = 'select-x'
      histogram_Lz
```

```
Histogram(children=[ToolsToolbar(interact_items=[{'value': 'pan-zoom', 'icon': 'pan_
↪tool', 'tooltip': 'Pan & z...
```

```
[30]: # You can graphically select a particular region, in this case we do it␣
      ↪programmatically
      # for reproducability of this notebook
      histogram_Lz.plot.figure.interaction.selected = [1200, 1300]
```

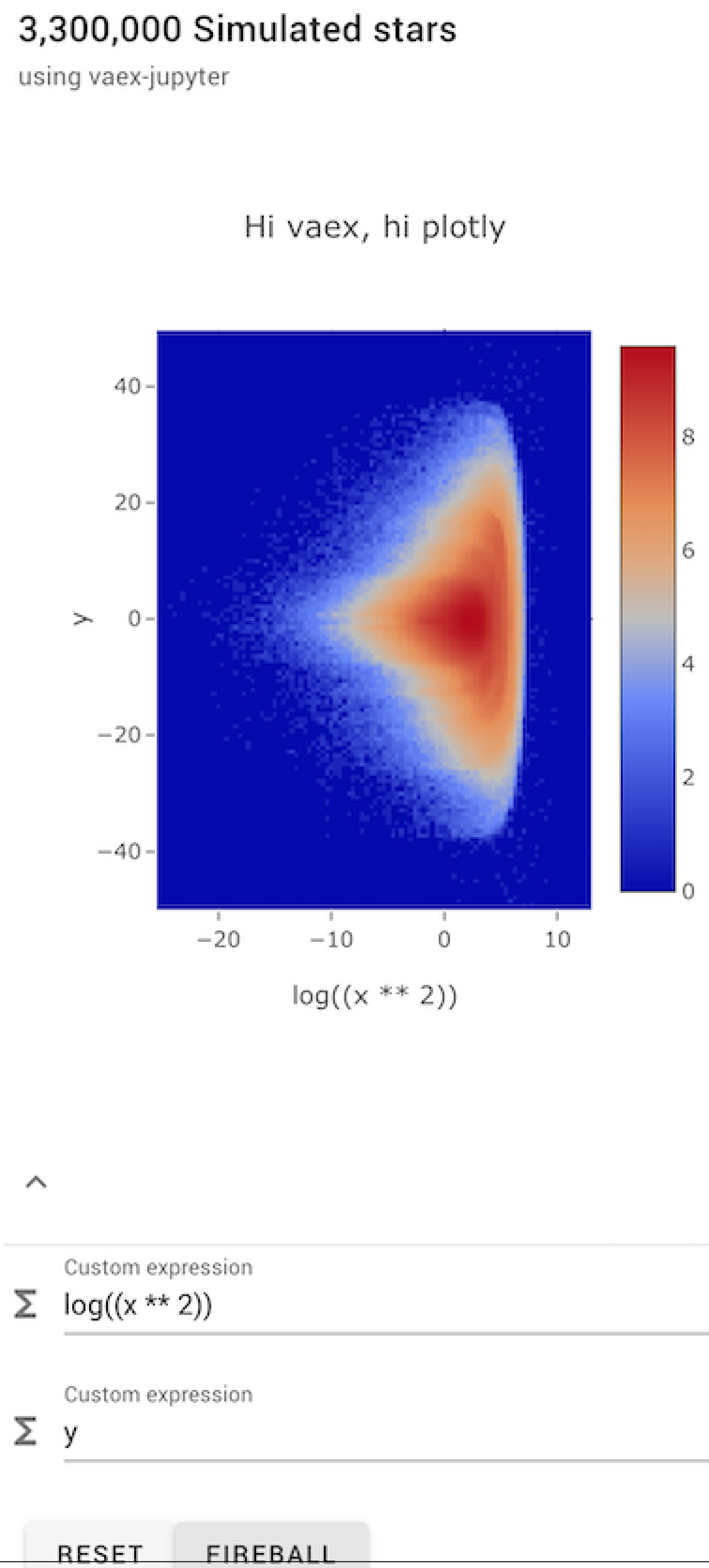
This shows an interesting structure in the heatmap above

4.3.8 Creating your own visualizations

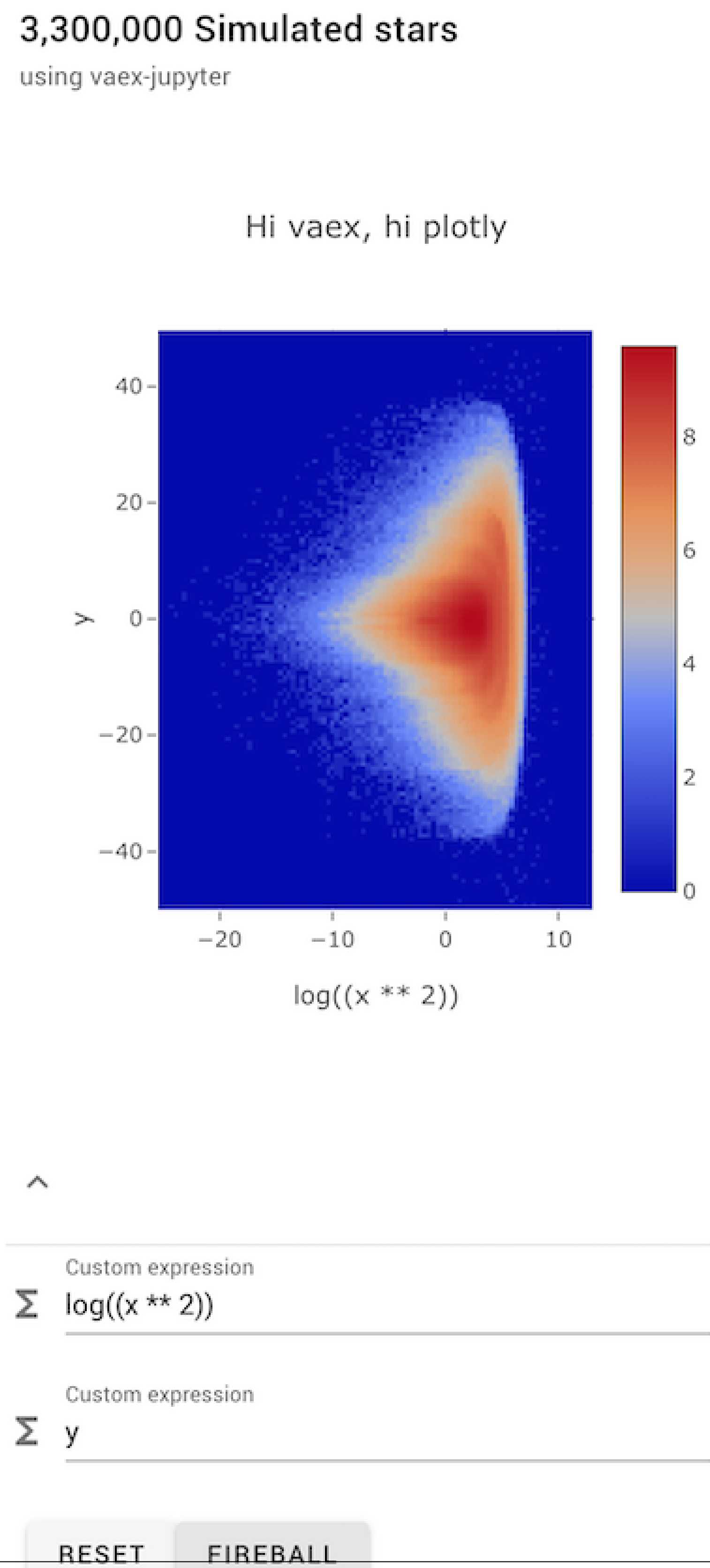
The primary goal of Vaex-Jupyter is to provide users with a framework to create dashboard and new visualizations. Over time more visualizations will go into the vaex-jupyter package, but giving you the option to create new ones is more important. To help you create new visualization, we have examples on how to create your own:

If you want to create your own visualization on this framework, check out these examples:

ipyvolume example



plotly example



The examples can also be found at the Examples page.

CHAPTER 5

Examples

5.1 Arrow

Vaex supports Arrow. We will demonstrate vaex+arrow by giving a quick look at a large dataset that does not fit into memory. The NYC taxi dataset for the year 2015 contains about 150 million rows containing information about taxi trips in New York, and is about 23GB in size. You can download it here:

- https://docs.vaex.io/en/latest/datasets.html

In case you want to convert it to the arrow format, use the code below:

```
ds_hdf5 = vaex.open('/Users/maartenbreddels/datasets/nytaxi/nyc_taxi2015.hdf5')
# this may take a while to export
ds_hdf5.export('./nyc_taxi2015.arrow')
```

Also make sure you install vaex-arrow:

```
$ pip install vaex-arrow
```

[1]:
```
!ls -alh /Users/maartenbreddels/datasets/nytaxi/nyc_taxi2015.arrow
```

```
-rw-r--r--  1 maartenbreddels  staff    23G Oct 31 18:56 /Users/maartenbreddels/
↪datasets/nytaxi/nyc_taxi2015.arrow
```

[3]:
```
import vaex
```

5.1.1 Opens instantly

Opening the file goes instantly, since nothing is being copied to memory. The data is only memory mapped, a technique that will only read the data when needed.

[4]:
```
%time
df = vaex.open('/Users/maartenbreddels/datasets/nytaxi/nyc_taxi2015.arrow')
```

```
CPU times: user 3 µs, sys: 1 µs, total: 4 µs
Wall time: 6.91 µs
```

[5]:
```
df
```

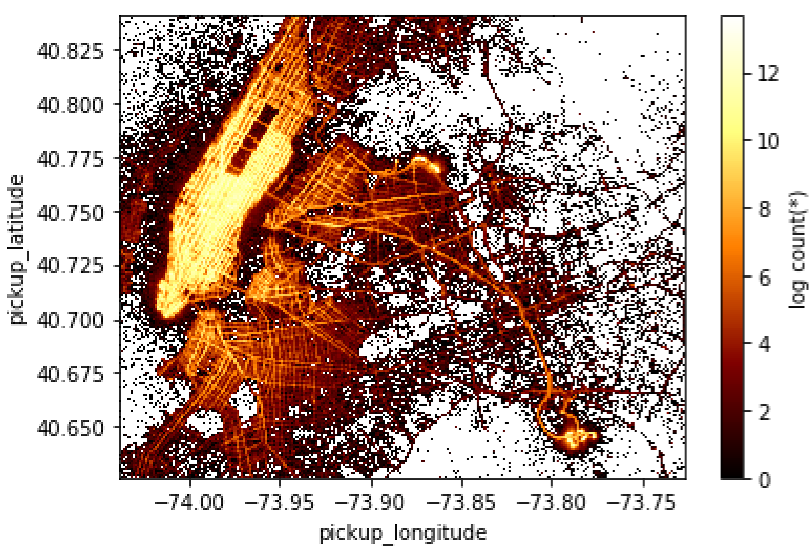
```
<IPython.core.display.HTML object>
```

[5]:
```
<vaex_arrow.dataset.DatasetArrow at 0x11d87e6a0>
```

5.1.2 Quick viz of 146 million rows

As can be seen, this dataset contains 146 million rows. Using plot, we can generate a quick overview what the data contains. The pickup locations nicely outline Manhattan.

[6]:
```
df.plot(df.pickup_longitude, df.pickup_latitude, f='log');
```



[7]:
```
df.total_amount.minmax()
```

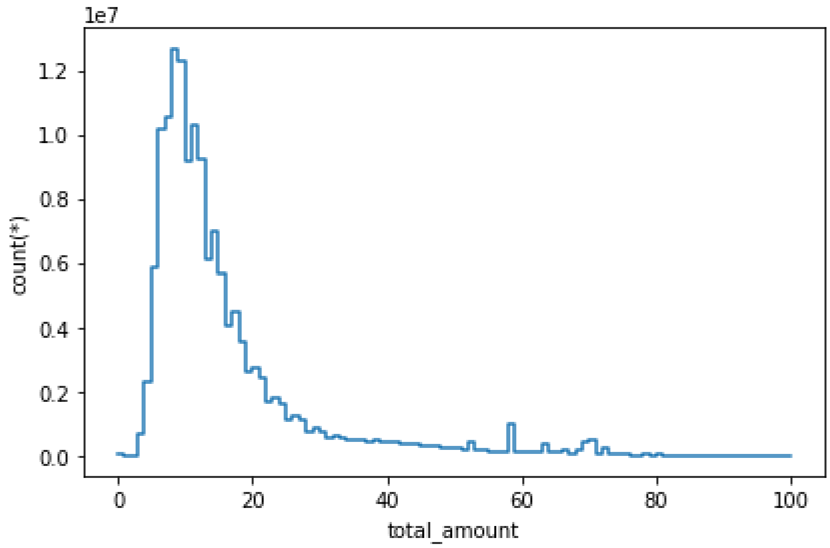
[7]:
```
array([-4.9630000e+02,  3.9506116e+06])
```

5.1.3 Data cleansing: outliers

As can be seen from the total_amount columns (how much people payed), this dataset contains outliers. From a quick 1d plot, we can see reasonable ways to filter the data

[8]:
```
df.plot1d(df.total_amount, shape=100, limits=[0, 100])
```

[8]:
```
[<matplotlib.lines.Line2D at 0x121d26320>]
```



[9]:
```
# filter the dataset
dff = df[(df.total_amount >= 0) & (df.total_amount < 100)]
```

5.1.4 Shallow copies

This filtered dataset did not copy any data (otherwise it would have costed us about ~23GB of RAM). Shallow copies of the data are made instead and a booleans mask tracks which rows should be used.

[10]:
```
dff['ratio'] = dff.tip_amount/dff.total_amount
```

5.1.5 Virtual column

The new column `ratio` does not do any computation yet, it only stored the expression and does not waste any memory. However, the new (virtual) column can be used in calculations as if it were a normal column.

[11]:
```
dff.ratio.mean()
```

```
<string>:1: RuntimeWarning: invalid value encountered in true_divide
```

[11]:
```
0.09601926650107262
```

5.1.6 Result

Our final result, the percentage of the tip, can be easily calcualted for this large dataset, it did not require any excessive amount of memory.

5.1.7 Interoperability

Since the data lives as Arrow arrays, we can pass them around to other libraries such as pandas, or even pass it to other processes.

[12]:
```
arrow_table = df.to_arrow_table()
arrow_table
```

[12]:
```
pyarrow.Table
VendorID: int64
dropoff_dayofweek: double
dropoff_hour: double
dropoff_latitude: double
dropoff_longitude: double
extra: double
fare_amount: double
improvement_surcharge: double
mta_tax: double
passenger_count: int64
payment_type: int64
pickup_dayofweek: double
pickup_hour: double
pickup_latitude: double
pickup_longitude: double
tip_amount: double
tolls_amount: double
total_amount: double
tpep_dropoff_datetime: timestamp[ns]
tpep_pickup_datetime: timestamp[ns]
trip_distance: double
```

[13]:
```
# Although you can 'convert' (pass the data) in to pandas,
# some memory will be wasted (at least an index will be created by pandas)
# here we just pass a subset of the data
df_pandas = df[:10000].to_pandas_df()
df_pandas
```

[13]:
```
      VendorID  dropoff_dayofweek  dropoff_hour  dropoff_latitude  \
0            2                3.0          19.0         40.750618
1            1                5.0          20.0         40.759109
2            1                5.0          20.0         40.824413
3            1                5.0          20.0         40.719986
4            1                5.0          20.0         40.742653
5            1                5.0          20.0         40.758194
6            1                5.0          20.0         40.749634
7            1                5.0          20.0         40.726326
8            1                5.0          21.0         40.759357
9            1                5.0          20.0         40.759365
10           1                5.0          20.0         40.728584
11           1                5.0          20.0         40.757217
12           1                5.0          20.0         40.707726
13           1                5.0          21.0         40.735210
14           1                5.0          20.0         40.739895
15           2                3.0          19.0         40.757889
16           2                3.0          19.0         40.786858
17           2                3.0          19.0         40.785782
18           2                3.0          19.0         40.786083
19           2                3.0          19.0         40.718590
20           2                3.0          19.0         40.714596
21           2                3.0          19.0         40.734650
22           2                3.0          19.0         40.735512
23           2                3.0          19.0         40.704220
24           2                3.0          19.0         40.761856
```

(continues on next page)

(continued from previous page)

```
25          2              3.0          19.0          40.811089
26          2              3.0          19.0          40.734890
27          2              3.0          19.0          40.743530
28          2              3.0          19.0          40.757721
29          2              3.0          19.0          40.704689
...       ...              ...           ...                ...
9970        1              4.0          11.0          40.719917
9971        1              4.0          10.0          40.720398
9972        1              4.0          11.0          40.755405
9973        2              1.0          19.0          40.763626
9974        2              1.0          19.0          40.772366
9975        2              1.0          19.0          40.733429
9976        2              1.0          19.0          40.774780
9977        2              1.0          19.0          40.751698
9978        2              1.0          19.0          40.752941
9979        2              1.0          19.0          40.735130
9980        2              1.0          19.0          40.745541
9981        2              1.0          19.0          40.793671
9982        2              1.0          19.0          40.754639
9983        2              1.0          18.0          40.723721
9984        2              1.0          19.0          40.774590
9985        2              1.0          19.0          40.774872
9986        2              1.0          19.0          40.787998
9987        2              1.0          19.0          40.790218
9988        2              1.0          19.0          40.739487
9989        2              1.0          19.0          40.780548
9990        2              1.0          19.0          40.761524
9991        2              1.0          19.0          40.720646
9992        2              1.0          19.0          40.795898
9993        2              1.0          18.0          40.769939
9994        2              4.0          18.0          40.773521
9995        2              4.0          18.0          40.774670
9996        2              4.0          18.0          40.758148
9997        2              4.0          18.0          40.768131
9998        2              4.0          18.0          40.759171
9999        2              4.0          18.0          40.752113

      dropoff_longitude  extra  fare_amount  improvement_surcharge  mta_tax  \
0            -73.974785    1.0         12.0                    0.3      0.5
1            -73.994415    0.5         14.5                    0.3      0.5
2            -73.951820    0.5          9.5                    0.3      0.5
3            -74.004326    0.5          3.5                    0.3      0.5
4            -74.004181    0.5         15.0                    0.3      0.5
5            -73.986977    0.5         27.0                    0.3      0.5
6            -73.992470    0.5         14.0                    0.3      0.5
7            -73.995010    0.5          7.0                    0.3      0.5
8            -73.987595    0.0         52.0                    0.3      0.5
9            -73.985916    0.5          6.5                    0.3      0.5
10           -74.004395    0.5          7.0                    0.3      0.5
11           -73.967407    0.5          7.5                    0.3      0.5
12           -74.009773    0.5          3.0                    0.3      0.5
13           -73.997345    0.5         19.0                    0.3      0.5
14           -73.995216    0.5          6.0                    0.3      0.5
15           -73.983978    1.0         16.5                    0.3      0.5
16           -73.955124    1.0         12.5                    0.3      0.5
17           -73.952713    1.0         26.0                    0.3      0.5
18           -73.980850    1.0         11.5                    0.3      0.5
```

(continues on next page)

(continued from previous page)

```
19          -73.952377    1.0         21.5                    0.3      0.5
20          -73.998924    1.0         17.5                    0.3      0.5
21          -73.999939    1.0          5.5                    0.3      0.5
22          -74.003563    1.0          5.5                    0.3      0.5
23          -74.007919    1.0          6.5                    0.3      0.5
24          -73.978172    1.0         11.5                    0.3      0.5
25          -73.953339    1.0          7.5                    0.3      0.5
26          -73.988609    1.0          9.0                    0.3      0.5
27          -73.985603    0.0         52.0                    0.3      0.5
28          -73.994514    1.0         10.0                    0.3      0.5
29          -74.009079    1.0         17.5                    0.3      0.5
...                ...    ...          ...                    ...      ...
9970        -73.955521    0.0         20.0                    0.3      0.5
9971        -73.984940    1.0          6.5                    0.3      0.5
9972        -74.002457    0.0          8.5                    0.3      0.5
9973        -73.969666    1.0         24.5                    0.3      0.5
9974        -73.960800    1.0          5.5                    0.3      0.5
9975        -73.984154    1.0          9.0                    0.3      0.5
9976        -73.957779    1.0         20.0                    0.3      0.5
9977        -73.989746    1.0          8.5                    0.3      0.5
9978        -73.977470    1.0          7.5                    0.3      0.5
9979        -73.976120    1.0          8.5                    0.3      0.5
9980        -73.984383    1.0          8.5                    0.3      0.5
9981        -73.974327    1.0          5.0                    0.3      0.5
9982        -73.986343    1.0         11.0                    0.3      0.5
9983        -73.989494    1.0          4.5                    0.3      0.5
9984        -73.963249    1.0          5.5                    0.3      0.5
9985        -73.982613    1.0          7.0                    0.3      0.5
9986        -73.953888    1.0          5.0                    0.3      0.5
9987        -73.975128    1.0         11.5                    0.3      0.5
9988        -73.989059    1.0          9.5                    0.3      0.5
9989        -73.959030    1.0          8.5                    0.3      0.5
9990        -73.960602    1.0         15.0                    0.3      0.5
9991        -73.989716    1.0          8.0                    0.3      0.5
9992        -73.972610    1.0         20.5                    0.3      0.5
9993        -73.981316    1.0          4.5                    0.3      0.5
9994        -73.955353    1.0         31.0                    0.3      0.5
9995        -73.947845    1.0         11.5                    0.3      0.5
9996        -73.985626    1.0          8.5                    0.3      0.5
9997        -73.964516    1.0         10.5                    0.3      0.5
9998        -73.975189    1.0          6.5                    0.3      0.5
9999        -73.975189    1.0          5.0                    0.3      0.5

      passenger_count      ...       pickup_dayofweek  pickup_hour  \
0                   1      ...                    3.0         19.0
1                   1      ...                    5.0         20.0
2                   1      ...                    5.0         20.0
3                   1      ...                    5.0         20.0
4                   1      ...                    5.0         20.0
5                   1      ...                    5.0         20.0
6                   1      ...                    5.0         20.0
7                   3      ...                    5.0         20.0
8                   3      ...                    5.0         20.0
9                   2      ...                    5.0         20.0
10                  1      ...                    5.0         20.0
11                  1      ...                    5.0         20.0
12                  1      ...                    5.0         20.0
```

(continues on next page)

(continued from previous page)

```
13                  1      ...                      5.0         20.0
14                  1      ...                      5.0         20.0
15                  1      ...                      3.0         19.0
16                  5      ...                      3.0         19.0
17                  5      ...                      3.0         19.0
18                  1      ...                      3.0         19.0
19                  2      ...                      3.0         19.0
20                  1      ...                      3.0         19.0
21                  1      ...                      3.0         19.0
22                  1      ...                      3.0         19.0
23                  2      ...                      3.0         19.0
24                  5      ...                      3.0         19.0
25                  5      ...                      3.0         19.0
26                  1      ...                      3.0         19.0
27                  1      ...                      3.0         19.0
28                  1      ...                      3.0         19.0
29                  6      ...                      3.0         19.0
...               ...      ...                      ...          ...
9970                1      ...                      4.0         10.0
9971                1      ...                      4.0         10.0
9972                2      ...                      4.0         10.0
9973                1      ...                      1.0         18.0
9974                5      ...                      1.0         18.0
9975                1      ...                      1.0         18.0
9976                3      ...                      1.0         18.0
9977                2      ...                      1.0         18.0
9978                1      ...                      1.0         18.0
9979                1      ...                      1.0         18.0
9980                1      ...                      1.0         18.0
9981                2      ...                      1.0         18.0
9982                1      ...                      1.0         18.0
9983                1      ...                      1.0         18.0
9984                5      ...                      1.0         18.0
9985                1      ...                      1.0         18.0
9986                2      ...                      1.0         18.0
9987                1      ...                      1.0         18.0
9988                1      ...                      1.0         18.0
9989                1      ...                      1.0         18.0
9990                1      ...                      1.0         18.0
9991                1      ...                      1.0         18.0
9992                1      ...                      1.0         18.0
9993                1      ...                      1.0         18.0
9994                1      ...                      4.0         18.0
9995                1      ...                      4.0         18.0
9996                2      ...                      4.0         18.0
9997                1      ...                      4.0         18.0
9998                3      ...                      4.0         18.0
9999                1      ...                      4.0         18.0

      pickup_latitude  pickup_longitude  tip_amount  tolls_amount  \
0           40.750111        -73.993896        3.25          0.00
1           40.724243        -74.001648        2.00          0.00
2           40.802788        -73.963341        0.00          0.00
3           40.713818        -74.009087        0.00          0.00
4           40.762428        -73.971176        0.00          0.00
5           40.774048        -73.874374        6.70          5.33
6           40.726009        -73.983276        0.00          0.00
```

(continues on next page)

(continued from previous page)

```
7           40.734142      -74.002663        1.66          0.00
8           40.644356      -73.783043        0.00          5.33
9           40.767948      -73.985588        1.55          0.00
10          40.723103      -73.988617        1.66          0.00
11          40.751419      -73.993782        1.00          0.00
12          40.704376      -74.008362        0.00          0.00
13          40.760448      -73.973946        3.00          0.00
14          40.731777      -74.006721        0.00          0.00
15          40.739811      -73.976425        4.38          0.00
16          40.754246      -73.968704        0.00          0.00
17          40.769581      -73.863060        8.08          5.33
18          40.779423      -73.945541        0.00          0.00
19          40.774010      -73.874458        4.50          0.00
20          40.751896      -73.976601        0.00          0.00
21          40.745079      -73.994957        1.62          0.00
22          40.747063      -74.000938        1.30          0.00
23          40.717892      -74.002777        1.50          0.00
24          40.736362      -73.997459        2.50          0.00
25          40.823994      -73.952278        1.70          0.00
26          40.750080      -73.991127        0.00          0.00
27          40.644127      -73.786575        6.00          5.33
28          40.741447      -73.993668        2.36          0.00
29          40.744083      -73.985291        3.70          0.00
...               ...             ...         ...           ...
9970        40.725979      -74.009071        4.00          0.00
9971        40.732452      -73.985001        1.65          0.00
9972        40.751358      -73.990479        1.00          0.00
9973        40.708790      -74.017281        5.10          0.00
9974        40.780003      -73.954681        1.00          0.00
9975        40.749680      -73.991531        0.00          0.00
9976        40.751801      -74.002327        2.00          0.00
9977        40.768433      -73.986137        0.00          0.00
9978        40.745071      -73.987068        1.00          0.00
9979        40.751259      -73.977814        0.00          0.00
9980        40.731110      -74.001350        0.00          0.00
9981        40.791222      -73.965118        0.00          0.00
9982        40.764175      -73.968994        1.00          0.00
9983        40.714985      -73.992409        2.00          0.00
9984        40.764881      -73.968529        1.30          0.00
9985        40.762344      -73.985695        1.60          0.00
9986        40.779526      -73.957619        1.20          0.00
9987        40.762226      -73.985916        2.50          0.00
9988        40.725056      -73.984329        2.10          0.00
9989        40.778542      -73.981949        1.00          0.00
9990        40.746319      -74.001114        0.00          0.00
9991        40.738167      -73.987434        1.00          0.00
9992        40.740582      -73.989738        4.30          0.00
9993        40.772015      -73.979416        1.10          0.00
9994        40.713215      -74.013542        5.00          0.00
9995        40.773186      -73.978043        0.00          0.00
9996        40.752003      -73.973198        0.00          0.00
9997        40.740456      -73.986252        2.46          0.00
9998        40.770500      -73.981323        2.08          0.00
9999        40.761505      -73.968452        0.00          0.00

      total_amount  tpep_dropoff_datetime tpep_pickup_datetime trip_distance
0            17.05    2015-01-15 19:23:42  2015-01-15 19:05:39          1.59
```

(continues on next page)

(continued from previous page)

```
1           17.80   2015-01-10 20:53:28  2015-01-10 20:33:38          3.30
2           10.80   2015-01-10 20:43:41  2015-01-10 20:33:38          1.80
3            4.80   2015-01-10 20:35:31  2015-01-10 20:33:39          0.50
4           16.30   2015-01-10 20:52:58  2015-01-10 20:33:39          3.00
5           40.33   2015-01-10 20:53:52  2015-01-10 20:33:39          9.00
6           15.30   2015-01-10 20:58:31  2015-01-10 20:33:39          2.20
7            9.96   2015-01-10 20:42:20  2015-01-10 20:33:39          0.80
8           58.13   2015-01-10 21:11:35  2015-01-10 20:33:39         18.20
9            9.35   2015-01-10 20:40:44  2015-01-10 20:33:40          0.90
10           9.96   2015-01-10 20:41:39  2015-01-10 20:33:40          0.90
11           9.80   2015-01-10 20:43:26  2015-01-10 20:33:41          1.10
12           4.30   2015-01-10 20:35:23  2015-01-10 20:33:41          0.30
13          23.30   2015-01-10 21:03:04  2015-01-10 20:33:41          3.10
14           7.30   2015-01-10 20:39:23  2015-01-10 20:33:41          1.10
15          22.68   2015-01-15 19:32:00  2015-01-15 19:05:39          2.38
16          14.30   2015-01-15 19:21:00  2015-01-15 19:05:40          2.83
17          41.21   2015-01-15 19:28:18  2015-01-15 19:05:40          8.33
18          13.30   2015-01-15 19:20:36  2015-01-15 19:05:41          2.37
19          27.80   2015-01-15 19:20:22  2015-01-15 19:05:41          7.13
20          19.30   2015-01-15 19:31:00  2015-01-15 19:05:41          3.60
21           8.92   2015-01-15 19:10:22  2015-01-15 19:05:41          0.89
22           8.60   2015-01-15 19:10:55  2015-01-15 19:05:41          0.96
23           9.80   2015-01-15 19:12:36  2015-01-15 19:05:41          1.25
24          15.80   2015-01-15 19:22:11  2015-01-15 19:05:41          2.11
25          11.00   2015-01-15 19:14:05  2015-01-15 19:05:41          1.15
26          10.80   2015-01-15 19:16:18  2015-01-15 19:05:42          1.53
27          64.13   2015-01-15 19:49:07  2015-01-15 19:05:42         18.06
28          14.16   2015-01-15 19:18:33  2015-01-15 19:05:42          1.76
29          23.00   2015-01-15 19:21:40  2015-01-15 19:05:42          5.19
...           ...                   ...                  ...           ...
9970        24.80   2015-01-30 11:20:08  2015-01-30 10:51:40          3.70
9971         9.95   2015-01-30 10:58:58  2015-01-30 10:51:40          1.10
9972        10.30   2015-01-30 11:03:41  2015-01-30 10:51:41          0.70
9973        31.40   2015-01-13 19:22:18  2015-01-13 18:55:41          7.08
9974         8.30   2015-01-13 19:02:03  2015-01-13 18:55:41          0.64
9975        10.80   2015-01-13 19:06:56  2015-01-13 18:55:41          1.67
9976        23.80   2015-01-13 19:18:39  2015-01-13 18:55:42          5.28
9977        10.30   2015-01-13 19:06:38  2015-01-13 18:55:42          1.38
9978        10.30   2015-01-13 19:05:34  2015-01-13 18:55:42          0.88
9979        10.30   2015-01-13 19:05:41  2015-01-13 18:55:42          1.58
9980        10.30   2015-01-13 19:05:32  2015-01-13 18:55:42          1.58
9981         6.80   2015-01-13 19:00:05  2015-01-13 18:55:42          0.63
9982        13.80   2015-01-13 19:11:57  2015-01-13 18:55:43          1.63
9983         8.30   2015-01-13 18:59:19  2015-01-13 18:55:43          0.70
9984         8.60   2015-01-13 19:01:19  2015-01-13 18:55:44          0.94
9985        10.40   2015-01-13 19:03:54  2015-01-13 18:55:44          1.04
9986         8.00   2015-01-13 19:00:06  2015-01-13 18:55:44          0.74
9987        15.80   2015-01-13 19:10:46  2015-01-13 18:55:44          2.19
9988        13.40   2015-01-13 19:08:40  2015-01-13 18:55:44          1.48
9989        11.30   2015-01-13 19:04:44  2015-01-13 18:55:45          1.83
9990        16.80   2015-01-13 19:14:59  2015-01-13 18:55:45          3.27
9991        10.80   2015-01-13 19:04:58  2015-01-13 18:55:45          1.56
9992        26.60   2015-01-13 19:18:18  2015-01-13 18:55:45          5.40
9993         7.40   2015-01-13 18:59:40  2015-01-13 18:55:45          0.34
9994        37.80   2015-01-23 18:59:52  2015-01-23 18:22:55          9.05
9995        13.30   2015-01-23 18:37:44  2015-01-23 18:22:55          2.32
9996        10.30   2015-01-23 18:34:48  2015-01-23 18:22:56          0.92
```

(continues on next page)

(continued from previous page)

```
9997         14.76    2015-01-23 18:33:58  2015-01-23 18:22:56         2.36
9998         10.38    2015-01-23 18:29:22  2015-01-23 18:22:56         1.05
9999          6.80    2015-01-23 18:27:58  2015-01-23 18:22:57         0.75

[10000 rows x 21 columns]
```

5.1.8 Tutorial

If you want to learn more on vaex, take a look at the tutorials to see what is possible.

5.2 Dask

If you want to try out this notebook with a live Python kernel, use mybinder:

5.2.1 Dask.array

A vaex dataframe can be lazily converted to a dask.array using *DataFrame.to_dask_array*.

[2]:
```
import vaex
df = vaex.example()
df
```

[2]:
```
#        x             y             z             vx            vy            vz          ␣
↪    E                 L                   Lz                    FeH
0        -0.777470767  2.10626292    1.93743467    53.276722     288.386047    -95.
↪2649078  -121238.171875   831.0799560546875   -336.426513671875    -2.
↪309227609164518
1        3.77427316    2.23387194    3.76209331    252.810791    -69.9498444   -56.
↪3121033  -100819.9140625  1435.1839599609375  -828.7567749023438   -1.
↪788735491591229
2        1.3757627     -6.3283844    2.63250017    96.276474     226.440201    -34.
↪7527161  -100559.9609375  1039.2989501953125  920.802490234375     -0.
↪7618109022478798
3        -7.06737804   1.31737781    -6.10543537   204.968842    -205.679016   -58.
↪9777031  -70174.8515625   2441.724853515625   1183.5899658203125   -1.
↪5208778422936413
4        0.243441463   -0.822781682  -0.206593871  -311.742371   -238.41217    186.
↪824127   -144138.75       374.8164367675781   -314.5353088378906   -2.
↪655341358427361
...      ...           ...           ...           ...           ...           ...         ␣
↪    ...               ...                 ...                   ...
329,995  3.76883793    4.66251659    -4.42904139   107.432999    -2.13771296   17.
↪5130272   -119687.3203125  746.8833618164062   -508.96484375        -1.
↪6499842518381402
329,996  9.17409325    -8.87091351   -8.61707687   32.0          108.089264    179.
↪060638   -68933.8046875   2395.633056640625   1275.490234375       -1.
↪4336036247720836
329,997  -1.14041007   -8.4957695    2.25749826    8.46711349    -38.2765236   -127.
↪541473   -112580.359375   1182.436279296875   115.58557891845703   -1.
↪9306227597361942
```

(continues on next page)

(continued from previous page)

```
329,998  -14.2985935   -5.51750422   -8.65472317   110.221558   -31.3925591  86.
↪2726822   -74862.90625     1324.5926513671875  1057.017333984375    -1.
↪225019818838568
329,999  10.5450506    -8.86106777   -4.65835428   -2.10541415  -27.6108856  3.
↪80799961   -95361.765625    351.0955505371094   -309.81439208984375  -2.
↪5689636894079477
```

[10]:
```
# convert a set of columns in the dataframe to a 2d dask array
A = df[['x', 'y', 'z']].to_dask_array()
A
```

[10]:
```
dask.array<vaex-df-d741baee-10eb-11ea-b19a, shape=(330000, 3), dtype=float64,␣
↪chunksize=(330000, 3), chunktype=numpy.ndarray>
```

[11]:
```
import dask.array as da
# lazily compute with dask
r = da.sqrt(A[:,0]**2 + A[:,1]**2 + A[:,2]**2)
r
```

[11]:
```
dask.array<sqrt, shape=(330000,), dtype=float64, chunksize=(330000,), chunktype=numpy.
↪ndarray>
```

[12]:
```
# materialize the data
r_computed = r.compute()
r_computed
```

[15]:
```
# put it back in the dataframe
df['r'] = r_computed
df
```

[15]:
```
#        x            y            z            vx           vy           vz          ␣
↪    E                    L                Lz                   FeH                  r
0        -0.777470767  2.10626292   1.93743467   53.276722    288.386047   -95.
↪2649078  -121238.171875   831.0799560546875   -336.426513671875    -2.
↪309227609164518   2.9655450396553587
1        3.77427316    2.23387194   3.76209331   252.810791   -69.9498444  -56.
↪3121033  -100819.9140625  1435.1839599609375  -828.7567749023438   -1.
↪788735491591229   5.77829281049018
2        1.3757627     -6.3283844   2.63250017   96.276474    226.440201   -34.
↪7527161  -100559.9609375  1039.2989501953125  920.802490234375     -0.
↪7618109022478798  6.99079603950256
3        -7.06737804   1.31737781   -6.10543537  204.968842   -205.679016  -58.
↪9777031  -70174.8515625   2441.724853515625   1183.5899658203125   -1.
↪5208778422936413  9.431842752707537
4        0.243441463   -0.822781682 -0.206593871 -311.742371  -238.41217   186.
↪824127   -144138.75       374.8164367675781   -314.5353088378906   -2.
↪655341358427361   0.8825613121347967
...      ...          ...          ...          ...          ...          ...         ␣
↪    ...              ...              ...                  ...                  ␣
↪...
329,995  3.76883793   4.66251659   -4.42904139  107.432999   -2.13771296  17.
↪5130272  -119687.3203125  746.8833618164062   -508.96484375         -1.
↪6499842518381402  7.453831761514681
329,996  9.17409325   -8.87091351  -8.61707687  32.0         108.089264   179.
↪060638   -68933.8046875   2395.633056640625   1275.490234375        -1.
↪4336036247720836  15.398412491068198
329,997  -1.14041007  -8.4957695   2.25749826   8.46711349   -38.2765236  -127.
↪541473   -112580.359375   1182.436279296875   115.58557891845703   -1.
↪9306227597361942  8.864250273925633
```

(continues on next page)

(continued from previous page)

```
329,998  -14.2985935   -5.51750422   -8.65472317   110.221558   -31.3925591  86.
↪2726822   -74862.90625     1324.5926513671875  1057.017333984375    -1.
↪225019818838568   17.601047186042507
329,999  10.5450506    -8.86106777   -4.65835428   -2.10541415  -27.6108856  3.
↪80799961   -95361.765625    351.0955505371094   -309.81439208984375  -2.
↪5689636894079477  14.540181524970293
```

[ ]:

5.3 GraphQL

If you want to try out this notebook with a live Python kernel, use mybinder:

vaex-graphql is a plugin package that exposes a DataFrame via a GraphQL interface. This allows easy sharing of data or aggregations/statistics or machine learning models to frontends or other programs with a standard query languages.

(Install with `$ pip install vaex-graphql`, no conda-forge support yet)

[3]:

```
import vaex.ml
df = vaex.ml.datasets.load_titanic()
df
```

[3]:

```
#      pclass    survived    name                                          sex   ␣
↪age     sibsp    parch    ticket    fare      cabin    embarked    boat    body  ␣
↪home_dest
0      1         True        Allen, Miss. Elisabeth Walton                 female ␣
↪29.0    0        0        24160     211.3375  B5       S           2       nan   ␣
↪St Louis, MO
1      1         True        Allison, Master. Hudson Trevor                male  ␣
↪0.9167  1        2        113781    151.55    C22 C26  S           11      nan   ␣
↪Montreal, PQ / Chesterville, ON
2      1         False       Allison, Miss. Helen Loraine                  female ␣
↪2.0     1        2        113781    151.55    C22 C26  S           None    nan   ␣
↪Montreal, PQ / Chesterville, ON
3      1         False       Allison, Mr. Hudson Joshua Creighton          male  ␣
↪30.0    1        2        113781    151.55    C22 C26  S           None    135.0 ␣
↪Montreal, PQ / Chesterville, ON
4      1         False       Allison, Mrs. Hudson J C (Bessie Waldo Daniels)  female ␣
↪25.0    1        2        113781    151.55    C22 C26  S           None    nan   ␣
↪Montreal, PQ / Chesterville, ON
...    ...       ...         ...                                           ...   ␣
↪...     ...      ...      ...       ...       ...      ...         ...     ...   ␣
↪...
1,304  3         False       Zabour, Miss. Hileni                          female ␣
↪14.5    1        0        2665      14.4542   None     C           None    328.0 ␣
↪None
1,305  3         False       Zabour, Miss. Thamine                         female ␣
↪nan     1        0        2665      14.4542   None     C           None    nan   ␣
↪None
1,306  3         False       Zakarian, Mr. Mapriededer                     male  ␣
↪26.5    0        0        2656      7.225     None     C           None    304.0 ␣
↪None
1,307  3         False       Zakarian, Mr. Ortin                           male  ␣
↪27.0    0        0        2670      7.225     None     C           None    nan   ␣
↪None
```

(continues on next page)

(continued from previous page)

```
1,308  3         False        Zimmerman, Mr. Leo                               male    ␣
↪29.0    0         0         315082     7.875      None      S            None     nan    ␣
↪None
```

[10]:
```
result = df.graphql.execute("""
    {
        df {
            min {
                age
                fare
            }
            mean {
                age
                fare
            }
            max {
                age
                fare
            }
            groupby {
                sex {
                   count
                   mean {
                       age
                   }
                }
            }
        }
    }
    """)
result.data
```

[10]:
```
OrderedDict([('df',
              OrderedDict([('min',
                            OrderedDict([('age', 0.1667), ('fare', 0.0)])),
                           ('mean',
                            OrderedDict([('age', 29.8811345124283),
                                         ('fare', 33.29547928134572)])),
                           ('max',
                            OrderedDict([('age', 80.0), ('fare', 512.3292)])),
                           ('groupby',
                            OrderedDict([('sex',
                                          OrderedDict([('count', [466, 843]),
                                                       ('mean',
                                                        OrderedDict([('age',
                                                                      [28.
↪6870706185567,
                                                                       30.
↪585232978723408])]))]))]))]))])
```

5.3.1 Pandas support

After importing vaex.graphql, vaex also installs a pandas accessor, so it is also accessible for Pandas DataFrames.

[11]:
```
df_pandas = df.to_pandas_df()
```

[20]:
```
df_pandas.graphql.execute("""
    {
        df(where: {age: {_gt: 20}}) {
            row(offset: 3, limit: 2) {
                name
                survived
            }
        }
    }
    """
).data
```

[20]:
```
OrderedDict([('df',
              OrderedDict([('row',
                            [OrderedDict([('name', 'Anderson, Mr. Harry'),
                                          ('survived', True)]),
                             OrderedDict([('name',
                                           'Andrews, Miss. Kornelia Theodosia'),
                                          ('survived', True)])])]))])
```

5.3.2 Server

The easiest way to learn to use the GraphQL language/vaex interface is to launch a server, and play with the GraphiQL graphical interface, its autocomplete, and the schema explorer.

We try to stay close to the Hasura API: https://docs.hasura.io/1.0/graphql/manual/api-reference/graphql-api/query.html

A server can be started from the command line:

```
$ python -m vaex.graphql myfile.hdf5
```

Or from within Python using df.graphql.serve

5.3.3 GraphiQL

See https://github.com/mariobuikhuizen/ipygraphql for a graphical widget, or a mybinder to try out a live example.

[ ]:

5.4 I/O Kung-Fu: get your data in and out of Vaex

If you want to try out this notebook with a live Python kernel, use mybinder:

5.4.1 Data input

Every project starts with reading in some data. Vaex supports several data sources:

- Binary file formats:
  - HDF5

  - Apache Arrow
  - Apache Parquet
  - FITS
- Text based file formats:
  - CSV
  - ASCII
  - JSON
- In-memory data representations:
  - pandas DataFrames and everything that pandas can read
  - Apache Arrow Tables
  - numpy arrays
  - Python dictionaries
  - Single row DataFrames

The following examples show the best practices of getting your data in Vaex.

Binary file formats

If your data is already in one of the supported binary file formats (HDF5, Apache Arrow, Apache Parquet, FITS), opening it with Vaex rather simple:

[1]:
```
import vaex

# Reading a HDF5 file
df_names = vaex.open('./data/io/sample_names_1.hdf5')
df_names
```

[1]:

#	name	age	city
0	John	17	Edinburgh
1	Sally	33	Groningen

[2]:
```
# Reading an arrow file
df_fruits = vaex.open('./data/io/sample_fruits.arrow')
df_fruits
```

[2]:

#	fruit	amount	origin
0	mango	5	Malaya
1	banana	10	Ecuador
2	orange	7	Spain

Opening such data is instantenous regardless of the file size on disk: Vaex will just memory-map the data instead of reading it in memory. This is the optimal way of working with large datasets that are larger than available RAM.

If your data is contained within multiple files, one can open them all simultaneously like this:

[3]:
```
df_names_all = vaex.open('./data/io/sample_names_*.hdf5')
df_names_all
```

[3]:
```
#   name      age  city
0   John       17  Edinburgh
1   Sally      33  Groningen
2   Maria      23  Caracas
3   Monica     55  New York
```

Alternatively, one can use the `open_many` method to pass a list of files to open:

[4]:
```
df_names_all = vaex.open_many(['./data/io/sample_names_1.hdf5',
                               './data/io/sample_names_2.hdf5'])
df_names_all
```

[4]:
```
#   name      age  city
0   John       17  Edinburgh
1   Sally      33  Groningen
2   Maria      23  Caracas
3   Monica     55  New York
```

The result will be a single DataFrame object containing all of the data coming from all files.

The data does not necessarily have to be local. With Vaex you can open a HDF5 file straight from Amazon's S3:

[5]:
```
df_from_s3 = vaex.open('s3://vaex/testing/xys.hdf5?anon=true')
df_from_s3
```

[5]:
```
#    x    y    s
0    1    3    5
1    2    4    6
```

In this case the data will be lazily downloaded and cached to the local machine. "Lazily downloaded" means that Vaex will only download the portions of the data you really need. For example: imagine that we have a file hosted on S3 that has 100 columns and 1 billion rows. Getting a preview of the DataFrame via `print(df)` for instance will download only the first and last 5 rows. If we than proceed to make calculations or plots with only 5 columns, only the data from those columns will be downloaded and cached to the local machine.

By default, data that is streamed from S3 is cached at `$HOME/.vaex/file-cache/s3`, and thus successive access is as fast as native disk access. One can also use the `profile_name` argument to use a specific S3 profile, which will than be passed to `s3fs.core.S3FileSystem`.

With Vaex one can also read-in parquet files:

[6]:
```
# Reading a parquet file
df_cars = vaex.open('./data/io/sample_cars.parquet')
df_cars
```

[6]:
```
#   car      color     year
0   renault  red       1996
1   audi     black     2005
2   toyota   blue      2000
```

Text based file formats

Datasets are still commonly stored in text-based file formats such as CSV. Since text-based file formats are not memory-mappable, they have to be read in memory. If the contents of a CSV file fits into the available RAM, one can simply do:

[7]:
```
df_nba = vaex.from_csv('./data/io/sample_nba_1.csv', copy_index=False)
df_nba
```

[7]:
```
   #  city          team     player
   0  Indianopolis  Pacers   Reggie Miller
   1  Chicago       Bulls    Michael Jordan
   2  Boston        Celtics  Larry Bird
```

or alternatively:

[8]:
```
df_nba = vaex.read_csv('./data/io/sample_nba_1.csv', copy_index=False)
df_nba
```

[8]:
```
   #  city          team     player
   0  Indianopolis  Pacers   Reggie Miller
   1  Chicago       Bulls    Michael Jordan
   2  Boston        Celtics  Larry Bird
```

Vaex is using pandas for reading CSV files in the background, so one can pass any arguments to the `vaex.from_csv` or `vaex.read_csv` as one would pass to `pandas.read_csv` and specify for example separators, column names and column types. The `copy_index` parameter specifies if the index column of the pandas DataFrame should be read as a regular column, or left out to save memory. In addition to this, if you specify the `convert=True` argument, the data will be automatically converted to an HDF5 file behind the scenes, thus freeing RAM and allowing you to work with your data in a memory-efficient, out-of-core manner.

If the CSV file is so large that it can not fit into RAM all at one time, one can convert the data to HDF5 simply by:

```
df = vaex.from_csv('./my_data/my_big_file.csv', convert=True, chunk_size=5_000_000)
```

When the above line is executed, Vaex will read the CSV in chunks, and convert each chunk to a temporary HDF5 file on disk. All temporary files are then concatenated into a single HDF5 file, and the temporary files deleted. The size of the individual chunks to be read can be specified via the `chunk_size` argument. Note that this automatic conversion requires free disk space of twice the final HDF5 file size.

It often happens that the data we need to analyse is spread over multiple CSV files. One can convert them to the HDF5 file format like this:

[9]:
```
list_of_files = ['./data/io/sample_nba_1.csv',
                 './data/io/sample_nba_2.csv',
                 './data/io/sample_nba_3.csv',]

# Convert each CSV file to HDF5
for file in list_of_files:
    df_tmp = vaex.from_csv(file, convert=True, copy_index=False)
```

The above code block converts in turn each CSV file to the HDF5 format. Note that the conversion will work regardless of the file size of each individual CSV file, provided there is sufficient storage space.

Working with all of the data is now easy: just open all of the relevant HDF5 files as described above:

[10]:
```
df = vaex.open('./data/io/sample_nba_*.csv.hdf5')
df
```

[10]:
```
   #  city          team     player
   0  Indianopolis  Pacers   Reggie Miller
   1  Chicago       Bulls    Michael Jordan
   2  Boston        Celtics  Larry Bird
   3  Los Angeles   Lakers   Kobe Bryant
   4  Toronto       Raptors  Vince Carter
   5  Philadelphia  76ers    Allen Iverson
   6  San Antonio   Spurs    Tim Duncan
```

One can than additionally export this combined DataFrame to a single HDF5 file. This should lead to minor performance improvements.

```
[11]: df.export('./data/io/sample_nba_combined.hdf5')
```

It is also common the data to be stored in JSON files. To read such data in Vaex one can do:

```
[12]: df_isles = vaex.from_json('./data/io/sample_isles.json', orient='table', copy_
      ↪index=False)
      df_isles
```

```
[12]:  #  isle             size_sqkm
       0  Easter Island       163.6
       1  Fiji                 18.333
       2  Tortuga             178.7
```

This is a convenience method which simply wraps `pandas.read_json`, so the same arguments and file reading strategy applies. If the data is distributed amongs multiple JSON files, one can apply a similar strategy as in the case of multiple CSV files: read each JSON file with the `vaex.from_json` method, convert it to a HDF5 or Arrow file format. Than use `vaex.open` or `vaex.open_many` methods to open all the converted files as a single DataFrame.

To learn more about different options of exporting data with Vaex, please read the next section below.

In-memory data representations

One can construct a Vaex DataFrame from a variety of in-memory data representations. Such a common operation is converting a pandas into a Vaex DataFrame. Let us read in a CSV file with pandas and than convert it to a Vaex DataFrame:

```
[13]: import pandas as pd

      pandas_df = pd.read_csv('./data/io/sample_nba_1.csv')
      pandas_df
```

```
[13]:           city     team          player
      0  Indianopolis   Pacers   Reggie Miller
      1       Chicago    Bulls  Michael Jordan
      2        Boston  Celtics      Larry Bird
```

```
[14]: df = vaex.from_pandas(df=pandas_df, copy_index=True)
      df
```

```
[14]:  #  city          team     player            index
       0  Indianopolis  Pacers   Reggie Miller         0
       1  Chicago       Bulls    Michael Jordan        1
       2  Boston        Celtics  Larry Bird            2
```

The `copy_index` argument specifies whether the index column of a pandas DataFrame should be imported into the Vaex DataFrame. Converting a pandas into a Vaex DataFrame is particularly useful since pandas can read data from a large variety of file formats. For instance, we can use pandas to read data from a database, and then pass it to Vaex like so:

```
import vaex
import pandas as pd
import sqlalchemy

connection_string = 'postgresql://readonly:' + 'my_password' + '@server.company.com:
↪1234/database_name'
```

(continues on next page)

(continued from previous page)

```
engine = sqlalchemy.create_engine(connection_string)

pandas_df = pd.read_sql_query('SELECT * FROM MYTABLE', con=engine)
df = vaex.from_pandas(pandas_df, copy_index=False)
```

Another example is using pandas to read in SAS files:

[15]:
```
pandas_df = pd.read_sas('./data/io/sample_airline.sas7bdat')
df = vaex.from_pandas(pandas_df, copy_index=False)
df
```

[15]:
```
#     YEAR    Y                   W                     R                     L                   ␣
↪          K
0     1948.0  1.2139999866485596  0.24300000071525574   0.1454000025987625    1.
↪4149999618530273  0.6119999885559082
1     1949.0  1.3539999723434448  0.25999999046325684   0.21809999644756317   1.
↪3839999437332153  0.5590000152587891
2     1950.0  1.569000005722046   0.27799999713897705   0.3156999945640564    1.
↪3880000114440918  0.5730000138282776
3     1951.0  1.9479999542236328  0.296999990940094     0.39399999380111694   1.
↪5499999523162842  0.5640000104904175
4     1952.0  2.265000104904175   0.3100000023841858    0.35589998960494995   1.
↪8020000457763672  0.5740000009536743
...   ...     ...                 ...                   ...                   ...                 ␣
↪          ...
27    1975.0  18.72100067138672   1.246999979019165     0.23010000586509705   5.
↪7220001220703125  9.062000274658203
28    1976.0  19.25               1.375                 0.3452000021934509    5.
↪76200008392334    8.26200008392334
29    1977.0  20.64699935913086   1.5440000295639038    0.45080000162124634   5.
↪876999855041504   7.473999977111816
30    1978.0  22.72599983215332   1.7029999494552612    0.5877000093460083    6.
↪107999801635742   7.104000091552734
31    1979.0  23.618999481201172  1.7790000438690186    0.534600019454956     6.
↪8520002365112305  6.874000072479248
```

One can read in an arrow table as a Vaex DataFrame in a similar manner. Let us first use pyarrow to read in a CSV file as an arrow table.

[16]:
```
import pyarrow.csv

arrow_table = pyarrow.csv.read_csv('./data/io/sample_nba_1.csv')
arrow_table
```

[16]:
```
pyarrow.Table
city: string
team: string
player: string
```

Once we have the arrow table, converting it to a DataFrame is simple:

[17]:
```
df = vaex.from_arrow_table(arrow_table)
df
```

[17]:

#	city	team	player
0	Indianopolis	Pacers	Reggie Miller
1	Chicago	Bulls	Michael Jordan
2	Boston	Celtics	Larry Bird

It also common to construct a Vaex DataFrame from numpy arrays. That can be done like this:

```
[18]: import numpy as np

x = np.arange(2)
y = np.array([10, 20])
z = np.array(['dog', 'cat'])


df_numpy = vaex.from_arrays(x=x, y=y, z=z)
df_numpy
```

[18]:

#	x	y	z
0	0	10	dog
1	1	20	cat

Constructing a DataFrame from a Python dict is also straight-forward:

```
[19]: # Construct a DataFrame from Python dictionary
data_dict = dict(x=[2, 3], y=[30, 40], z=['cow', 'horse'])

df_dict = vaex.from_dict(data_dict)
df_dict
```

[19]:

#	x	y	z
0	2	30	cow
1	3	40	horse

At times, one may need to create a single row DataFrame. Vaex has a convenience method which takes individual elements (scalars) and creates the DataFrame:

```
[20]: df_single_row = vaex.from_scalars(x=4, y=50, z='mouse')
df_single_row
```

[20]:

#	x	y	z
0	4	50	mouse

Finally, we can choose to concatenate different DataFrames, without any memory penalties like so:

```
[21]: df = vaex.concat([df_numpy, df_dict, df_single_row])
df
```

[21]:

#	x	y	z
0	0	10	dog
1	1	20	cat
2	2	30	cow
3	3	40	horse
4	4	50	mouse

5.4.2 Data export

One can export Vaex DataFrames to multiple file or in-memory data representations:

- Binary file formats:
  - HDF5
  - Apache Arrow
  - Apache Parquet

  - FITS
- Text based file formats:
  - CSV
  - ASCII
- In-memory data representations:
  - DataFrames:
    * panads DataFrame
    * Apache Arrow Table
    * numpy arrays
    * Dask arrays
    * Python dictionaries
    * Python items list (a list of ('column_name', data) tuples)
  - Expressions:
    * panads Series
    * numpy array
    * Dask array
    * Python list

Binary file formats

The most efficient way to store data on disk when you work with Vaex is to use binary file formats. Vaex can export a DataFrame to HDF5, Apache Arrow, Apache Parquet and FITS:

[22]:
```
df.export_hdf5('./data/io/output_data.hdf5')
df.export_arrow('./data/io/output_data.arrow')
df.export_parquet('./data/io/output_data.parquet')
```

Alternatively, one can simply use:

[23]:
```
df.export('./data/io/output_data.hdf5')
df.export('./data/io/output_data.arrow')
df.export('./data/io/output_data.parquet')
```

where Vaex will determine the file format of the based on the specified extension of the file name. If the extension is not recognized, an exception will be raised.

If your data is large, i.e. larger than the available RAM, we recomment exporting to HDF5.

Text based file format

At times, it may be useful to export the data to disk in a text based file format such as CSV. In that case one can simply do:

[24]:
```
df.export_csv('./data/io/output_data.csv')  # `chunk_size` has a default value of 1_
↪000_000
```

The `df.export_csv` method is using `pandas_df.to_csv` behind the scenes, and thus one can pass any argument to `df.export_csv` as would to `pandas_df.to_csv`. The data is exported in chunks and the size of those chunks can be specified by the `chunk_size` argument in `df.export_csv`. In this way, data that is too large to fit in RAM can be saved to disk.

In memory data representation

Python has a rich ecosystem comprised of various libraries for data manipulation, that offer different functionality. Thus, it is often useful to be able to pass data from one library to another. Vaex is able to pass on its data to other libraries via a number of in-memory representations.

DataFrame representations

A Vaex DataFrame can be converted to a pandas DataFrame like so:

[25]:
```
pandas_df = df.to_pandas_df()
pandas_df  # looks the same doesn't it?
```

[25]:
```
   x   y      z
0  0  10    dog
1  1  20    cat
2  2  30    cow
3  3  40  horse
4  4  50  mouse
```

For DataFrames that are too large to fit in memory, one can specify the `chunk_size` argument, in which case the `to_pandas_df`method returns a generator yileding a pandas DataFrame with as many rows as indicated by the `chunk_size` argument:

[26]:
```
gen = df.to_pandas_df(chunk_size=3)

for i1, i2, chunk in gen:
    print(i1, i2)
    print(chunk)
    print()
```

```
0 3
   x   y    z
0  0  10  dog
1  1  20  cat
2  2  30  cow

3 5
   x   y      z
0  3  40  horse
1  4  50  mouse
```

The generator also yields the row number of the first and the last element of that chunk, so we know exactly where in the parent DataFrame we are. The following DataFrame methods also support the `chunk_size` argument with the same behaviour.

Converting a Vaex DataFrame into an arrow table is similar:

[27]:
```
arrow_table = df.to_arrow_table()
arrow_table
```

[27]:
```
pyarrow.Table
x: int64
y: int64
z: string
```

One can simply convert the DataFrame to a list of arrays. By default, the data is exposed as a list of numpy arrays:

[28]:
```
arrays = df.to_arrays()
arrays
```

[28]:
```
[array([0, 1, 2, 3, 4]),
 array([10, 20, 30, 40, 50]),
 array(['dog', 'cat', 'cow', 'horse', 'mouse'], dtype=object)]
```

By specifying the `array_type` argument, one can choose whether the data will be represented by numpy arrays, xarrays, or Python lists.

[29]:
```
arrays = df.to_arrays(array_type='xarray')
arrays  # list of xarrays
```

[29]:
```
[<xarray.DataArray (dim_0: 5)>
 array([0, 1, 2, 3, 4])
 Dimensions without coordinates: dim_0, <xarray.DataArray (dim_0: 5)>
 array([10, 20, 30, 40, 50])
 Dimensions without coordinates: dim_0, <xarray.DataArray (dim_0: 5)>
 array(['dog', 'cat', 'cow', 'horse', 'mouse'], dtype=object)
 Dimensions without coordinates: dim_0]
```

[30]:
```
arrays = df.to_arrays(array_type='list')
arrays  # list of lists
```

[30]:
```
[[0, 1, 2, 3, 4],
 [10, 20, 30, 40, 50],
 ['dog', 'cat', 'cow', 'horse', 'mouse']]
```

Keeping it close to pure Python, one can export a Vaex DataFrame as a dictionary. The same `array_type` keyword argument applies here as well:

[31]:
```
d_dict = df.to_dict(array_type='numpy')
d_dict
```

[31]:
```
{'x': array([0, 1, 2, 3, 4]),
 'y': array([10, 20, 30, 40, 50]),
 'z': array(['dog', 'cat', 'cow', 'horse', 'mouse'], dtype=object)}
```

Alternatively, one can also convert a DataFrame to a list of tuples, were the first element of the tuple is the column name, while the second element is the array representation of the data.

[32]:
```
# Get a single item list
items = df.to_items(array_type='list')
items
```

[32]:
```
[('x', [0, 1, 2, 3, 4]),
 ('y', [10, 20, 30, 40, 50]),
 ('z', ['dog', 'cat', 'cow', 'horse', 'mouse'])]
```

As mentioned earlier, with all of the above example, one can use the `chunk_size` argument which creates a generator, yielding a portion of the DataFrame in the specified format. In the case of `.to_dict` method:

```
[33]: gen = df.to_dict(array_type='list', chunk_size=2)

      for i1, i2, chunk in gen:
          print(i1, i2, chunk)
```

```
0 2 {'x': [0, 1], 'y': [10, 20], 'z': ['dog', 'cat']}
2 4 {'x': [2, 3], 'y': [30, 40], 'z': ['cow', 'horse']}
4 5 {'x': [4], 'y': [50], 'z': ['mouse']}
```

Last but not least, a Vaex DataFrame can be lazily exposed as a Dask array:

```
[34]: dask_arrays = df[['x', 'y']].to_dask_array()   # String support coming soon
      dask_arrays
```

```
[34]: dask.array<vaex-df-7e85845a-8bcd-11ea-a451, shape=(5, 2), dtype=int64, chunksize=(5,␣
      ↪2), chunktype=numpy.ndarray>
```

Expression representations

A single Vaex Expression can be also converted to a variety of in-memory representations:

```
[35]: # pandas Series
      x_series = df.x.to_pandas_series()
      x_series
```

```
[35]: 0    0
      1    1
      2    2
      3    3
      4    4
      dtype: int64
```

```
[36]: # numpy array
      x_numpy = df.x.to_numpy()
      x_numpy
```

```
[36]: array([0, 1, 2, 3, 4])
```

```
[37]: # Python list
      x_list = df.x.tolist()
      x_list
```

```
[37]: [0, 1, 2, 3, 4]
```

```
[38]: # Dask array
      x_dask_array = df.x.to_dask_array()
      x_dask_array
```

```
[38]: dask.array<vaex-expression-7e8e9f18-8bcd-11ea-a451, shape=(5,), dtype=int64,␣
      ↪chunksize=(5,), chunktype=numpy.ndarray>
```

5.5 Machine Learning (basic): the Iris dataset

If you want to try out this notebook with a live Python kernel, use mybinder:

While `vaex.ml` does not yet implement predictive models, we provide wrappers to powerful libraries (e.g. Scikit-learn, xgboost) and make them work efficiently with `vaex`. `vaex.ml` does implement a variety of standard data transformers (e.g. PCA, numerical scalers, categorical encoders) and a very efficient KMeans algorithm that take full advantage of `vaex`.

The following is a simple example on use of `vaex.ml`. We will be using the well known Iris dataset, and we will use it to build a model which distinguishes between the three Irish species (Iris setosa, Iris virginica and Iris versicolor).

Lets start by importing the common libraries, load and inspect the data.

[1]:
```
import vaex
import vaex.ml

import pylab as plt


df = vaex.ml.datasets.load_iris()
df
```

[1]:

#	sepal_length	sepal_width	petal_length	petal_width	class_
0	5.9	3.0	4.2	1.5	1
1	6.1	3.0	4.6	1.4	1
2	6.6	2.9	4.6	1.3	1
3	6.7	3.3	5.7	2.1	2
4	5.5	4.2	1.4	0.2	0
...	...	...	...	...	...
145	5.2	3.4	1.4	0.2	0
146	5.1	3.8	1.6	0.2	0
147	5.8	2.6	4.0	1.2	1
148	5.7	3.8	1.7	0.3	0
149	6.2	2.9	4.3	1.3	1

Splitting the data into *train* and *test* steps should be done immediately, before any manipulation is done on the data. `vaex.ml` contains a `train_test_split` method which creates shallow copies of the main DataFrame, meaning that no extra memory is used when defining train and test sets. Note that the `train_test_split` method does an ordered split of the main DataFrame to create the two sets. In some cases, one may need to shuffle the data.

If shuffling is required, we recommend the following:

```
df.export("shuffled", shuffle=True)
df = vaex.open("shuffled.hdf5)
df_train, df_test = df.ml.train_test_split(test_size=0.2)
```

In the present scenario, the dataset is already shuffled, so we can simply do the split right away.

[2]:
```
# Orderd split in train and test
df_train, df_test = df.ml.train_test_split(test_size=0.2)
```

```
/Users/jovan/PyLibrary/vaex/packages/vaex-core/vaex/ml/__init__.py:209: UserWarning:␣
↪Make sure the DataFrame is shuffled
  warnings.warn('Make sure the DataFrame is shuffled')
```

As this is a very simple tutorial, we will just use the columns already provided as features for training the model.

[3]:
```
features = df_train.column_names[:4]
features
```

[3]:
```
['sepal_length', 'sepal_width', 'petal_length', 'petal_width']
```

5.5.1 PCA

The `vaex.ml` module contains several classes for dataset transformations that are commonly used to pre-process data prior to building a model. These include numerical feature scalers, category encoders, and PCA transformations. We have adopted the scikit-learn API, meaning that all transformers have the `.fit` and `.transform` methods.

Let's use apply a PCA transformation on the training set. There is no need to scale the data beforehand, since the PCA also normalizes the data.

[4]:
```
pca = vaex.ml.PCA(features=features, n_components=4)
df_train = pca.fit_transform(df_train)
df_train
```

[4]:
```
#    sepal_length    sepal_width    petal_length    petal_width    class_    PCA_0   ␣
↪              PCA_1                       PCA_2                      PCA_3
0    5.4             3.0            4.5             1.5            1         -0.
↪5819340944906611   -0.5192084328455534   -0.4079706950207428   -0.22843325658378022
1    4.8             3.4            1.6             0.2            0         2.
↪628040487885542     -0.05578001049524599  -0.09961452867004605  -0.14960589756342935
2    6.9             3.1            4.9             1.5            1         -1.
↪438496521671396    0.5307778852279289    0.32322065776316616   -0.
↪0066478967991949744
3    4.4             3.2            1.3             0.2            0         3.
↪00633586736142      -0.41909744036887703  -0.17571839830952185  -0.05420541515837107
4    5.6             2.8            4.9             2.0            2         -1.
↪1948465297428466   -0.6200295372229213   -0.4751905348367903   0.08724845774327505
...  ...             ...            ...             ...            ...       ...     ␣
↪              ...                         ...                        ...
115  5.2             3.4            1.4             0.2            0         2.
↪6608856211270933    0.2619681501203415    0.12886483875694454   0.06429707648769989
116  5.1             3.8            1.6             0.2            0         2.
↪561545765055359     0.4288927940763031    -0.18633294617759266  -0.20573646329612738
117  5.8             2.6            4.0             1.2            1         -0.
↪22075578997244774  -0.40152336651555137  0.25417836518749715   0.04952191889168374
118  5.7             3.8            1.7             0.3            0         2.
↪23068249078231      0.826166758833374     0.07863720599424912   0.
↪0004035597987264161
119  6.2             2.9            4.3             1.3            1         -0.
↪6256358184862005   0.023930474333675168  0.21203674475657858   -0.
↪0077954052328795265
```

The result of pca `.fit_transform` method is a shallow copy of the DataFrame which contains the resulting columns of the transformation, in this case the PCA components, as virtual columns. This means that the transformed DataFrame takes no memory at all! So while this example is made with only 120 sample, this would work in the same way even for millions or billions of samples.

5.5.2 Gradient boosting trees

Now let's train a gradient boosting model. While `vaex.ml` does not currently include this type of models, we support the popular boosted trees libraries xgboost, lightgbm, and catboost. In this tutorial we will use the `lightgbm` classifier.

[9]:
```
import lightgbm
import vaex.ml.sklearn

# Features on which to train the model
train_features = df_train.get_column_names(regex='PCA_.*')
```

(continues on next page)

(continued from previous page)

```
# The target column
target = 'class_'

# Instantiate the LightGBM Classifier
booster = lightgbm.sklearn.LGBMClassifier(num_leaves=5,
                                          max_depth=5,
                                          n_estimators=100,
                                          random_state=42)

# Make it a vaex transformer (for the automagic pipeline and lazy predictions)
model = vaex.ml.sklearn.SKLearnPredictor(features=train_features,
                                         target=target,
                                         model=booster,
                                         prediction_name='prediction')

# Train and predict
model.fit(df=df_train)
df_train = model.transform(df=df_train)

df_train
```

```
[9]: #    sepal_length    sepal_width     petal_length     petal_width     class_     PCA_0   ␣
     ↪              PCA_1                   PCA_2                  PCA_3                    ␣
     ↪prediction
     0    5.4              3.0             4.5              1.5             1          -0.
     ↪5819340944906611   -0.5192084328455534   -0.4079706950207428   -0.22843325658378022␣
     ↪    1
     1    4.8              3.4             1.6              0.2             0          2.
     ↪628040487885542     -0.05578001049524599  -0.09961452867004605  -0.
     ↪14960589756342935    0
     2    6.9              3.1             4.9              1.5             1          -1.
     ↪438496521671396     0.5307778852279289    0.32322065776316616   -0.
     ↪0066478967991949744  1
     3    4.4              3.2             1.3              0.2             0          3.
     ↪00633586736142       -0.41909744036887703  -0.17571839830952185  -0.
     ↪05420541515837107    0
     4    5.6              2.8             4.9              2.0             2          -1.
     ↪1948465297428466    -0.6200295372229213   -0.4751905348367903   0.08724845774327505 ␣
     ↪    2
     ...  ...              ...             ...              ...             ...        ...   ␣
     ↪              ...                     ...                    ...                     ...
     115  5.2              3.4             1.4              0.2             0          2.
     ↪6608856211270933     0.2619681501203415    0.12886483875694454    0.06429707648769989␣
     ↪     0
     116  5.1              3.8             1.6              0.2             0          2.
     ↪561545765055359      0.4288927940763031    -0.18633294617759266  -0.
     ↪20573646329612738    0
     117  5.8              2.6             4.0              1.2             1          -0.
     ↪22075578997244774   -0.40152336651555137  0.25417836518749715   0.04952191889168374 ␣
     ↪    1
     118  5.7              3.8             1.7              0.3             0          2.
     ↪23068249078231       0.826166758833374     0.07863720599424912    0.
     ↪00040355979872641 61   0
     119  6.2              2.9             4.3              1.3             1          -0.
     ↪6256358184862005    0.023930474333675168  0.21203674475657858   -0.
     ↪0077954052328795265  1
```

Notice that after training the model, we use the `.transform` method to obtain a shallow copy of the DataFrame which contains the prediction of the model, in a form of a virtual column. This makes it easy to evaluate the model, and easily create various diagnostic plots. If required, one can call the `.predict` method, which will result in an in-memory `numpy.array` housing the predictions.

5.5.3 Automatic pipelines

Assuming we are happy with the performance of the model, we can continue and apply our transformations and model to the test set. Unlike other libraries, we do not need to explicitly create a pipeline here in order to propagate the transformations. In fact, with `vaex` and `vaex.ml`, a pipeline is automatically being created as one is doing the exploration of the data. Each `vaex` DataFrame contains a *state*, which is a (serializable) object containing information of all transformations applied to the DataFrame (filtering, creation of new virtual columns, transformations).

Recall that the outputs of both the PCA transformation and the boosted model were in fact virtual columns, and thus are stored in the state of `df_train`. All we need to do, is to apply this state to another similar DataFrame (e.g. the test set), and all the changes will be propagated.

[6]:
```
state = df_train.state_get()
df_test.state_set(state)

df_test
```

[6]:
```
#    sepal_length    sepal_width    petal_length    petal_width    class_    PCA_0    ␣
↪              PCA_1                    PCA_2                    PCA_3             ␣
↪prediction
0    5.9             3.0            4.2             1.5            1         -0.
↪4978687101343986   -0.11289245880584761  -0.11962601206069637  0.0625954090178564  ␣
↪  1
1    6.1             3.0            4.6             1.4            1         -0.
↪8754765898560835   -0.03902402119573594  0.022944044447894815  -0.14143773065379384␣
↪  1
2    6.6             2.9            4.6             1.3            1         -1.
↪0228803632878913   0.2503709022470443    0.4130613754204865    -0.
↪030391911559003282  1
3    6.7             3.3            5.7             2.1            2         -2.
↪2544508624315838   0.3431374410700749    -0.28908707579214765  -0.07059175451207655␣
↪  2
4    5.5             4.2            1.4             0.2            0         2.
↪632289228948536     1.020394958612415     -0.20769510079946696  -0.
↪13744144140286718   0
...  ...             ...            ...             ...            ...       ...    ␣
↪              ...                      ...                      ...              ...
25   5.5             2.5            4.0             1.3            1         -0.
↪16189655085432594  -0.6871827581512436   0.09773053160021669   0.07093166682594204 ␣
↪  1
26   5.8             2.7            3.9             1.2            1         -0.
↪12526327170089271  -0.3148233189949767   0.19720893202789733   0.06041982692766706 4␣
↪  1
27   4.4             2.9            1.4             0.2            0         2.
↪8918941837640526    -0.6426744898497139   0.006171795874510444  0.
↪007700652884580328   0
28   4.5             2.3            1.3             0.3            0         2.
↪850207707200544     -0.9710397723109179   0.38501428492268475   0.377723418991853  ␣
↪   0
29   6.9             3.2            5.7             2.3            2         -2.
↪405639277483925    0.4027072938482219    -0.22944817803540973  0.17443211711742812 ␣
↪  2
```

5.5.4 Production

Now `df_test` contains all the transformations we applied on the training set (`df_train`), including the model prediction. The transfer of state from one DataFrame to another can be extremely valuable for putting models in production.

5.5.5 Performance

Finally, let's check the model performance.

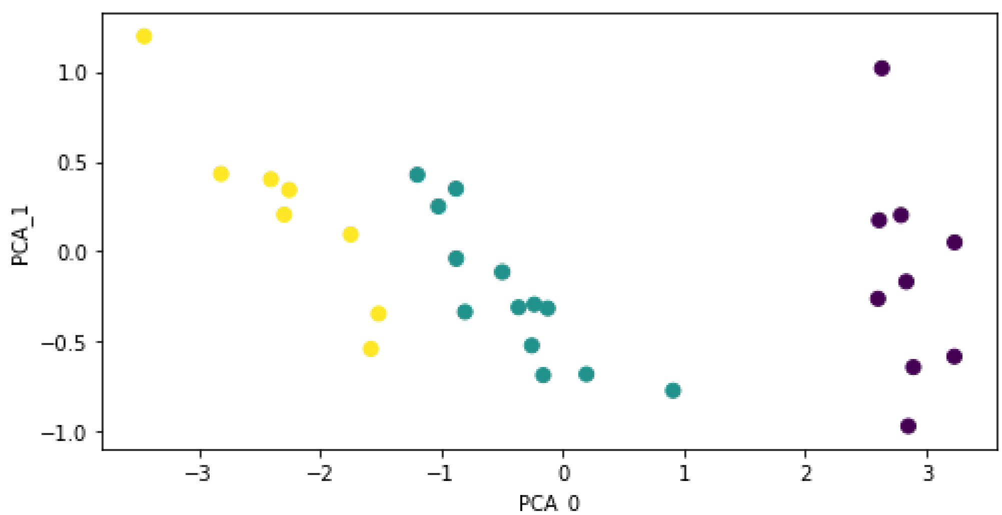
[7]:
```
from sklearn.metrics import accuracy_score

acc = accuracy_score(y_true=df_test.class_.values, y_pred=df_test.prediction.values)
acc *= 100.
print(f'Test set accuracy: {acc}%')
```

```
Test set accuracy: 100.0%
```

The model get perfect accuracy of 100%. This is not surprising as this problem is rather easy: doing a PCA transformation on the features nicely separates the 3 flower species. Plotting the first two PCA axes, and colouring the samples according to their class already shows an almost perfect separation.

[8]:
```
plt.figure(figsize=(8, 4))
df_test.scatter(df_test.PCA_0, df_test.PCA_1, c_expr=df_test.class_, s=50)
plt.show()
```



5.6 Machine Learning (advanced): the Titanic dataset

If you want to try out this notebook with a live Python kernel, use mybinder:

In the following is a more involved machine learning example, in which we will use a larger variety of method in `veax` to do data cleaning, feature engineering, pre-processing and finally to train a couple of models. To do this, we will use the well known *Titanic dataset*. Our task is to predict which passengers are more likely to have survived the disaster.

Before we begin, thare there are two important notes to consider: - The following example is not to provide a competitive score for any competitions that might use the *Titanic dataset*. It's primary goal is to show how various methods provided by `vaex` and `vaex.ml` can be used to clean data, create new features, and do general data manipulations in a machine learning context. - While the *Titanic dataset* is rather small in side, all the methods and operations presented in the solution below will work on a dataset of arbitrary size, as long as it fits on the hard-drive of your machine.

Now, with that out of the way, let's get started!

[1]:
```
import vaex
import vaex.ml

import numpy as np
import pylab as plt
```

5.6.1 Adjusting `matplotlib` parmeters

Intermezzo: we modify some of the `matplotlib` default settings, just to make the plots a bit more legible.

[2]:
```
SMALL_SIZE = 12
MEDIUM_SIZE = 14
BIGGER_SIZE = 16

plt.rc('font', size=SMALL_SIZE)          # controls default text sizes
plt.rc('axes', titlesize=SMALL_SIZE)     # fontsize of the axes title
plt.rc('axes', labelsize=MEDIUM_SIZE)    # fontsize of the x and y labels
plt.rc('xtick', labelsize=SMALL_SIZE)    # fontsize of the tick labels
plt.rc('ytick', labelsize=SMALL_SIZE)    # fontsize of the tick labels
plt.rc('legend', fontsize=SMALL_SIZE)    # legend fontsize
plt.rc('figure', titlesize=BIGGER_SIZE)  # fontsize of the figure title
```

5.6.2 Get the data

First of all we need to read in the data. Since the *Titanic dataset* is quite well known for trying out different classification algorithms, as well as commonly used as a teaching tool for aspiring data scientists, it ships (no pun intended) together with `vaex.ml`. So let's read it in, see the description of its contents, and get a preview of the data.

[3]:
```
# Load the titanic dataset
df = vaex.ml.datasets.load_titanic()

# See the description
df.info()
```

```
<IPython.core.display.HTML object>
```

```
<IPython.core.display.HTML object>
```

Shuffling

From the preview of the DataFrame we notice that the data is sorted alphabetically by name and by passenger class. Thus we need to shuffle it before we split it into train and test sets.

[4]:
```
# The dataset is ordered, so let's shuffle it
df = df.sample(frac=1, random_state=31)
```

Shuffling for large datasets

As mentioned in The ML introduction tutorial, shuffling large datasets in-memory is not a good idea. In case you work with a large dataset, consider shuffling while exporting:

```
df.export("shuffled", shuffle=True)
df = vaex.open("shuffled.hdf5)
df_train, df_test = df.ml.train_test_split(test_size=0.2)
```

Split into train and test

Once the data is shuffled, let's split it into train and test sets. The test set will comprise 20% of the data. Note that we do not shuffle the data for you, since vaex cannot assume your data fits into memory, you are responsible for either writing it in shuffled order on disk, or shuffle it in memory (the previous step).

[5]:
```
# Train and test split, no shuffling occurs
df_train, df_test = df.ml.train_test_split(test_size=0.2, verbose=False)
```

Sanity checks

Before we move on to process the data, let's verify that our train and test sets are "similar" enough. We will not be very rigorous here, but just look at basic statistics of some of the key features.

For starters, let's check that the fraction of survivals is similar between the train and test sets.

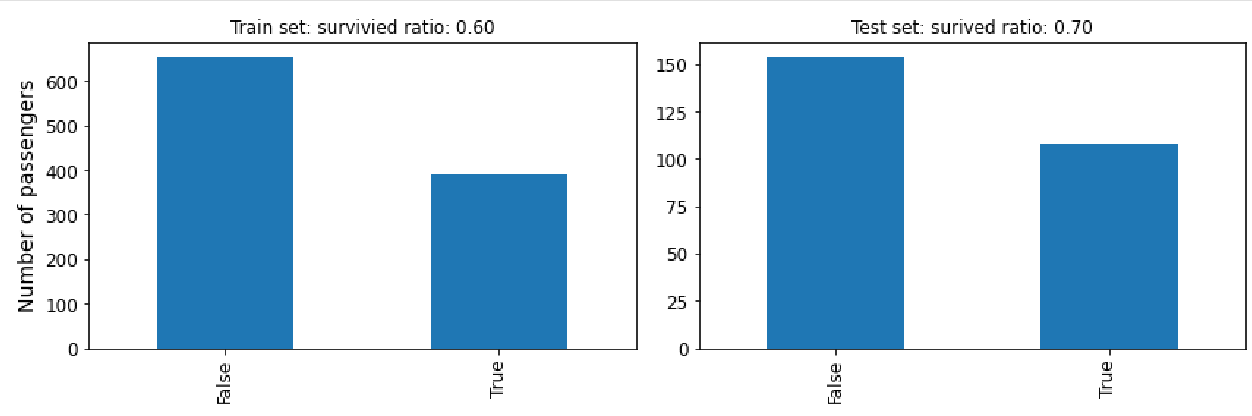
[6]:
```
# Inspect the target variable
train_survived_value_counts = df_train.survived.value_counts()
test_survived_value_counts = df_test.survived.value_counts()


plt.figure(figsize=(12, 4))

plt.subplot(121)
train_survived_value_counts.plot.bar()
train_sex_ratio = train_survived_value_counts[True]/train_survived_value_counts[False]
plt.title(f'Train set: survivied ratio: {train_sex_ratio:.2f}')
plt.ylabel('Number of passengers')

plt.subplot(122)
test_survived_value_counts.plot.bar()
test_sex_ratio = test_survived_value_counts[True]/test_survived_value_counts[False]
plt.title(f'Test set: surived ratio: {test_sex_ratio:.2f}')


plt.tight_layout()
plt.show()
```



Next up, let's check whether the ratio of male to female passengers is not too dissimilar between the two sets.

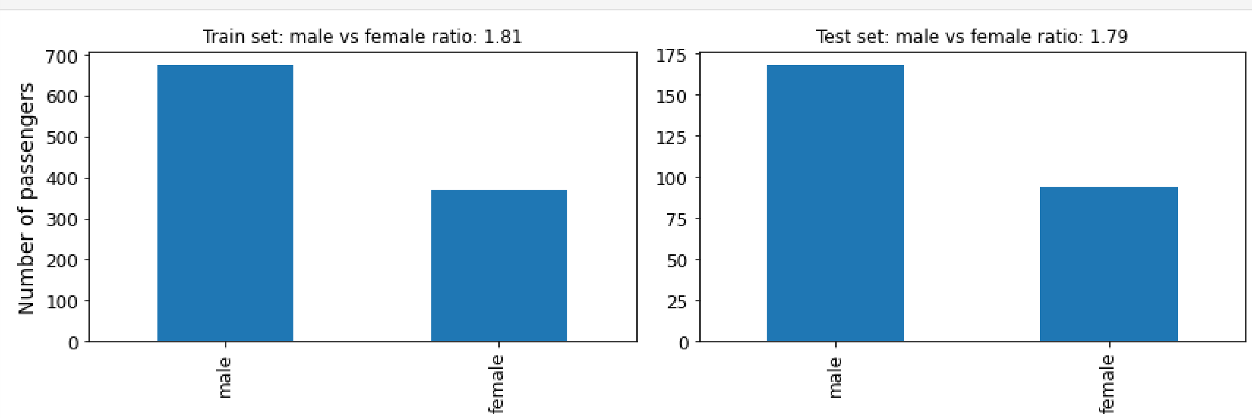
[7]:
```
# Check the sex balance
train_sex_value_counts = df_train.sex.value_counts()
test_sex_value_counts = df_test.sex.value_counts()

plt.figure(figsize=(12, 4))

plt.subplot(121)
train_sex_value_counts.plot.bar()
train_sex_ratio = train_sex_value_counts['male']/train_sex_value_counts['female']
plt.title(f'Train set: male vs female ratio: {train_sex_ratio:.2f}')
plt.ylabel('Number of passengers')

plt.subplot(122)
test_sex_value_counts.plot.bar()
test_sex_ratio = test_sex_value_counts['male']/test_sex_value_counts['female']
plt.title(f'Test set: male vs female ratio: {test_sex_ratio:.2f}')


plt.tight_layout()
plt.show()
```



Finally, lets check that the relative number of passenger per class is similar between the train and test sets.

[8]:
```
# Check the class balance
train_pclass_value_counts = df_train.pclass.value_counts()
test_pclass_value_counts = df_test.pclass.value_counts()
```

(continues on next page)

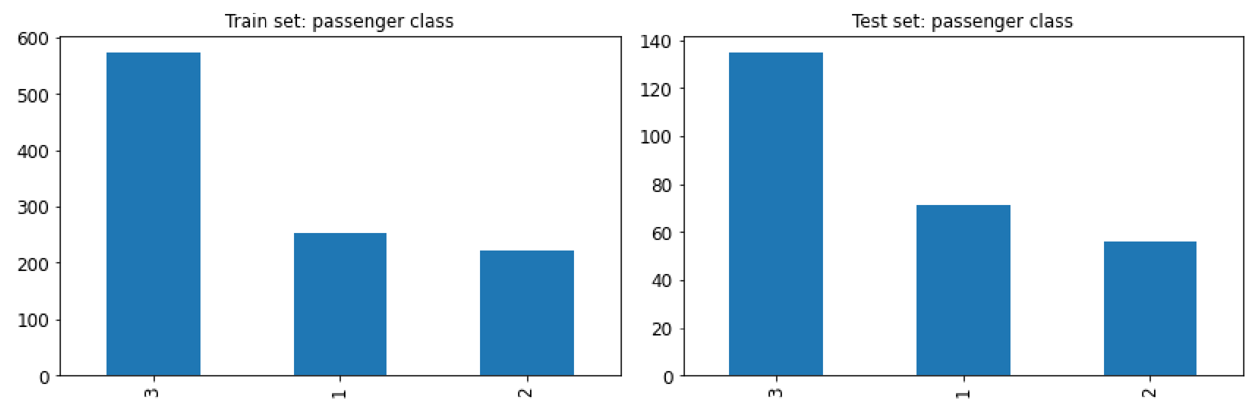
(continued from previous page)

```
plt.figure(figsize=(12, 4))

plt.subplot(121)
plt.title('Train set: passenger class')
train_pclass_value_counts.plot.bar()

plt.subplot(122)
plt.title('Test set: passenger class')
test_pclass_value_counts.plot.bar()

plt.tight_layout()
plt.show()
```



From the above diagnostics, we are satisfied that, at least in these few categories, the train and test are similar enough, and we can move forward.

5.6.3 Feature engineering

In this section we will use `vaex` to create meaningful features that will be used to train a classification model. To start with, let's get a high level overview of the training data.

```
[9]: df_train.describe()
```

```
[9]:
                   pclass            survived  name   sex                 age  \
dtype               int64                bool   str   str             float64
count                1047                1047  1047  1047                 841
NA                      0                   0     0     0                 206
mean   2.3075453677172875  0.3744030563514804    --    --  29.565299286563608
std              0.833269            0.483968    --    --              14.162
min                     1               False    --    --              0.1667
max                     3                True    --    --                  80

                    sibsp               parch ticket                fare  \
dtype               int64               int64    str             float64
count                1047                1047   1047                1046
NA                      0                   0      0                   1
mean   0.5100286532951289  0.3982808022922636     --  32.926091013384294
std               1.07131            0.890852     --             50.6783
min                     0                   0     --                   0
max                     8                   9     --             512.329
```

(continues on next page)

(continued from previous page)

```
      cabin embarked boat                body home_dest
dtype   str       str  str             float64       str
count   233      1046  380                 102       592
NA      814         1  667                 945       455
mean     --        --   --   159.6764705882353        --
std      --        --   --             96.2208        --
min      --        --   --                   1        --
max      --        --   --                 327        --
```

Imputing

We notice that there are 3 columns that have missing data, so our first task will be to impute the missing values with suitable substitutes. This is our strategy:

- age: impute with the median age value
- fare: impute with the mean fare of the 5 most common values.
- cabin: impute with “M” for “Missing”
- Embarked: Impute with with the most common value.

[10]:
```
# Handle missing values

# Age - just do the mean of the training set for now
median_age = df_train.percentile_approx(expression='age', percentage=50.0)
df_train['age'] = df_train.age.fillna(value=median_age)

# Fare: the mean of the 5 most common ticket prices.
fill_fares = df_train.fare.value_counts(dropna=True)
fill_fare = fill_fares.iloc[:5].index.values.mean()
df_train['fare'] = df_train.fare.fillna(value=fill_fare)

# Cabing: this is a string column so let's mark it as "M" for "Missing"
df_train['cabin'] = df_train.cabin.fillna(value='M')

# Embarked: Similar as for Cabin, let's mark the missing values with "U" for unknown
fill_embarked = df_train.embarked.value_counts(dropna=True).index[0]
df_train['embarked'] = df_train.embarked.fillna(value=fill_embarked)
```

String processing

Next up, let’s engineer some new, more meaningful features out of the “raw” data that is present in the dataset. Starting with the name of the passengers, we are going to extract the titles, as well as we are going to count the number of words a name contains. These features can be a loose proxy to the age and status of the passengers.

[11]:
```
# Engineer features from the names

# Titles
df_train['name_title'] = df_train['name'].str.replace('.* ([A-Z][a-z]+)\..*', "\\1",␣
↪regex=True)
display(df_train['name_title'])

# Number of words in the name
```

(continues on next page)

(continued from previous page)

```
df_train['name_num_words'] = df_train['name'].str.count("[ ]+", regex=True) + 1
display(df_train['name_num_words'])
```

```
Expression = name_title
Length: 1,047 dtype: str (column)
---------------------------------
   0      Mr
   1      Mr
   2     Mrs
   3    Miss
   4      Mr
    ...
1042  Master
1043     Mrs
1044  Master
1045      Mr
1046      Mr
```

```
Expression = name_num_words
Length: 1,047 dtype: int64 (column)
-----------------------------------
   0  3
   1  4
   2  5
   3  4
   4  4
  ...
1042  4
1043  6
1044  4
1045  4
1046  3
```

From the cabin colum, we will engineer 3 features: - "deck": extacting the deck on which the cabin is located, which is encoded in each cabin value; - "multi_cabin: a boolean feature indicating whether a passenger is allocated more than one cabin - "has_cabin": since there were plenty of values in the original cabin column that had missing values, we are just going to build a feature which tells us whether a passenger had an assigned cabin or not.

```
[12]: #  Extract the deck
df_train['deck'] = df_train.cabin.str.slice(start=0, stop=1)
display(df_train['deck'])

# Passengers under which name have several rooms booked, these are all for 1st class␣
↪passengers
df_train['multi_cabin'] = ((df_train.cabin.str.count(pat='[A-Z]', regex=True) > 1) &\
                          ~(df_train.deck == 'F')).astype('int')
display(df_train['multi_cabin'])

# Out of these, cabin has the most missing values, so let's create a feature tracking␣
↪if a passenger had a cabin
df_train['has_cabin'] = df_train.cabin.notna().astype('int')
display(df_train['has_cabin'])
```

```
Expression = deck
Length: 1,047 dtype: str (column)
---------------------------------
   0  M
   1  B
```

(continues on next page)

(continued from previous page)

```
   2   M
   3   M
   4   M
  ...
1042   M
1043   M
1044   M
1045   B
1046   M
```

```
Expression = multi_cabin
Length: 1,047 dtype: int64 (column)
-----------------------------------
   0  0
   1  0
   2  0
   3  0
   4  0
  ...
1042  0
1043  0
1044  0
1045  1
1046  0
```

```
Expression = has_cabin
Length: 1,047 dtype: int64 (column)
-----------------------------------
   0  1
   1  1
   2  1
   3  1
   4  1
  ...
1042  1
1043  1
1044  1
1045  1
1046  1
```

More features

There are two features that give an indication whether a passenger is travelling alone, or with a famly. These are the "sibsp" and "parch" columns that tell us the number of siblinds or spouses and the number of parents or children each passenger has on-board respectively. We are going to use this information to build two columns: - "family_size" the size of the family of each passenger; - "is_alone" an additional boolean feature which indicates whether a passenger is traveling without their family.

[13]:
```
# Size of family that are on board: passenger + number of siblings, spouses, parents,␣
↪children.
df_train['family_size'] = (df_train.sibsp + df_train.parch + 1)
display(df_train['family_size'])

# Whether or not a passenger is alone
df_train['is_alone'] = (df_train.family_size == 0).astype('int')
display(df_train['is_alone'])
```

```
Expression = family_size
Length: 1,047 dtype: int64 (column)
-----------------------------------
   0  1
   1  1
   2  3
   3  4
   4  1
  ...
1042  8
1043  2
1044  3
1045  2
1046  1
```

```
Expression = is_alone
Length: 1,047 dtype: int64 (column)
-----------------------------------
   0  0
   1  0
   2  0
   3  0
   4  0
  ...
1042  0
1043  0
1044  0
1045  0
1046  0
```

Finally, let's create two new features: - age $\times$ class - fare per family member, i.e. fare / family_size

[14]:
```
# Create new features
df_train['age_times_class'] = df_train.age * df_train.pclass

# fare per person in the family
df_train['fare_per_family_member'] = df_train.fare / df_train.family_size
```

5.6.4 Modeling (part 1): gradient boosted trees

Since this dataset contains a lot of categorical features, we will start with a tree based model. This we will gear the following feature pre-processing towards the use of tree-based models.

Feature pre-processing for boosted tree models

The features "sex", "embarked", and "deck" can be simply label encoded. The feature "name_tite" contains certain a larger degree of cardinality, relative to the size of the training set, and in this case we will use the Frequency Encoder.

[15]:
```
label_encoder = vaex.ml.LabelEncoder(features=['sex', 'embarked', 'deck'], allow_
↪unseen=True)
df_train = label_encoder.fit_transform(df_train)

# While doing a transform, previously unseen values will be encoded as "zero".
frequency_encoder = vaex.ml.FrequencyEncoder(features=['name_title'], unseen='zero')
```

(continues on next page)

(continued from previous page)

```
df_train = frequency_encoder.fit_transform(df_train)
df_train
```

```
INFO:MainThread:numexpr.utils:NumExpr defaulting to 4 threads.
```

[15]:
```
#      pclass    survived    name                                          sex    ␣
↪age    sibsp    parch    ticket      fare       cabin     embarked    boat    body    ␣
↪home_dest                          name_title     name_num_words     deck     multi_
↪cabin    has_cabin    family_size    is_alone    age_times_class    fare_per_family_
↪member    label_encoded_sex    label_encoded_embarked    label_encoded_deck    ␣
↪frequency_encoded_name_title
0      3          False       Stoytcheff, Mr. Ilia                           male   ␣
↪19.0   0         0        349205      7.8958     M         S           None    nan    ␣
↪None                                  Mr             3                  M        0    ␣
↪          1            1              0           57.0              7.8958         ␣
↪           0                    0                         0                     0.
↪5787965616045845
1      1          False       Payne, Mr. Vivian Ponsonby                     male   ␣
↪23.0   0         0        12749       93.5       B24       S           None    nan    ␣
↪Montreal, PQ                          Mr             4                  B        0    ␣
↪          1            1              0           23.0              93.5           ␣
↪           0                    0                         1                     0.
↪5787965616045845
2      3          True        Abbott, Mrs. Stanton (Rosa Hunt)               female ␣
↪35.0   1         1        C.A. 2673   20.25      M         S           A       nan    ␣
↪East Providence, RI                   Mrs            5                  M        0    ␣
↪          1            3              0           105.0             6.75           ␣
↪           1                    0                         0                     0.
↪1451766953199618
3      2          True        Hocking, Miss. Ellen "Nellie"                  female ␣
↪20.0   2         1        29105       23.0       M         S           4       nan    ␣
↪Cornwall / Akron, OH                  Miss           4                  M        0    ␣
↪          1            4              0           40.0              5.75           ␣
↪           1                    0                         0                     0.
↪20152817574021012
4      3          False       Nilsson, Mr. August Ferdinand                  male   ␣
↪21.0   0         0        350410      7.8542     M         S           None    nan    ␣
↪None                                  Mr             4                  M        0    ␣
↪          1            1              0           63.0              7.8542         ␣
↪           0                    0                         0                     0.
↪5787965616045845
...    ...        ...         ...                                            ...    ␣
↪...    ...       ...      ...         ...        ...       ...         ...     ...    ␣
↪...                                   ...            ...                ...      ...  ␣
↪          ...          ...            ...         ...               ...            ␣
↪           ...                  ...                       ...                   ...
1,042  3          False       Goodwin, Master. Sidney Leonard                male   ␣
↪1.0    5         2        CA 2144     46.9       M         S           None    nan    ␣
↪Wiltshire, England Niagara Falls, NY  Master         4                  M        0    ␣
↪          1            8              0           3.0               5.8625         ␣
↪           0                    0                         0                     0.
↪045845272206303724
1,043  3          False       Ahlin, Mrs. Johan (Johanna Persdotter Larsson) female ␣
↪40.0   1         0        7546        9.475      M         S           None    nan    ␣
↪Sweden Akeley, MN                     Mrs            6                  M        0    ␣
↪          1            2              0           120.0             4.7375         ␣
↪           1                    0                         0                     0.
↪1451766953199618
```

(continues on next page)

(continued from previous page)

```
1,044  3         True        Johnson, Master. Harold Theodor                  male   ␣
↪4.0    1        1        347742     11.1333   M        S          15      nan    ␣
↪None                                 Master        4                M       0     ␣
↪         1            3            0           12.0               3.7111          ␣
↪          0                    0                         0                    0.
↪045845272206303724
1,045  1         False       Baxter, Mr. Quigg Edmond                         male   ␣
↪24.0   0        1        PC 17558   247.5208  B58 B60  C          None    nan    ␣
↪Montreal, PQ                         Mr            4                B       1     ␣
↪         1            2            0           24.0               123.7604        ␣
↪          0                    2                         1                    0.
↪5787965616045845
1,046  3         False       Coleff, Mr. Satio                                male   ␣
↪24.0   0        0        349209     7.4958    M        S          None    nan    ␣
↪None                                 Mr            3                M       0     ␣
↪         1            1            0           72.0               7.4958          ␣
↪          0                    0                         0                    0.
↪5787965616045845
```

Once all the categorical data is encoded, we can select the features we are going to use for training the model.

[16]:
```
# features to use for the trainin of the boosting model
encoded_features = df_train.get_column_names(regex='^freque|^label')
features = encoded_features + ['multi_cabin', 'name_num_words',
                               'has_cabin', 'is_alone',
                               'family_size', 'age_times_class',
                               'fare_per_family_member',
                               'age', 'fare']

# Preview the feature matrix
df_train[features].head(5)
```

[16]:
```
  #    label_encoded_sex    label_encoded_embarked    label_encoded_deck    frequency_
↪encoded_name_title    multi_cabin    name_num_words    has_cabin    is_alone   ␣
↪family_size    age_times_class    fare_per_family_member    age     fare
  0                    0                         0                      0          ␣
↪           0.578797          0                 3            1           0         ␣
↪     1                  57                      7.8958      19    7.8958
  1                    0                         0                      1          ␣
↪           0.578797          0                 4            1           0         ␣
↪     1                  23                     93.5         23   93.5
  2                    1                         0                      0          ␣
↪           0.145177          0                 5            1           0         ␣
↪     3                 105                      6.75        35   20.25
  3                    1                         0                      0          ␣
↪           0.201528          0                 4            1           0         ␣
↪     4                  40                      5.75        20   23
  4                    0                         0                      0          ␣
↪           0.578797          0                 4            1           0         ␣
↪     1                  63                      7.8542      21    7.8542
```

Estimator: xgboost

Now let's feed this data into an a tree based estimator. In this example we will use xgboost. In principle, any algorithm that follows the scikit-learn API convention, i.e. it contains the `.fit`, `.predict` methods is compatable with `vaex`. However, the data will be materialized, i.e. will be read into memory before it is passed on to the estimators. We are hard at work trying to make at least some of the estimators from scikit-learn run out-of-core!

[17]:
```
import xgboost
import vaex.ml.sklearn

# Instantiate the xgboost model normally, using the scikit-learn API
xgb_model = xgboost.sklearn.XGBClassifier(max_depth=11,
                                          learning_rate=0.1,
                                          n_estimators=500,
                                          subsample=0.75,
                                          colsample_bylevel=1,
                                          colsample_bytree=1,
                                          scale_pos_weight=1.5,
                                          reg_lambda=1.5,
                                          reg_alpha=5,
                                          n_jobs=-1,
                                          random_state=42,
                                          verbosity=0)

# Make it work with vaex (for the automagic pipeline and lazy predictions)
vaex_xgb_model = vaex.ml.sklearn.Predictor(features=features,
                                           target='survived',
                                           model=xgb_model,
                                           prediction_name='prediction_xgb')
# Train the model
vaex_xgb_model.fit(df_train)
# Get the prediction of the model on the training data
df_train = vaex_xgb_model.transform(df_train)

# Preview the resulting train dataframe that contans the predictions
df_train
```

[17]:
```
#      pclass    survived    name                                          sex    ␣
↪age    sibsp    parch    ticket      fare       cabin     embarked    boat    body    ␣
↪home_dest                             name_title     name_num_words     deck     multi_
↪cabin     has_cabin    family_size     is_alone     age_times_class      fare_per_family_
↪member     label_encoded_sex     label_encoded_embarked     label_encoded_deck    ␣
↪frequency_encoded_name_title     prediction_xgb
0      3          False       Stoytcheff, Mr. Ilia                          male    ␣
↪19.0    0         0         349205      7.8958     M          S            None     nan     ␣
↪None                                  Mr            3                 M       0     ␣
↪          1             1              0           57.0              7.8958         ␣
↪           0                    0                         0                   0.
↪5787965616045845              False
1      1          False       Payne, Mr. Vivian Ponsonby                    male    ␣
↪23.0    0         0         12749       93.5       B24        S            None     nan     ␣
↪Montreal, PQ                          Mr            4                 B       0     ␣
↪          1             1              0           23.0              93.5           ␣
↪           0                    0                         1                   0.
↪5787965616045845              False
2      3          True        Abbott, Mrs. Stanton (Rosa Hunt)              female  ␣
↪35.0    1         1         C.A. 2673   20.25      M          S            A        nan     ␣
↪East Providence, RI                   Mrs           5                 M       0     ␣
↪          1             3              0           105.0             6.75           ␣
↪           1                    0                         0                   0.
↪1451766953199618              True
3      2          True        Hocking, Miss. Ellen "Nellie"                 female  ␣
↪20.0    2         1         29105       23.0       M          S            4        nan     ␣
↪Cornwall / Akron, OH                  Miss          4                 M       0     ␣
↪          1             4              0           40.0              5.75           ␣
↪           1                    0                         0                   0.
↪20152817574021012             True
```

(continues on next page)

(continued from previous page)

```
4       3          False       Nilsson, Mr. August Ferdinand                     male    ␣
↪21.0   0         0         350410     7.8542    M        S             None    nan    ␣
↪None                                  Mr              4                M       0     ␣
↪          1             1              0           63.0                7.8542          ␣
↪           0                   0                              0                     0.
↪5787965616045845              False
...     ...        ...         ...                                               ...    ␣
↪...    ...       ...       ...        ...       ...      ...         ...     ...    ␣
↪...                                    ...            ...              ...     ...  ␣
↪          ...           ...            ...         ...                 ...             ␣
↪           ...                 ...                      ...                      ...  ␣
↪                                ...
1,042   3          False       Goodwin, Master. Sidney Leonard                   male    ␣
↪1.0    5         2         CA 2144    46.9      M        S             None    nan    ␣
↪Wiltshire, England Niagara Falls, NY  Master          4                M       0     ␣
↪          1             8              0           3.0                 5.8625          ␣
↪           0                   0                              0                     0.
↪045845272206303724              False
1,043   3          False       Ahlin, Mrs. Johan (Johanna Persdotter Larsson)   female  ␣
↪40.0   1         0         7546       9.475     M        S             None    nan    ␣
↪Sweden Akeley, MN                     Mrs             6                M       0     ␣
↪          1             2              0           120.0               4.7375          ␣
↪           1                   0                              0                     0.
↪1451766953199618              False
1,044   3          True        Johnson, Master. Harold Theodor                   male    ␣
↪4.0    1         1         347742     11.1333   M        S             15      nan    ␣
↪None                                  Master          4                M       0     ␣
↪          1             3              0           12.0                3.7111          ␣
↪           0                   0                              0                     0.
↪045845272206303724              True
1,045   1          False       Baxter, Mr. Quigg Edmond                          male    ␣
↪24.0   0         1         PC 17558   247.5208  B58 B60  C             None    nan    ␣
↪Montreal, PQ                          Mr              4                B       1     ␣
↪          1             2              0           24.0                123.7604        ␣
↪           0                   2                              1                     0.
↪5787965616045845              False
1,046   3          False       Coleff, Mr. Satio                                 male    ␣
↪24.0   0         0         349209     7.4958    M        S             None    nan    ␣
↪None                                  Mr              3                M       0     ␣
↪          1             1              0           72.0                7.4958          ␣
↪           0                   0                              0                     0.
↪5787965616045845              False
```

Notice that in the above cell block, we call `.transform` on the `vaex_xgb_model` object. This adds the "prediction_xgb" column as *virtual column* in the output dataframe. This can be quite convenient when calculating various metrics and making diagnosic plots. Of course, one can call a `.predict` on the `vaex_xgb_model` object, which returns an in-memory `numpy` array object housing the predictions.

Performance on training set

Anyway, let's see what the performance is of the model on the training set. First let's create a convenience function that will help us get multiple metrics at once.

```
[18]: from sklearn.metrics import accuracy_score, f1_score, roc_auc_score
def binary_metrics(y_true, y_pred):
```

(continues on next page)

(continued from previous page)

```
    acc = accuracy_score(y_true=y_true, y_pred=y_pred)
    f1 = f1_score(y_true=y_true, y_pred=y_pred)
    roc = roc_auc_score(y_true=y_true, y_score=y_pred)
    print(f'Accuracy: {acc:.3f}')
    print(f'f1 score: {f1:.3f}')
    print(f'roc-auc: {roc:.3f}')
```

Now let's check the performance of the model on the training set.

[19]:
```
print('Metrics for the training set:')
binary_metrics(y_true=df_train.survived.values, y_pred=df_train.prediction_xgb.values)
```

```
Metrics for the training set:
Accuracy: 0.924
f1 score: 0.896
roc-auc: 0.914
```

Automatic pipelines

Now, let's inspect the performance of the model on the test set. You probably noticed that, unlike when using other libraries, we did not bother to create a pipeline while doing all the cleaning, inputing, feature engineering and categorial encoding. Well, we did not *explicitly* create a pipeline. In fact `veax` keeps track of all the changes one applies to a DataFrame in something called a state. A state is the place which contains all the informations regarding, for instance, the virtual columns we've created, which includes the newly engineered features, the categorically encoded columns, and even the model prediction! So all we need to do, is to extract the state from the training DataFrame, and apply it to the test DataFrame.

[20]:
```
# state transfer to the test set
state = df_train.state_get()
df_test.state_set(state)

# Preview of the "transformed" test set
df_test.head(5)
```

[20]:
```
  #    pclass  survived    name                                              sex       ␣
↪age     sibsp     parch  ticket                fare  cabin     embarked     boat     ␣
↪body  home_dest                   name_title       name_num_words  deck       multi_
↪cabin     has_cabin     family_size     is_alone     age_times_class     fare_per_family_
↪member     label_encoded_sex     label_encoded_embarked     label_encoded_deck    ␣
↪frequency_encoded_name_title  prediction_xgb
  0         3  False       O'Connor, Mr. Patrick                                 male     28.
↪032        0         0  366713              7.75     M          Q             None      ␣
↪nan  None                         Mr                            3  M                    ␣
↪0           1              1           0              84.096                         7.
↪75                  0                          1                     0                  ␣
↪             0.578797  False
  1         3  False       Canavan, Mr. Patrick                                  male     21 ␣
↪         0         0  364858              7.75     M          Q             None       nan␣
↪ Ireland Philadelphia, PA  Mr                              3  M                     0    ␣
↪        1              1           0              63                          7.75    ␣
↪                0                          1                     0                     ␣
↪      0.578797  False
  2         1  False       Ovies y Rodriguez, Mr. Servando                       male     28.5␣
↪         0         0  PC 17562          27.7208  D43       C             None        189␣
↪ ?Havana, Cuba             Mr                              5  D                     0    ␣
↪        1              1           0              28.5                       27.7208  ␣
↪                0                          2                     4                     ␣
↪      0.578797  True
```

(continues on next page)

(continued from previous page)

```
 3         3  False       Windelov, Mr. Einar                          male    21 ␣
↪         0        0  SOTON/OQ 3101317   7.25    M         S           None        nan␣
↪ None                        Mr                            3  M                   0  ␣
↪        1              1           0             63                       7.25   ␣
↪                0                       0                     0                  ␣
↪      0.578797  False
 4         2  True        Shelley, Mrs. William (Imanita Parrish Hall)  female  25 ␣
↪         0        1  230433           26        M         S           12          nan␣
↪ Deer Lodge, MT              Mrs                           6  M                   0  ␣
↪        1              2           0             50                       13     ␣
↪                1                       0                     0                  ␣
↪      0.145177  True
```

Notice that once we apply the state from the train to the test set, the test DataFrame contains all the features we created or modified in the training data, and even the predictions of the xgboost model!

The state is a simple Python dictionary, which can be easily stored as JSON to disk, which makes it very easy to deploy.

Performance on test set

Now it is trivial to check the model performance on the test set:

[21]:
```python
print('Metrics for the test set:')
binary_metrics(y_true=df_test.survived.values, y_pred=df_test.prediction_xgb.values)
```

```
Metrics for the test set:
Accuracy: 0.798
f1 score: 0.744
roc-auc: 0.785
```

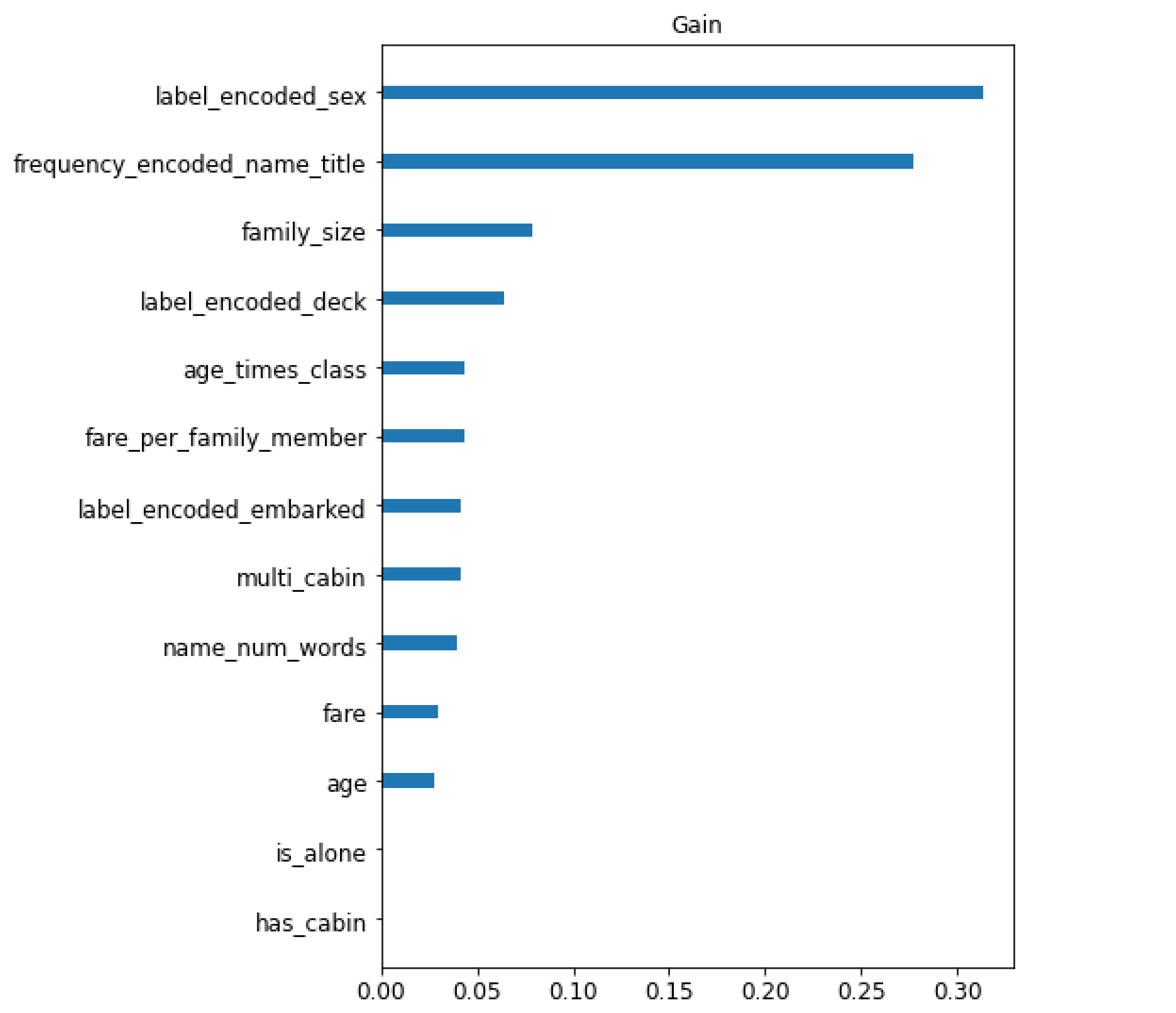
Feature importance

Let's now look at the feature importance of the `xgboost` model.

[22]:
```python
plt.figure(figsize=(6, 9))

ind = np.argsort(xgb_model.feature_importances_)[::-1]
features_sorted = np.array(features)[ind]
importances_sorted = xgb_model.feature_importances_[ind]

plt.barh(y=range(len(features)), width=importances_sorted, height=0.2)
plt.title('Gain')
plt.yticks(ticks=range(len(features)), labels=features_sorted)
plt.gca().invert_yaxis()
plt.show()
```



5.6.5 Modeling (part 2): Linear models & Ensembles

Given the randomness of the *Titanic dataset* , we can be satisfied with the performance of `xgboost` model above. Still, it is always usefull to try a variety of models and approaches, especially since `vaex` makes makes this process rather simple.

In the following part we will use a couple of linear models as our predictors, this time straight from `scikit-learn`. This requires us to pre-process the data in a slightly different way.

Feature pre-processing for linear models

When using linear models, the safest option is to encode categorical variables with the one-hot encoding scheme, especially if they have low cardinality. We will do this for the "family_size" and "deck" features. Note that the "sex" feature is already encoded since it has only unique values options.

The "name_title" feature is a bit more tricky. Since in its original form it has some values that only appear a couple of times, we will do a trick: we will one-hot encode the frequency encoded values. This will reduce cardinality of the feature, while also preserving the most important, i.e. most common values.

Regarding the "age" and "fare", to add some variance in the model, we will not convert them to categorical as before, but simply remove their mean and standard-deviations (standard-scaling). We will do the same to the "fare_per_family_member" feature.

Finally, we will drop out any other features.

[23]:
```
# One-hot encode categorical features
one_hot = vaex.ml.OneHotEncoder(features=['deck', 'family_size', 'name_title'])
df_train = one_hot.fit_transform(df_train)
```

[24]:
```
# Standard scale numerical features
standard_scaler = vaex.ml.StandardScaler(features=['age', 'fare', 'fare_per_family_
↪member'])
df_train = standard_scaler.fit_transform(df_train)
```

[25]:
```
# Get the features for training a linear model
features_linear = df_train.get_column_names(regex='^deck_|^family_size_|^frequency_
↪encoded_name_title_')
features_linear += df_train.get_column_names(regex='^standard_scaled_')
features_linear += ['label_encoded_sex']
features_linear
```

[25]:
```
['deck_A',
 'deck_B',
 'deck_C',
 'deck_D',
 'deck_E',
 'deck_F',
 'deck_G',
 'deck_M',
 'family_size_1',
 'family_size_2',
 'family_size_3',
 'family_size_4',
 'family_size_5',
 'family_size_6',
 'family_size_7',
 'family_size_8',
 'family_size_11',
 'standard_scaled_age',
 'standard_scaled_fare',
 'standard_scaled_fare_per_family_member',
 'label_encoded_sex']
```

Estimators: SVC and LogisticRegression

[26]:
```
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
```

[27]:
```
# The Support Vector Classifier
vaex_svc = vaex.ml.sklearn.Predictor(features=features_linear,
                                     target='survived',
                                     model=SVC(max_iter=1000, random_state=42),
                                     prediction_name='prediction_svc')

# Logistic Regression
```

(continues on next page)

(continued from previous page)

```
vaex_logistic = vaex.ml.sklearn.Predictor(features=features_linear,
                                          target='survived',
                                          model=LogisticRegression(max_iter=1000,␣
↪random_state=42),
                                          prediction_name='prediction_lr')

# Train the new models and apply the transformation to the train dataframe
for model in [vaex_svc, vaex_logistic]:
    model.fit(df_train)
    df_train = model.transform(df_train)

# Preview of the train DataFrame
df_train.head(5)
```

```
/Users/jovan/miniconda3/lib/python3.7/site-packages/sklearn/svm/_base.py:231:␣
↪ConvergenceWarning: Solver terminated early (max_iter=1000).  Consider pre-
↪processing your data with StandardScaler or MinMaxScaler.
  % self.max_iter, ConvergenceWarning)
```

[27]:

```
  #    pclass  survived    name                           sex       age    sibsp  ␣
↪ parch  ticket        fare   cabin    embarked    boat       body   home_dest   ␣
↪   name_title      name_num_words  deck      multi_cabin    has_cabin     family_
↪size    is_alone    age_times_class    fare_per_family_member    label_encoded_sex ␣
↪  label_encoded_embarked    label_encoded_deck    frequency_encoded_name_title ␣
↪prediction_xgb     deck_A     deck_B     deck_C     deck_D     deck_E     deck_F  ␣
↪deck_G    deck_M    family_size_1    family_size_2    family_size_3    family_size_
↪4    family_size_5    family_size_6    family_size_7    family_size_8    family_
↪size_11    name_title_Capt    name_title_Col    name_title_Countess    name_title_
↪Don    name_title_Dona    name_title_Dr    name_title_Jonkheer    name_title_Lady  ␣
↪ name_title_Major    name_title_Master    name_title_Miss    name_title_Mlle   ␣
↪name_title_Mme    name_title_Mr    name_title_Mrs    name_title_Ms    name_title_
↪Rev    standard_scaled_age    standard_scaled_fare    standard_scaled_fare_per_
↪family_member  prediction_svc    prediction_lr
  0         3  False         Stoytcheff, Mr. Ilia           male       19        0  ␣
↪     0  349205      7.8958  M         S           None        nan  None          ␣
↪   Mr                      3  M                    0            1               ␣
↪1           0                 57                     7.8958                   0  ␣
↪               0                      0                        0.578797  False  ␣
↪                    0         0         0         0         0         0         0  ␣
↪   1                 1                 0                 0                 0     ␣
↪     0                 0                 0                 0                  0    ␣
↪        0                 0                     0                 0              ␣
↪   0                 0                      0                   0                 0␣
↪                   0                  0                  0                 0     ␣
↪        1                 0                 0                 0                -0.␣
↪807704                   -0.493719                                 -0.342804   False  ␣
↪        False
  1         1  False         Payne, Mr. Vivian Ponsonby     male       23        0  ␣
↪     0  12749       93.5      B24       S           None        nan  Montreal, PQ  ␣
↪   Mr                      4  B                    0            1               ␣
↪1           0                 23                    93.5                      0  ␣
↪               0                      1                        0.578797  False  ␣
↪                    0         1         0         0         0         0         0  ␣
↪   0                 1                 0                 0                 0     ␣
↪     0                 0                 0                 0                  0    ␣
↪        0                 0                     0                 0              ␣
↪   0                 0                      0                   0                 0␣
↪                   0                  0                  0                 0     ␣
↪        1                 0                 0                 0                 0.␣
↪492921                    1.19613                                   1.99718    False  ␣
↪        True
```

(continues on next page)

(continued from previous page)

```
 2          3  True         Abbott, Mrs. Stanton (Rosa Hunt)  female     35         1 ␣
↪     1  C.A. 2673  20.25     M         S            A           nan  East Providence,␣
↪RI   Mrs                          5  M                 0            1             ␣
↪ 3          0                 105                    6.75                    1    ␣
↪                 0                      0                      0.145177  True ␣
↪                0         0         0         0         0         0         0     ␣
↪     1               0                0                1                0         ␣
↪      0                0                0                0                 0      ␣
↪          0                  0                    0                 0             ␣
↪    0                 0                      0                 0                 ␣
↪0                    0                  0                  0                 0    ␣
↪          0                 1                0                 0              0.  ␣
↪45143                -0.249845                                  -0.374124  True   ␣
↪        True
 3          2  True         Hocking, Miss. Ellen "Nellie"     female     20         2 ␣
↪     1  29105       23       M         S            4           nan  Cornwall / Akron,␣
↪OH  Miss                          4  M                 0            1             ␣
↪4          0                 40                     5.75                     1    ␣
↪                 0                      0                      0.201528  True     ␣
↪                0         0         0         0         0         0         0     ␣
↪    1                 0                0                0                1        ␣
↪     0                0                0                0                 0       ␣
↪         0                 0                     0                 0              ␣
↪   0                 0                      0                  0                  0␣
↪                0                  1                  0                 0         ␣
↪        0                 0                0                 0                -0. ␣
↪729008               -0.195559                                  -0.401459  True   ␣
↪        True
 4          3  False        Nilsson, Mr. August Ferdinand     male       21         0 ␣
↪     0  350410      7.8542   M         S            None        nan  None          ␣
↪    Mr                            4  M                 0            1             ␣
↪1          0                 63                     7.8542                   0    ␣
↪                 0                      0                      0.578797  False    ␣
↪                0         0         0         0         0         0         0     ␣
↪    1                 1                0                0                0        ␣
↪     0                0                0                0                 0       ␣
↪         0                 0                     0                 0              ␣
↪   0                 0                      0                  0                  0␣
↪                0                  0                  0                 0         ␣
↪        1                 0                0                 0                -0. ␣
↪650312               -0.494541                                  -0.343941  False  ␣
↪        False
```

Ensemble

Just as before, the predictions from the `SVC` and the `LogisticRegression` classifiers are added as virtual columns in the training dataset. This is quite powerful, since now we can easily use them to create an ensemble! For example, let's do a weighted mean.

[28]:
```
# Weighed mean of the classes
prediction_final = (df_train.prediction_xgb.astype('int') * 0.3 +
                    df_train.prediction_svc.astype('int') * 0.5 +
                    df_train.prediction_xgb.astype('int') * 0.2)
# Get the predicted class
prediction_final = (prediction_final >= 0.5)
```

(continues on next page)

(continued from previous page)

```
# Add the expression to the train DataFrame
df_train['prediction_final'] = prediction_final

# Preview
df_train[df_train.get_column_names(regex='^predict')]
```

[28]:

#	prediction_xgb	prediction_svc	prediction_lr	prediction_final
0	False	False	False	False
1	False	False	True	False
2	True	True	True	True
3	True	True	True	True
4	False	False	False	False
...	...	...	...	...
1,042	False	False	False	False
1,043	False	True	True	True
1,044	True	True	False	True
1,045	False	True	True	True
1,046	False	False	False	False

Performance (part 2)

Applying the ensembler to the test set is just as easy as before. We just need to get the new state of the training DataFrame, and transfer it to the test DataFrame.

[29]:

```
# State transfer
state_new = df_train.state_get()
df_test.state_set(state_new)

# Preview
df_test.head(5)
```

[29]:

```
 #    pclass  survived    name                                                    sex
↪age    sibsp    parch  ticket               fare  cabin    embarked    boat
↪body  home_dest                 name_title      name_num_words  deck       multi_
↪cabin     has_cabin     family_size     is_alone     age_times_class     fare_per_family_
↪member     label_encoded_sex     label_encoded_embarked     label_encoded_deck
↪frequency_encoded_name_title  prediction_xgb       deck_A      deck_B     deck_C
↪deck_D     deck_E     deck_F     deck_G     deck_M     family_size_1     family_size_2
↪family_size_3     family_size_4     family_size_5     family_size_6     family_size_7
↪ family_size_8     family_size_11     name_title_Capt     name_title_Col     name_title_
↪Countess     name_title_Don     name_title_Dona     name_title_Dr     name_title_
↪Jonkheer     name_title_Lady     name_title_Major     name_title_Master     name_title_
↪Miss     name_title_Mlle     name_title_Mme     name_title_Mr     name_title_Mrs
↪name_title_Ms     name_title_Rev     standard_scaled_age     standard_scaled_fare
↪standard_scaled_fare_per_family_member  prediction_svc     prediction_lr
↪prediction_final
 0          3   False        O'Connor, Mr. Patrick                              male    28.
↪032        0         0  366713               7.75     M         Q             None
↪nan   None                        Mr                                3   M
↪0           1              1            0             84.096                    7.
↪75                     0                     1                     0
↪              0.578797   False                      0          0          0          0
↪    0          0          0          1              1               0
↪  0                0                0                0                0
↪   0                 0                   0                 0                     0
↪              0                 0                0                    0
↪         0                   0                    0                   0
↪    0                 0                 1                 0                 0
↪        0            -0.096924                 -0.496597
↪   -0.346789   False                 False                 False
```

(continues on next page)

(continued from previous page)

```
 1          3  False       Canavan, Mr. Patrick                              male    21 ␣
↪          0        0  364858              7.75    M        Q           None       nan␣
↪ Ireland Philadelphia, PA  Mr                                   3  M               0 ␣
↪       1             1          0             63                        7.75     ␣
↪                0                        1                     0                 ␣
↪      0.578797  False                  0          0          0          0          0 ␣
↪      0         0         1                 1               0                0     ␣
↪          0                0                0                0                0    ␣
↪            0                  0                  0                   0            ␣
↪      0                  0                 0                      0               ␣
↪ 0                  0                     0                  0                  0  ␣
↪             0                1                 0                 0              ␣
↪0             -0.650312                -0.496597                                 -0.
↪346789  False            False            False
 2          1  False       Ovies y Rodriguez, Mr. Servando                   male    28.5␣
↪          0        0  PC 17562          27.7208  D43      C           None       189␣
↪ ?Havana, Cuba              Mr                                  5  D               0 ␣
↪       1             1          0             28.5                    27.7208    ␣
↪                0                        2                     4                 ␣
↪      0.578797  True                   0          0          0          1          0 ␣
↪      0         0         0                 1               0                0     ␣
↪          0                0                0                0                0    ␣
↪            0                  0                  0                   0            ␣
↪      0                  0                 0                      0               ␣
↪ 0                  0                     0                  0                  0  ␣
↪             0                1                 0                 0              ␣
↪0             -0.0600935               -0.102369                                  0.
↪19911   False            False            True
 3          3  False       Windelov, Mr. Einar                               male    21 ␣
↪          0        0  SOTON/OQ 3101317   7.25     M        S           None       nan␣
↪ None                       Mr                                  3  M               0 ␣
↪       1             1          0             63                        7.25     ␣
↪                0                        0                     0                 ␣
↪      0.578797  False                  0          0          0          0          0 ␣
↪      0         0         1                 1               0                0     ␣
↪          0                0                0                0                0    ␣
↪            0                  0                  0                   0            ␣
↪      0                  0                 0                      0               ␣
↪ 0                  0                     0                  0                  0  ␣
↪             0                1                 0                 0              ␣
↪0             -0.650312                -0.506468                                 -0.
↪360456  False            False            False
 4          2  True        Shelley, Mrs. William (Imanita Parrish Hall)  female  25 ␣
↪          0        1  230433            26        M        S           12         nan␣
↪ Deer Lodge, MT             Mrs                                 6  M               0 ␣
↪       1             2          0             50                      13         ␣
↪                1                        0                     0                 ␣
↪      0.145177  True                   0          0          0          0          0 ␣
↪      0         0         1                 0               1                0     ␣
↪          0                0                0                0                0    ␣
↪            0                  0                  0                   0            ␣
↪      0                  0                 0                      0               ␣
↪ 0                  0                     0                  0                  0  ␣
↪             0                0                 1                 0              ␣
↪0             -0.335529                -0.136338                                 -0.
↪203281  True             True             True
```

Finally, let's check the performance of all the individual models as well as on the ensembler, on the test set.

[30]:
```
pred_columns = df_train.get_column_names(regex='^prediction_')
for i in pred_columns:
    print(i)
    binary_metrics(y_true=df_test.survived.values, y_pred=df_test[i].values)
    print(' ')
```

```
prediction_xgb
Accuracy: 0.798
f1 score: 0.744
roc-auc: 0.785

prediction_svc
Accuracy: 0.802
f1 score: 0.743
roc-auc: 0.786

prediction_lr
Accuracy: 0.779
f1 score: 0.713
roc-auc: 0.762

prediction_final
Accuracy: 0.821
f1 score: 0.785
roc-auc: 0.817
```

We see that our ensembler is doing a better job than any idividual model, as expected.

Thanks you for going over this example. Feel free to copy, modify, and in general play around with this notebook.

5.7 Vaex-jupyter examples

Warning: This notebook needs a running kernel to be fully interactive, please run it locally or run it on mybinder.

Dashboard: Or get a dashboard by rendering this notebook with Voila:

5.7.1 ipyvolume: 3d bar chart

Make sure you go through the Vaex-jupyter tutorial first.

Following https://ipyvolume.readthedocs.io/en/latest/examples/bars.html we take a similar approach to create a 3d bar chart.

[1]:
```
import vaex
import numpy as np
import vaex.jupyter.model as vjm
```

```
[2]: import ipyvolume as ipv
import bqplot

class IpyvolumeBarChart:
    def __init__(self, x_axis, y_axis):
        self.x_axis = x_axis
        self.y_axis = y_axis
        self.fig = ipv.figure()
        self.color_scale = bqplot.ColorScale(scheme='Reds', min=0, max=1)
        ipv.style.set_style_dark()
        ipv.style.box_off()
        ipv.style.use({'axes': {'y': {'visible': False}}})
        self.scatter = None

    def _scale_change(self, change):
        self.last1 = self.x_axis.max
        self.last2 = self.fig.scales['x'].max
        self.x_axis.min = self.fig.scales['x'].min
        self.x_axis.max = self.fig.scales['x'].max
        self.y_axis.min = self.fig.scales['z'].min
        self.y_axis.max = self.fig.scales['z'].max

    def __call__(self, da):
        ar = da.data
        assert ar.ndim == 2
        dim_x = da.dims[0]
        dim_y = da.dims[1]

        Nx, Ny = ar.shape
        x0, x1 = da.coords[dim_x].attrs['min'], da.coords[dim_x].attrs['max']
        y0, y1 = da.coords[dim_y].attrs['min'], da.coords[dim_y].attrs['max']
        x = np.linspace(x0, x1, Nx)
        y = np.linspace(y0, y1, Ny)

        X, Y = np.meshgrid(x, y, indexing='ij')
        xf = X.flatten()
        yf = Y.flatten()
        ar = np.log1p(ar)
        zf = ar.flatten().astype('f8')

        self.dx = dx = x[1] - x[0]
        self.dy = dy = y[1] - y[0]
        if self.scatter is None:
            with self.fig:
                self.scatter = ipv.scatter(xf, 0, yf, aux=zf,
                                           color=zf,
                                           marker="box",
                                           size=1,
                                           color_scale=self.color_scale,
                                           size_x_scale=self.fig.scales['x'],
                                           size_y_scale=self.fig.scales['y'],
                                           size_z_scale=self.fig.scales['z'])
            self.scatter.shader_snippets = {'size': 'size_vector.y = SCALE_SIZE_Y(aux_
↪current) - SCALE_SIZE_Y(0.0) ; '}
            # since we see the boxes with negative sizes inside out, we made the␣
↪material double sided
            self.scatter.material.side = "DoubleSide"
```

(continues on next page)

(continued from previous page)

```
            ipv.xlim(x0, x1)
            ipv.zlim(y0, y1)
            # only start observing now that the limits have been set to avoid an␣
↪initial re-gridding
            for scale in [self.fig.scales['x'], self.fig.scales['z']]:
                scale.observe(self._scale_change, ['min', 'max'])
        else:
            with self.scatter.hold_sync():
                self.scatter.x = xf
                self.scatter.z = yf
                self.scatter.aux = zf
                self.scatter.color = zf
        # we patch holes by making the boxes larger
        patch = 1.05
        self.scatter.geo_matrix = [dx*patch, 0, 0, 0,    0, 1, 0, 0,    0, 0, dy*patch,␣
↪0,   0.0, 0.5, 0, 1]
        self.color_scale.max = zf.max().item()
        with self.fig:
            # make the x and z lim half a 'box' larger
            ipv.xlim(x0, x1)
            ipv.zlim(y0, y1)
            ipv.ylim(0, zf.max() * 1.2)
            ipv.xlabel(dim_x)
            ipv.zlabel(dim_y)
            ipv.ylabel('counts')
# barchart3d = IpyvolumeBarChart(x_axis, y_axis)
```

[3]:
```
# x_limits, y_limits = limits = df.limits([df.pickup_longitude, df.pickup_latitude],
↪'95%')

# pre calculated values:
x_limits, y_limits = [-74.37857997, -73.53860359], [40.49456025, 40.91851631]
```

[4]:
```
# Data is hosted on S3
# df = vaex.open('s3://vaex/taxi/yellow_taxi_2009_2015_f32.hdf5?anon=true')[:800_000_
↪000]

# Or use the Vaex DataFrame server to do the computations!
df = vaex.open('ws://dataframe.vaex.io:80/yellow_taxi_2009_2015_f32')

x_axis = vjm.Axis(df=df, expression=df.pickup_longitude, min=x_limits[0], max=x_
↪limits[1])
y_axis = vjm.Axis(df=df, expression=df.pickup_latitude, min=y_limits[0], max=y_
↪limits[1])

barchart3dtaxi = IpyvolumeBarChart(x_axis, y_axis)

# we use `barchart3d` as a callable function
da_view = df.widget.data_array(axes=[x_axis, y_axis], display_function=barchart3dtaxi,
↪ shape=400)

# we display the progress bar and possible output (stack traces)
display(da_view)
```

(continues on next page)

(continued from previous page)

```
# and the figure widget, display(barchart3d.fig) would also have worked
with barchart3dtaxi.fig:
    ipv.show()
```

```
DataArray(children=[Container(children=[ProgressCircularNoAnimation(color='#9ECBF5',␣
↪size=30, text='', value=1...
```

```
VBox(children=(Figure(camera=PerspectiveCamera(fov=45.0, position=(0.0, 0.0, 2.0),␣
↪quaternion=(0.0, 0.0, 0.0, ...
```

```
[5]: await vaex.jupyter.gather()
```

Voila-vuetify setup

```
[6]: import traitlets
import ipywidgets as widgets
import ipyvuetify as v
from vaex.jupyter.widgets import ContainerCard, Html, LinkList, VuetifyTemplate
```

```
[7]: class SchemeTemplate(VuetifyTemplate):
    value = traitlets.Unicode('Reds').tag(sync=True)
    @traitlets.default('template')
    def _template(self):
         return """
    <v-btn-toggle v-model="value">
      <v-btn :value="'Reds'" text >
          <v-icon color="red">mdi-palette</v-icon>
      </v-btn>
      <v-btn :value="'Blues'" text>
          <v-icon color="blue">mdi-palette</v-icon>
      </v-btn>
    </v-btn-toggle>sdd
        """
scheme_widget = SchemeTemplate()
widgets.jslink((scheme_widget, 'value'), (barchart3dtaxi.color_scale, 'scheme'))
scheme_widget
```

```
SchemeTemplate(template='\n    <v-btn-toggle v-model="value">\n      <v-btn :value="\
↪'Reds\'" text >\n        ...
```

```
[8]: card_widget = ContainerCard(title=f'{len(df):,} Taxi pickup locations',
                            subtitle="using vaex-jupyter",
                            main=barchart3dtaxi.fig,
                            controls=[scheme_widget],
                            show_controls=True,
                            card_props={'style': 'width: 520px;', 'class': 'pa-2 ma-4
↪'},
                            _metadata={'mount_id': 'content-main'},
                            text='<i>Hold the control key to zoom in and out</i>'
                           )
```

```
[9]: # You do not have to render the widget for it to show up in voila-vuetify
card_widget
```

```
ContainerCard(card_props={'style': 'width: 520px;', 'class': 'pa-2 ma-4'},␣
↪controls=[SchemeTemplate(template='...
```

[11]:
```
LinkList(items=
    [{'title': 'Vaex', 'url': 'https://vaex.io', 'img': 'https://vaex.io/img/logos/
↪logo-grey.svg', },
     {'title': 'Vaex on GitHub', 'url': 'https://github.com/vaexio/vaex', 'img':
↪'https://github.githubassets.com/pinned-octocat.svg'},
     {'title': 'Vaex DataFrame server', 'url': 'http://dataframe.vaex.io/', 'icon':
↪'mdi-database'},
     {'title': 'ipyvolume', 'url': 'https://github.com/maartenbreddels/ipyvolume',
↪'img': 'https://raw.githubusercontent.com/maartenbreddels/ipyvolume/master/misc/
↪icon.svg'},
     {'title': 'Voila (dashboard)', 'url': 'https://github.com/voila-dashboards/voila
↪', 'icon': 'dashboard'},
     {'title': 'jupyter widgets', 'url': 'https://github.com/jupyter-widgets/
↪ipywidgets', 'icon': 'widgets'},
    ], _metadata={'mount_id': 'content-nav'})
```

```
LinkList(items=[{'title': 'Vaex', 'url': 'https://vaex.io', 'img': 'https://vaex.io/
↪img/logos/logo-grey.svg'},...
```

[15]:
```
v.theme.dark = True
```

[16]:
```
Html(tag='span',
     children=['New york taxi dataset with ipyvolume'],
     _metadata={'mount_id': 'content-bar'});

Html(tag='span',
     children=['Resources'],
     _metadata={'mount_id': 'content-title'});
```

screenshot

Warning: This notebook needs a running kernel to be fully interactive, please run it locally or run it on mybinder.

Dashboard: Or get a dashboard by rendering this notebook with Voila:

5.7.2 A Plotly heatmap

Make sure you go through the Vaex-jupyter tutorial first.

The easiest way to create your own visualizations is to follow a similar approach as described in the Vaex-jupyter tutorial where we used matplotlib to create the figures. When using plotly however, we can first construct the widgets, and at each callback update the relevant components. This is much more efficient than creating an entirely new widget on each update.

To solve this two step process (initialization and updating), we write a wrapper class that implement the dunder call method, such that it acts as a callable (like a function).

[1]:
```
import vaex
import numpy as np
import vaex.jupyter.model as vjm
import matplotlib.pyplot as plt

# Fetch a dataset
df = vaex.datasets.helmi_de_zeeuw.fetch()
```

[2]:
```
# Define the axes
extend = 50
x_axis = vjm.Axis(df=df, expression=df.x, shape=100, min=-extend, max=extend)
y_axis = vjm.Axis(df=df, expression=df.y, shape=140, min=-extend, max=extend)
# in this case we need to know the min and max directly
await vaex.jupyter.gather()
```

[3]:
```
import plotly.graph_objs as go

class PlotlyHeatmap:
    def __init__(self, x_axis, y_axis, figure_height=500, figure_width=400, title="Hi␣
↪vaex, hi plotly"):
        self.x_axis = x_axis
        self.y_axis = y_axis
        self.heatmap = go.Heatmap()
        self.layout = go.Layout(height=figure_height,
                                width=figure_width,
                                title=title,
                                xaxis=go.layout.XAxis(title=str(x_axis.expression),
                                                      range=[x_axis.min, x_axis.max]
                                                     ),
                                yaxis=go.layout.YAxis(title=str(y_axis.expression),
                                                      range=[y_axis.min, y_axis.max]
                                                     )
                               )
        self.fig = go.FigureWidget(data=[self.heatmap], layout=self.layout)
        # we respond to zoom/pan
        self.fig.layout.on_change(self._pan_and_zoom, 'xaxis.range', 'yaxis.range')

    def _pan_and_zoom(self, layout, xrange, yrange):
        self.x_axis.min, self.x_axis.max = xrange
        self.y_axis.min, self.y_axis.max = yrange

    def __call__(self, data_array):
        ar = data_array.data  # take the numpy array data
        assert data_array.ndim == 2
        dim_x = data_array.dims[0]
        dim_y = data_array.dims[1]
        x0, x1 = data_array.coords[dim_x].attrs['min'], data_array.coords[dim_x].
↪attrs['max']
        y0, y1 = data_array.coords[dim_y].attrs['min'], data_array.coords[dim_y].
↪attrs['max']
        dx = (x1 - x0)/data_array.shape[0]
        dy = (y1 - y0)/data_array.shape[1]

        z = np.log1p(ar).T
        self.fig.update_traces(dict(z=z, x0=x0, y0=y0, dx=dx, dy=dy))
        heatmap_plotly.fig.update_layout(
            xaxis=go.layout.XAxis(title=dim_x, range=[x0, x1]),
```
(continues on next page)

(continued from previous page)

```
            yaxis=go.layout.YAxis(title=dim_y, range=[y0, y1])
        )


heatmap_plotly = PlotlyHeatmap(x_axis, y_axis)
```

[4]:
```
# we use `heatmap_plotly` as a callable function
da_view = df.widget.data_array(axes=[x_axis, y_axis], display_function=heatmap_plotly)

# we display the progress bar and possible output (stack traces)
display(da_view)

# and the plotly figure widget
display(heatmap_plotly.fig)
```

```
DataArray(children=[Container(children=[ProgressCircularNoAnimation(color='#9ECBF5',␣
↪size=30, text='', value=1...
```

```
FigureWidget({
    'data': [{'type': 'heatmap', 'uid': '709f37ba-c069-4ad4-a26e-5072a777d78e'}],
    'layout':...
```

We can also create expression widgets to directly edit the axis on the figure above

[5]:
```
x_widget = df.widget.expression(x_axis)
y_widget = df.widget.expression(y_axis)
display(x_widget)
display(y_widget)
```

```
Expression(label='Custom expression', placeholder='Enter a custom expression',␣
↪prepend_icon='functions', succe...
```

```
Expression(label='Custom expression', placeholder='Enter a custom expression',␣
↪prepend_icon='functions', succe...
```

Using ipyvuetify we can create pretty buttons and assign them some functionality:

[6]:
```
import ipyvuetify as v

# A button to reset the figure ot its initial state
button_reset = v.Btn(children=['reset'])

def reset(*ignore_arguments):
    x_axis.expression = df.x
    y_axis.expression = df.y
button_reset.on_event('click', reset)

# A button that presents a specific figure
button_fireball = v.Btn(children=['fireball'])

def fireball(*ignore_arguments):
    x_axis.expression = np.log(df.x**2)
    y_axis.expression = df.y
button_fireball.on_event('click', fireball)

preset_widget = v.Col(children=[button_reset, button_fireball])
preset_widget
```

```
Col(children=[Btn(children=['reset']), Btn(children=['fireball'])])
```

Voila vuetify setup

We can more elegantly present the visualisations created in this notebook using Voila.

[7]:
```
from vaex.jupyter.widgets import ContainerCard, Html, LinkList
```

[9]:
```
LinkList(items=
    [{'title': 'Vaex', 'url': 'https://vaex.io', 'img': 'https://vaex.io/img/logos/
↪logo-grey.svg', },
     {'title': 'Vaex on GitHub', 'url': 'https://github.com/vaexio/vaex', 'img':
↪'https://github.githubassets.com/pinned-octocat.svg'},
     {'title': 'Vaex DataFrame server', 'url': 'http://dataframe.vaex.io/', 'icon':
↪'mdi-database'},
     {'title': 'Voila (dashboard)', 'url': 'https://github.com/voila-dashboards/voila
↪', 'icon': 'dashboard'},
     {'title': 'Plotly', 'url': 'https://plotly.com/', 'img': 'https://plotly.com/img/
↪favicon.ico'},
    ], _metadata={'mount_id': 'content-nav'})
```

```
LinkList(items=[{'title': 'Vaex', 'url': 'https://vaex.io', 'img': 'https://vaex.io/
↪img/logos/logo-grey.svg'},...
```

[10]:
```
card_widget = ContainerCard(title=f'{len(df):,} Simulated stars',
                            subtitle="using vaex-jupyter",
                            main=heatmap_plotly.fig,
                            controls=[x_widget, y_widget, preset_widget],
                            show_controls=True,
                            card_props={'style': 'width: 420px;', 'class': 'pa-2 ma-4
↪'},
                            _metadata={'mount_id': 'content-main'}
                           )
```

[11]:
```
# You do not have to render the widget for it to show up in voila-vuetify
card_widget
```

```
ContainerCard(card_props={'style': 'width: 420px;', 'class': 'pa-2 ma-4'},␣
↪controls=[Expression(label='Custom ...
```

[12]:
```
Html(tag='span',
     children=['Simulated stars'],
     _metadata={'mount_id': 'content-bar'})
Html(tag='span',
     children=['Resources'],
     _metadata={'mount_id': 'content-title'});
```

screenshot

CHAPTER 6

Gallery

CHAPTER 7

API documentation for vaex library

7.1 Quick lists

7.1.1 Opening/reading in your data.

`vaex.open`(path[, convert, shuffle, copy_index])	Open a DataFrame from file given by path.
`vaex.from_arrow_table`(table)	Creates a vaex DataFrame from an arrow Table.
`vaex.from_arrays`(**arrays)	Create an in memory DataFrame from numpy arrays.
`vaex.from_dict`(data)	Create an in memory dataset from a dict with column names as keys and list/numpy-arrays as values
`vaex.from_csv`(filename_or_buffer[, ...])	Read a CSV file as a DataFrame, and optionally convert to an hdf5 file.
`vaex.from_ascii`(path[, seperator, names, ...])	Create an in memory DataFrame from an ascii file (whitespace seperated by default).
`vaex.from_pandas`(df[, name, copy_index, ...])	Create an in memory DataFrame from a pandas DataFrame.
`vaex.from_astropy_table`(table)	Create a vaex DataFrame from an Astropy Table.

7.1.2 Visualization.

`vaex.dataframe.DataFrame.plot`([x, y, z, ...])	Viz data in a 2d histogram/heatmap.
`vaex.dataframe.DataFrame.plot1d`([x, what, ...])	Viz data in 1d (histograms, running means etc)
`vaex.dataframe.DataFrame.scatter`(x, y[, ...])	Viz (small amounts) of data in 2d using a scatter plot
`vaex.dataframe.DataFrame.plot_widget`(x, y[, ...])	Deprecated: use df.widget.heatmap

Continued on next page

Table 2 – continued from previous page

vaex.dataframe.DataFrame.healpix_plot([…])	Viz data in 2d using a healpix column.

7.1.3 Statistics.

vaex.dataframe.DataFrame.count([expression, …])	Count the number of non-NaN values (or all, if expression is None or "*").
vaex.dataframe.DataFrame.mean(expression[, …])	Calculate the mean for expression, possibly on a grid defined by binby.
vaex.dataframe.DataFrame.std(expression[, …])	Calculate the standard deviation for the given expression, possible on a grid defined by binby
vaex.dataframe.DataFrame.var(expression[, …])	Calculate the sample variance for the given expression, possible on a grid defined by binby
vaex.dataframe.DataFrame.cov(x[, y, binby, …])	Calculate the covariance matrix for x and y or more expressions, possibly on a grid defined by binby.
vaex.dataframe.DataFrame.correlation(x[, y, …])	Calculate the correlation coefficient cov[x,y]/(std[x]*std[y]) between x and y, possibly on a grid defined by binby.
vaex.dataframe.DataFrame.median_approx(…)	Calculate the median, possibly on a grid defined by binby.
vaex.dataframe.DataFrame.mode(expression[, …])	Calculate/estimate the mode.
vaex.dataframe.DataFrame.min(expression[, …])	Calculate the minimum for given expressions, possibly on a grid defined by binby.
vaex.dataframe.DataFrame.max(expression[, …])	Calculate the maximum for given expressions, possibly on a grid defined by binby.
vaex.dataframe.DataFrame.minmax(expression)	Calculate the minimum and maximum for expressions, possibly on a grid defined by binby.
vaex.dataframe.DataFrame.mutual_information(x)	Estimate the mutual information between and x and y on a grid with shape mi_shape and mi_limits, possibly on a grid defined by binby.

7.2 vaex-core

Vaex is a library for dealing with larger than memory DataFrames (out of core).

The most important class (datastructure) in vaex is the `DataFrame`. A DataFrame is obtained by either opening the example dataset:

```
>>> import vaex
>>> df = vaex.example()
```

Or using `open()` to open a file.

```
>>> df1 = vaex.open("somedata.hdf5")
>>> df2 = vaex.open("somedata.fits")
>>> df2 = vaex.open("somedata.arrow")
>>> df4 = vaex.open("somedata.csv")
```

Or connecting to a remove server:

```
>>> df_remote = vaex.open("http://try.vaex.io/nyc_taxi_2015")
```

A few strong features of vaex are:

- Performance: works with huge tabular data, process over a billion (> 10^9) rows/second.
- Expression system / Virtual columns: compute on the fly, without wasting ram.
- Memory efficient: no memory copies when doing filtering/selections/subsets.
- Visualization: directly supported, a one-liner is often enough.
- User friendly API: you will only need to deal with a DataFrame object, and tab completion + docstring will help you out: *ds.mean<tab>*, feels very similar to Pandas.
- Very fast statistics on N dimensional grids such as histograms, running mean, heatmaps.

Follow the tutorial at https://docs.vaex.io/en/latest/tutorial.html to learn how to use vaex.

`vaex.`**`open`**(*path*, *convert=False*, *shuffle=False*, *copy_index=False*, **args*, ***kwargs*)

Open a DataFrame from file given by path.

Example:

```
>>> df = vaex.open('sometable.hdf5')
>>> df = vaex.open('somedata*.csv', convert='bigdata.hdf5')
```

Parameters

- **`or list path`** (*`str`*) – local or absolute path to file, or glob string, or list of paths
- **`convert`** – convert files to an hdf5 file for optimization, can also be a path
- **`shuffle`** (*`bool`*) – shuffle converted DataFrame or not
- **`args`** – extra arguments for file readers that need it
- **`kwargs`** – extra keyword arguments
- **`copy_index`** (*`bool`*) – copy index when source is read via pandas

Returns return a DataFrame on success, otherwise None

Return type *DataFrame*

S3 support:

Vaex supports streaming in hdf5 files from Amazon AWS object storage S3. Files are by default cached in $HOME/.vaex/file-cache/s3 such that successive access is as fast as native disk access. The following url parameters control S3 options:

- anon: Use anonymous access or not (false by default). (Allowed values are: true,True,1,false,False,0)
- use_cache: Use the disk cache or not, only set to false if the data should be accessed once. (Allowed values are: true,True,1,false,False,0)
- profile_name and other arguments are passed to `s3fs.core.S3FileSystem`

All arguments can also be passed as kwargs, but then arguments such as *anon* can only be a boolean, not a string.

Examples:

```
>>> df = vaex.open('s3://vaex/taxi/yellow_taxi_2015_f32s.hdf5?anon=true')
>>> df = vaex.open('s3://vaex/taxi/yellow_taxi_2015_f32s.hdf5', anon=True)   #␣
↪Note that anon is a boolean, not the string 'true'
>>> df = vaex.open('s3://mybucket/path/to/file.hdf5?profile_name=myprofile')
```

`vaex.from_arrays(**arrays)`

Create an in memory DataFrame from numpy arrays.

Example

```
>>> import vaex, numpy as np
>>> x = np.arange(5)
>>> y = x ** 2
>>> vaex.from_arrays(x=x, y=y)
  #    x    y
  0    0    0
  1    1    1
  2    2    4
  3    3    9
  4    4   16
>>> some_dict = {'x': x, 'y': y}
>>> vaex.from_arrays(**some_dict)  # in case you have your columns in a dict
  #    x    y
  0    0    0
  1    1    1
  2    2    4
  3    3    9
  4    4   16
```

Parameters **arrays** – keyword arguments with arrays

Return type *DataFrame*

`vaex.from_dict(data)`

Create an in memory dataset from a dict with column names as keys and list/numpy-arrays as values

Example

```
>>> data = {'A':[1,2,3],'B':['a','b','c']}
>>> vaex.from_dict(data)
  #    A    B
  0    1   'a'
  1    2   'b'
  2    3   'c'
```

Parameters **data** – A dict of {column:[value, value,. . .]}

Return type *DataFrame*

`vaex.from_items(*items)`

Create an in memory DataFrame from numpy arrays, in contrast to from_arrays this keeps the order of columns intact (for Python < 3.6).

Example

```
>>> import vaex, numpy as np
>>> x = np.arange(5)
```

(continues on next page)

(continued from previous page)

```
>>> y = x ** 2
>>> vaex.from_items(('x', x), ('y', y))
  #    x    y
  0    0    0
  1    1    1
  2    2    4
  3    3    9
  4    4   16
```

Parameters **items** – list of [(name, numpy array), . . .]

Return type *DataFrame*

vaex.**from_arrow_table**(*table*)

Creates a vaex DataFrame from an arrow Table.

Return type *DataFrame*

vaex.**from_csv**(*filename_or_buffer*, *copy_index=False*, *chunk_size=None*, *convert=False*, ***kwargs*)

Read a CSV file as a DataFrame, and optionally convert to an hdf5 file.

Parameters

- **or file filename_or_buffer** (*str*) – CSV file path or file-like
- **copy_index** (*bool*) – copy index when source is read via Pandas
- **chunk_size** (*int*) – if the CSV file is too big to fit in the memory this parameter can be used to read CSV file in chunks. For example:

```
>>> import vaex
>>> for i, df in enumerate(vaex.from_csv('taxi.csv', chunk_
↪size=100_000)):
>>>     df = df[df.passenger_count < 6]
>>>     df.export_hdf5(f'taxi_{i:02}.hdf5')
```

- **or str convert** (*bool*) – convert files to an hdf5 file for optimization, can also be a path. The CSV file will be read in chunks: either using the provided chunk_size argument, or a default size. Each chunk will be saved as a separate hdf5 file, then all of them will be combined into one hdf5 file. So for a big CSV file you will need at least double of extra space on the disk. Default chunk_size for converting is 5 million rows, which corresponds to around 1Gb memory on an example of NYC Taxi dataset.
- **kwargs** – extra keyword arguments, currently passed to Pandas read_csv function, but the implementation might change in future versions.

Returns DataFrame

vaex.**from_ascii**(*path*, *seperator=None*, *names=True*, *skip_lines=0*, *skip_after=0*, ***kwargs*)

Create an in memory DataFrame from an ascii file (whitespace seperated by default).

```
>>> ds = vx.from_ascii("table.asc")
>>> ds = vx.from_ascii("table.csv", seperator=",", names=["x", "y", "z"])
```

Parameters

- **path** – file path
- **seperator** – value seperator, by default whitespace, use "," for comma seperated values.

- **names** – If True, the first line is used for the column names, otherwise provide a list of strings with names
- **skip_lines** – skip lines at the start of the file
- **skip_after** – skip lines at the end of the file
- **kwargs** –

Return type *DataFrame*

vaex.**from_pandas**(*df*, *name='pandas'*, *copy_index=False*, *index_name='index'*)
Create an in memory DataFrame from a pandas DataFrame.

Param pandas.DataFrame df: Pandas DataFrame

Param name: unique for the DataFrame

```
>>> import vaex, pandas as pd
>>> df_pandas = pd.from_csv('test.csv')
>>> df = vaex.from_pandas(df_pandas)
```

Return type *DataFrame*

vaex.**from_astropy_table**(*table*)
Create a vaex DataFrame from an Astropy Table.

vaex.**from_samp**(*username=None*, *password=None*)
Connect to a SAMP Hub and wait for a single table load event, disconnect, download the table and return the DataFrame.

Useful if you want to send a single table from say TOPCAT to vaex in a python console or notebook.

vaex.**open_many**(*filenames*)
Open a list of filenames, and return a DataFrame with all DataFrames concatenated.

Parameters **filenames** (*list[str]*) – list of filenames/paths

Return type *DataFrame*

vaex.**register_function**(*scope=None*, *as_property=False*, *name=None*, *on_expression=True*, *df_accessor=None*)
Decorator to register a new function with vaex.

If on_expression is True, the function will be available as a method on an Expression, where the first argument will be the expression itself.

If *df_accessor* is given, it is added as a method to that dataframe accessor (see e.g. vaex/geo.py)

Example:

```
>>> import vaex
>>> df = vaex.example()
>>> @vaex.register_function()
>>> def invert(x):
>>>     return 1/x
>>> df.x.invert()
```

```
>>> import numpy as np
>>> df = vaex.from_arrays(departure=np.arange('2015-01-01', '2015-12-05', dtype=
↪'datetime64'))
```

(continues on next page)

(continued from previous page)

```
>>> @vaex.register_function(as_property=True, scope='dt')
>>> def dt_relative_day(x):
>>>     return vaex.functions.dt_dayofyear(x)/365.
>>> df.departure.dt.relative_day
```

`vaex.example()`

Returns an example DataFrame which comes with vaex for testing/learning purposes.

Return type *DataFrame*

`vaex.app(*args, **kwargs)`

Create a vaex app, the QApplication mainloop must be started.

In ipython notebook/jupyter do the following:

```
>>> import vaex.ui.main # this causes the qt api level to be set properly
>>> import vaex
```

Next cell:

```
>>> %gui qt
```

Next cell:

```
>>> app = vaex.app()
```

From now on, you can run the app along with jupyter

`vaex.delayed(f)`

Decorator to transparantly accept delayed computation.

Example:

```
>>> delayed_sum = ds.sum(ds.E, binby=ds.x, limits=limits,
>>>                     shape=4, delay=True)
>>> @vaex.delayed
>>> def total_sum(sums):
>>>     return sums.sum()
>>> sum_of_sums = total_sum(delayed_sum)
>>> ds.execute()
>>> sum_of_sums.get()
See the tutorial for a more complete example https://docs.vaex.io/en/latest/
↪tutorial.html#Parallel-computations
```

7.2.1 DataFrame class

class `vaex.dataframe.DataFrame(name, column_names, executor=None)`

Bases: `object`

All local or remote datasets are encapsulated in this class, which provides a pandas like API to your dataset.

Each DataFrame (df) has a number of columns, and a number of rows, the length of the DataFrame.

All DataFrames have multiple 'selection', and all calculations are done on the whole DataFrame (default) or for the selection. The following example shows how to use the selection.

```
>>> df.select("x < 0")
>>> df.sum(df.y, selection=True)
>>> df.sum(df.y, selection=[df.x < 0, df.x > 0])
```

__delitem__(*item*)
Removes a (virtual) column from the DataFrame.

Note: this does not check if the column is used in a virtual expression or in the filter and may lead to issues. It is safer to use `drop()`.

__getitem__(*item*)
Convenient way to get expressions, (shallow) copies of a few columns, or to apply filtering.

Example:

```
>>> df['Lz']  # the expression 'Lz
>>> df['Lz/2'] # the expression 'Lz/2'
>>> df[["Lz", "E"]] # a shallow copy with just two columns
>>> df[df.Lz < 0]  # a shallow copy with the filter Lz < 0 applied
```

__init__(*name*, *column_names*, *executor=None*)
Initialize self. See help(type(self)) for accurate signature.

__iter__()
Iterator over the column names.

__len__()
Returns the number of rows in the DataFrame (filtering applied).

__repr__()
Return repr(self).

__setitem__(*name*, *value*)
Convenient way to add a virtual column / expression to this DataFrame.

Example:

```
>>> import vaex, numpy as np
>>> df = vaex.example()
>>> df['r'] = np.sqrt(df.x**2 + df.y**2 + df.z**2)
>>> df.r
<vaex.expression.Expression(expressions='r')> instance at 0x121687e80␣
↪values=[2.9655450396553587, 5.77829281049018, 6.99079603950256, 9.
↪431842752707537, 0.8825613121347967 ... (total 330000 values) ... 7.
↪453831761514681, 15.398412491068198, 8.864250273925633, 17.601047186042507,␣
↪14.540181524970293]
```

__str__()
Return str(self).

__weakref__
list of weak references to the object (if defined)

add_column(*name*, *f_or_array*, *dtype=None*)
Add an in memory array as a column.

add_variable(*name*, *expression*, *overwrite=True*, *unique=True*)
Add a variable to a DataFrame.

A variable may refer to other variables, and virtual columns and expression may refer to variables.

Example

```
>>> df.add_variable('center', 0)
>>> df.add_virtual_column('x_prime', 'x-center')
>>> df.select('x_prime < 0')
```

Param str name: name of virtual varible

Param expression: expression for the variable

add_virtual_column (*name*, *expression*, *unique=False*)
Add a virtual column to the DataFrame.

Example:

```
>>> df.add_virtual_column("r", "sqrt(x**2 + y**2 + z**2)")
>>> df.select("r < 10")
```

Param str name: name of virtual column

Param expression: expression for the column

Parameters unique (*str*) – if name is already used, make it unique by adding a postfix, e.g. _1, or _2

apply (*f*, *arguments=None*, *dtype=None*, *delay=False*, *vectorize=False*)
Apply a function on a per row basis across the entire DataFrame.

Example:

```
>>> import vaex
>>> df = vaex.example()
>>> def func(x, y):
...     return (x+y)/(x-y)
...
>>> df.apply(func, arguments=[df.x, df.y])
Expression = lambda_function(x, y)
Length: 330,000 dtype: float64 (expression)
-------------------------------------------
     0  -0.460789
     1    3.90038
     2  -0.642851
     3   0.685768
     4  -0.543357
```

Parameters

- **f** – The function to be applied
- **arguments** – List of arguments to be passed on to the function f.

Returns A function that is lazily evaluated.

byte_size (*selection=False*, *virtual=False*)
Return the size in bytes the whole DataFrame requires (or the selection), respecting the active_fraction.

cat (*i1*, *i2*, *format='html'*)
Display the DataFrame from row i1 till i2

For format, see https://pypi.org/project/tabulate/

Parameters

- **i1** (*int*) – Start row
- **i2** (*int*) – End row.
- **format** (*str*) – Format to use, e.g. 'html', 'plain', 'latex'

close_files ()
Close any possible open file handles, the DataFrame will not be in a usable state afterwards.

col
Gives direct access to the columns only (useful for tab completion).

Convenient when working with ipython in combination with small DataFrames, since this gives tab-completion.

Columns can be accessed by their names, which are attributes. The attributes are currently expressions, so you can do computations with them.

Example

```
>>> ds = vaex.example()
>>> df.plot(df.col.x, df.col.y)
```

column_count (*hidden=False*)
Returns the number of columns (including virtual columns).

Parameters **hidden** (*bool*) – If True, include hidden columns in the tally

Returns Number of columns in the DataFrame

combinations (*expressions_list=None*, *dimension=2*, *exclude=None*, ***kwargs*)
Generate a list of combinations for the possible expressions for the given dimension.

Parameters

- **expressions_list** – list of list of expressions, where the inner list defines the subspace
- **dimensions** – if given, generates a subspace with all possible combinations for that dimension
- **exclude** – list of

correlation (*x*, *y=None*, *binby=[]*, *limits=None*, *shape=128*, *sort=False*, *sort_key=<ufunc 'absolute'>*, *selection=False*, *delay=False*, *progress=None*)
Calculate the correlation coefficient cov[x,y]/(std[x]*std[y]) between x and y, possibly on a grid defined by binby.

Example:

```
>>> df.correlation("x**2+y**2+z**2", "-log(-E+1)")
array(0.6366637382215669)
>>> df.correlation("x**2+y**2+z**2", "-log(-E+1)", binby="Lz", shape=4)
array([ 0.40594394,  0.69868851,  0.61394099,  0.65266318])
```

Parameters

- **x** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **y** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **binby** – List of expressions for constructing a binned grid
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)
- **progress** – A callable that takes one argument (a floating point value between 0 and 1) indicating the progress, calculations are cancelled when this callable returns False

Returns Numpy array with the given shape, or a scalar when no binby argument is given, with the statistic

count (*expression=None*, *binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *edges=False*, *progress=None*, *array_type=None*)

Count the number of non-NaN values (or all, if expression is None or "*").

Example:

```
>>> df.count()
330000
>>> df.count("*")
330000.0
>>> df.count("*", binby=["x"], shape=4)
array([  10925.,  155427.,  152007.,   10748.])
```

Parameters

- **expression** – Expression or column for which to count non-missing values, or None or '*' for counting the rows
- **binby** – List of expressions for constructing a binned grid
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)
- **progress** – A callable that takes one argument (a floating point value between 0 and 1) indicating the progress, calculations are cancelled when this callable returns False
- **edges** – Currently for internal use only (it includes nan's and values outside the limits at borders, nan and 0, smaller than at 1, and larger at -1

- **array_type** – Type of output array, possible values are None/"numpy" (ndarray), "xarray" for a xarray.DataArray, or "list" for a Python list

Returns Numpy array with the given shape, or a scalar when no binby argument is given, with the statistic

cov (*x*, *y=None*, *binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *progress=None*)
Calculate the covariance matrix for x and y or more expressions, possibly on a grid defined by binby.

Either x and y are expressions, e.g.:

```
>>> df.cov("x", "y")
```

Or only the x argument is given with a list of expressions, e.g.:

```
>>> df.cov(["x, "y, "z"])
```

Example:

```
>>> df.cov("x", "y")
array([[ 53.54521742,  -3.8123135 ],
[ -3.8123135 ,  60.62257881]])
>>> df.cov(["x", "y", "z"])
array([[ 53.54521742,  -3.8123135 ,  -0.98260511],
[ -3.8123135 ,  60.62257881,   1.21381057],
[ -0.98260511,   1.21381057,  25.55517638]])
```

```
>>> df.cov("x", "y", binby="E", shape=2)
array([[[  9.74852878e+00,  -3.02004780e-02],
[ -3.02004780e-02,   9.99288215e+00]],
[[  8.43996546e+01,  -6.51984181e+00],
[ -6.51984181e+00,   9.68938284e+01]]])
```

Parameters

- **x** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **y** – if previous argument is not a list, this argument should be given
- **binby** – List of expressions for constructing a binned grid
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)

Returns Numpy array with the given shape, or a scalar when no binby argument is given, with the statistic, the last dimensions are of shape (2,2)

covar (*x*, *y*, *binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *progress=None*)
Calculate the covariance cov[x,y] between x and y, possibly on a grid defined by binby.

Example:

```
>>> df.covar("x**2+y**2+z**2", "-log(-E+1)")
array(52.69461456005138)
>>> df.covar("x**2+y**2+z**2", "-log(-E+1)")/(df.std("x**2+y**2+z**2") * df.
↪std("-log(-E+1)"))
0.63666373822156686
>>> df.covar("x**2+y**2+z**2", "-log(-E+1)", binby="Lz", shape=4)
array([ 10.17387143,  51.94954078,  51.24902796,  20.2163929 ])
```

Parameters

- **x** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **y** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **binby** – List of expressions for constructing a binned grid
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)
- **progress** – A callable that takes one argument (a floating point value between 0 and 1) indicating the progress, calculations are cancelled when this callable returns False

Returns Numpy array with the given shape, or a scalar when no binby argument is given, with the statistic

data_type (*expression*, *internal=False*)
Return the numpy dtype for the given expression, if not a column, the first row will be evaluated to get the dtype.

delete_variable (*name*)
Deletes a variable from a DataFrame.

delete_virtual_column (*name*)
Deletes a virtual column from a DataFrame.

describe (*strings=True*, *virtual=True*, *selection=None*)
Give a description of the DataFrame.

```
>>> import vaex
>>> df = vaex.example()[['x', 'y', 'z']]
>>> df.describe()
                 x          y          z
dtype      float64    float64    float64
count       330000     330000     330000
missing          0          0          0
mean    -0.0671315 -0.0535899  0.0169582
std        7.31746    7.78605    5.05521
min       -128.294   -71.5524   -44.3342
max        271.366    146.466    50.7185
>>> df.describe(selection=df.x > 0)
                   x          y           z
```

(continues on next page)

(continued from previous page)

```
dtype        float64   float64    float64
count         164060    164060     164060
missing       165940    165940     165940
mean         5.13572 -0.486786 -0.0868073
std          5.18701   7.61621    5.02831
min      1.51635e-05  -71.5524   -44.3342
max          271.366   78.0724    40.2191
```

Parameters

- **strings** (*bool*) – Describe string columns or not
- **virtual** (*bool*) – Describe virtual columns or not
- **selection** – Optional selection to use.

Returns Pandas dataframe

drop(*columns*, *inplace=False*, *check=True*)
Drop columns (or a single column).

Parameters

- **columns** – List of columns or a single column name
- **inplace** – Make modifications to self or return a new DataFrame
- **check** – When true, it will check if the column is used in virtual columns or the filter, and hide it instead.

drop_filter(*inplace=False*)
Removes all filters from the DataFrame

dropmissing(*column_names=None*)
Create a shallow copy of a DataFrame, with filtering set using ismissing.

Parameters column_names – The columns to consider, default: all (real, non-virtual) columns

Return type *DataFrame*

dropna(*column_names=None*)
Create a shallow copy of a DataFrame, with filtering set using isna.

Parameters column_names – The columns to consider, default: all (real, non-virtual) columns

Return type *DataFrame*

dropnan(*column_names=None*)
Create a shallow copy of a DataFrame, with filtering set using isnan.

Parameters column_names – The columns to consider, default: all (real, non-virtual) columns

Return type *DataFrame*

dtypes
Gives a Pandas series object containing all numpy dtypes of all columns (except hidden).

evaluate(*expression*, *i1=None*, *i2=None*, *out=None*, *selection=None*, *filtered=True*, *internal=None*, *parallel=True*, *chunk_size=None*)
Evaluate an expression, and return a numpy array with the results for the full column or a part of it.

Note that this is not how vaex should be used, since it means a copy of the data needs to fit in memory.

To get partial results, use i1 and i2

Parameters

- **expression** (*str*) – Name/expression to evaluate
- **i1** (*int*) – Start row index, default is the start (0)
- **i2** (*int*) – End row index, default is the length of the DataFrame
- **out** (*ndarray*) – Output array, to which the result may be written (may be used to reuse an array, or write to a memory mapped array)
- **selection** – selection to apply

Returns

evaluate_iterator(*expression*, *s1=None*, *s2=None*, *out=None*, *selection=None*, *filtered=True*, *internal=None*, *parallel=True*, *chunk_size=None*, *prefetch=True*)

Generator to efficiently evaluate expressions in chunks (number of rows).

See `DataFrame.evaluate()` for other arguments.

Example:

```
>>> import vaex
>>> df = vaex.example()
>>> for i1, i2, chunk in df.evaluate_iterator(df.x, chunk_size=100_000):
...     print(f"Total of {i1} to {i2} = {chunk.sum()}")
...
Total of 0 to 100000 = -7460.610158279056
Total of 100000 to 200000 = -4964.85827154921
Total of 200000 to 300000 = -7303.271340043915
Total of 300000 to 330000 = -2424.65234724951
```

Parameters **prefetch** – Prefetch/compute the next chunk in parallel while the current value is yielded/returned.

evaluate_variable(*name*)

Evaluates the variable given by name.

execute()

Execute all delayed jobs.

execute_async()

Async version of execute

extract()

Return a DataFrame containing only the filtered rows.

Note: Note that no copy of the underlying data is made, only a view/reference is made.

The resulting DataFrame may be more efficient to work with when the original DataFrame is heavily filtered (contains just a small number of rows).

If no filtering is applied, it returns a trimmed view. For the returned df, len(df) == df.length_original() == df.length_unfiltered()

Return type *DataFrame*

fillna (*value*, *column_names=None*, *prefix='__original_'*, *inplace=False*)

Return a DataFrame, where missing values/NaN are filled with 'value'.

The original columns will be renamed, and by default they will be hidden columns. No data is lost.

Note: Note that no copy of the underlying data is made, only a view/reference is made.

Note: Note that filtering will be ignored (since they may change), you may want to consider running `extract()` first.

Example:

```
>>> import vaex
>>> import numpy as np
>>> x = np.array([3, 1, np.nan, 10, np.nan])
>>> df = vaex.from_arrays(x=x)
>>> df_filled = df.fillna(value=-1, column_names=['x'])
>>> df_filled
  #    x
  0    3
  1    1
  2   -1
  3   10
  4   -1
```

Parameters

- **value** (*float*) – The value to use for filling nan or masked values.
- **fill_na** (*bool*) – If True, fill np.nan values with *value*.
- **fill_masked** (*bool*) – If True, fill masked values with *values*.
- **column_names** (*list*) – List of column names in which to fill missing values.
- **prefix** (*str*) – The prefix to give the original columns.
- **inplace** – Make modifications to self or return a new DataFrame

filter (*expression*, *mode='and'*)

General version of df[<boolean expression>] to modify the filter applied to the DataFrame.

See `DataFrame.select()` for usage of selection.

Note that using *df = df[<boolean expression>]*, one can only narrow the filter (i.e. only less rows can be selected). Using the filter method, and a different boolean mode (e.g. "or") one can actually cause more rows to be selected. This differs greatly from numpy and pandas for instance, which can only narrow the filter.

Example:

```
>>> import vaex
>>> import numpy as np
>>> x = np.arange(10)
>>> df = vaex.from_arrays(x=x, y=x**2)
>>> df
#    x    y
```

(continues on next page)

(continued from previous page)

```
0    0    0
1    1    1
2    2    4
3    3    9
4    4   16
5    5   25
6    6   36
7    7   49
8    8   64
9    9   81
>>> dff = df[df.x<=2]
>>> dff
#    x    y
0    0    0
1    1    1
2    2    4
>>> dff = dff.filter(dff.x >=7, mode="or")
>>> dff
#    x    y
0    0    0
1    1    1
2    2    4
3    7   49
4    8   64
5    9   81
```

first (*expression*, *order_expression*, *binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *edges=False*, *progress=None*, *array_type=None*)

Return the first element of a binned *expression*, where the values each bin are sorted by *order_expression*.

Example:

```
>>> import vaex
>>> df = vaex.example()
>>> df.first(df.x, df.y, shape=8)
>>> df.first(df.x, df.y, shape=8, binby=[df.y])
>>> df.first(df.x, df.y, shape=8, binby=[df.y])
array([-4.81883764, 11.65378   ,  9.70084476, -7.3025589 ,  4.84954977,
        8.47446537, -5.73602629, 10.18783   ])
```

Parameters

- **expression** – The value to be placed in the bin.
- **order_expression** – Order the values in the bins by this expression.
- **binby** – List of expressions for constructing a binned grid
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)

- **progress** – A callable that takes one argument (a floating point value between 0 and 1) indicating the progress, calculations are cancelled when this callable returns False
- **edges** – Currently for internal use only (it includes nan's and values outside the limits at borders, nan and 0, smaller than at 1, and larger at -1
- **array_type** – Type of output array, possible values are None/"numpy" (ndarray), "xarray" for a xarray.DataArray, or "list" for a Python list

Returns Ndarray containing the first elements.

Return type numpy.array

get_active_fraction()

Value in the range (0, 1], to work only with a subset of rows.

get_column_names(*virtual=True*, *strings=True*, *hidden=False*, *regex=None*, *alias=True*)

Return a list of column names

Example:

```
>>> import vaex
>>> df = vaex.from_scalars(x=1, x2=2, y=3, s='string')
>>> df['r'] = (df.x**2 + df.y**2)**2
>>> df.get_column_names()
['x', 'x2', 'y', 's', 'r']
>>> df.get_column_names(virtual=False)
['x', 'x2', 'y', 's']
>>> df.get_column_names(regex='x.*')
['x', 'x2']
```

Parameters

- **virtual** – If False, skip virtual columns
- **hidden** – If False, skip hidden columns
- **strings** – If False, skip string columns
- **regex** – Only return column names matching the (optional) regular expression
- **alias** – Return the alias (True) or internal name (False).

Return type list of str

get_current_row()

Individual rows can be 'picked', this is the index (integer) of the current row, or None there is nothing picked.

get_names(*hidden=False*)

Return a list of column names and variable names.

get_private_dir(*create=False*)

Each DataFrame has a directory where files are stored for metadata etc.

Example

```
>>> import vaex
>>> ds = vaex.example()
>>> vaex.get_private_dir()
'/Users/users/breddels/.vaex/dfs/_Users_users_breddels_vaex-testing_data_
↪helmi-dezeeuw-2000-10p.hdf5'
```

Parameters **create** (*bool*) – is True, it will create the directory if it does not exist

get_selection (*name='default'*)
Get the current selection object (mostly for internal use atm).

get_variable (*name*)
Returns the variable given by name, it will not evaluate it.

For evaluation, see `DataFrame.evaluate_variable()`, see also `DataFrame.set_variable()`

has_current_row ()
Returns True/False if there currently is a picked row.

has_selection (*name='default'*)
Returns True if there is a selection with the given name.

head (*n=10*)
Return a shallow copy a DataFrame with the first n rows.

head_and_tail_print (*n=5*)
Display the first and last n elements of a DataFrame.

healpix_count (*expression=None*, *healpix_expression=None*, *healpix_max_level=12*, *healpix_level=8*, *binby=None*, *limits=None*, *shape=128*, *delay=False*, *progress=None*, *selection=None*)
Count non missing value for expression on an array which represents healpix data.

Parameters

- **expression** – Expression or column for which to count non-missing values, or None or '*' for counting the rows
- **healpix_expression** – {healpix_max_level}
- **healpix_max_level** – {healpix_max_level}
- **healpix_level** – {healpix_level}
- **binby** – {binby}, these dimension follow the first healpix dimension.
- **limits** – {limits}
- **shape** – {shape}
- **selection** – {selection}
- **delay** – {delay}
- **progress** – {progress}

Returns

healpix_plot (*healpix_expression='source_id/34359738368'*, *healpix_max_level=12*, *healpix_level=8*, *what='count(*)'*, *selection=None*, *grid=None*, *healpix_input='equatorial'*, *healpix_output='galactic'*, *f=None*, *colormap='afmhot'*, *grid_limits=None*, *image_size=800*, *nest=True*, *figsize=None*, *interactive=False*, *title="*, *smooth=None*, *show=False*, *colorbar=True*, *rotation=(0, 0, 0)*, ***kwargs*)
Viz data in 2d using a healpix column.

Parameters

- **healpix_expression** – {healpix_max_level}
- **healpix_max_level** – {healpix_max_level}

- **healpix_level** – {healpix_level}
- **what** – {what}
- **selection** – {selection}
- **grid** – {grid}
- **healpix_input** – Specificy if the healpix index is in "equatorial", "galactic" or "ecliptic".
- **healpix_output** – Plot in "equatorial", "galactic" or "ecliptic".
- **f** – function to apply to the data
- **colormap** – matplotlib colormap
- **grid_limits** – Optional sequence [minvalue, maxvalue] that determine the min and max value that map to the colormap (values below and above these are clipped to the the min/max). (default is [min(f(grid)), max(f(grid)))
- **image_size** – size for the image that healpy uses for rendering
- **nest** – If the healpix data is in nested (True) or ring (False)
- **figsize** – If given, modify the matplotlib figure size. Example (14,9)
- **interactive** – (Experimental, uses healpy.mollzoom is True)
- **title** – Title of figure
- **smooth** – apply gaussian smoothing, in degrees
- **show** – Call matplotlib's show (True) or not (False, defaut)
- **rotation** – Rotatate the plot, in format (lon, lat, psi) such that (lon, lat) is the center, and rotate on the screen by angle psi. All angles are degrees.

Returns

is_category(*column*)
Returns true if column is a category.

is_local()
Returns True if the DataFrame is local, False when a DataFrame is remote.

is_masked(*column*)
Return if a column is a masked (numpy.ma) column.

length_original()
the full length of the DataFrame, independent what active_fraction is, or filtering. This is the real length of the underlying ndarrays.

length_unfiltered()
The length of the arrays that should be considered (respecting active range), but without filtering.

limits(*expression*, *value=None*, *square=False*, *selection=None*, *delay=False*, *shape=None*)
Calculate the [min, max] range for expression, as described by value, which is 'minmax' by default.

If value is a list of the form [minvalue, maxvalue], it is simply returned, this is for convenience when using mixed forms.

Example:

```
>>> import vaex
>>> df = vaex.example()
>>> df.limits("x")
array([-128.293991,  271.365997])
>>> df.limits("x", "99.7%")
array([-28.86381927,  28.9261226 ])
>>> df.limits(["x", "y"])
(array([-128.293991,  271.365997]), array([ -71.5523682,  146.465836 ]))
>>> df.limits(["x", "y"], "99.7%")
(array([-28.86381927,  28.9261226 ]), array([-28.60476934,  28.96535249]))
>>> df.limits(["x", "y"], ["minmax", "90%"])
(array([-128.293991,  271.365997]), array([-13.37438402,  13.4224423 ]))
>>> df.limits(["x", "y"], ["minmax", [0, 10]])
(array([-128.293991,  271.365997]), [0, 10])
```

Parameters

- **expression** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **value** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)

Returns List in the form [[xmin, xmax], [ymin, ymax], ... ,[zmin, zmax]] or [xmin, xmax] when expression is not a list

limits_percentage(*expression*, *percentage=99.73*, *square=False*, *selection=False*, *delay=False*)
Calculate the [min, max] range for expression, containing approximately a percentage of the data as defined by percentage.

The range is symmetric around the median, i.e., for a percentage of 90, this gives the same results as:

Example:

```
>>> df.limits_percentage("x", 90)
array([-12.35081376,  12.14858052]
>>> df.percentile_approx("x", 5), df.percentile_approx("x", 95)
(array([-12.36813152]), array([ 12.13275818]))
```

NOTE: this value is approximated by calculating the cumulative distribution on a grid. NOTE 2: The values above are not exactly the same, since percentile and limits_percentage do not share the same code

Parameters

- **expression** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **percentage** (*float*) – Value between 0 and 100
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)

Returns List in the form [[xmin, xmax], [ymin, ymax], ... ,[zmin, zmax]] or [xmin, xmax] when expression is not a list

materialize(*virtual_column*, *inplace=False*)
Returns a new DataFrame where the virtual column is turned into an in memory numpy array.

Example:

```
>>> x = np.arange(1,4)
>>> y = np.arange(2,5)
>>> df = vaex.from_arrays(x=x, y=y)
>>> df['r'] = (df.x**2 + df.y**2)**0.5 # 'r' is a virtual column (computed on␣
↪the fly)
>>> df = df.materialize('r')  # now 'r' is a 'real' column (i.e. a numpy␣
↪array)
```

Parameters **inplace** – {inplace}

max (*expression*, *binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *progress=None*, *edges=False*, *array_type=None*)
Calculate the maximum for given expressions, possibly on a grid defined by binby.

Example:

```
>>> df.max("x")
array(271.365997)
>>> df.max(["x", "y"])
array([ 271.365997,  146.465836])
>>> df.max("x", binby="x", shape=5, limits=[-10, 10])
array([-6.00010443, -2.00002384,  1.99998057,  5.99983597,  9.99984646])
```

Parameters

- **expression** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **binby** – List of expressions for constructing a binned grid
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)
- **progress** – A callable that takes one argument (a floating point value between 0 and 1) indicating the progress, calculations are cancelled when this callable returns False
- **array_type** – Type of output array, possible values are None/"numpy" (ndarray), "xarray" for a xarray.DataArray, or "list" for a Python list

Returns Numpy array with the given shape, or a scalar when no binby argument is given, with the statistic, the last dimension is of shape (2)

mean (*expression*, *binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *progress=None*, *edges=False*, *array_type=None*)
Calculate the mean for expression, possibly on a grid defined by binby.

Example:

```
>>> df.mean("x")
-0.067131491264005971
>>> df.mean("(x**2+y**2)**0.5", binby="E", shape=4)
array([  2.43483742,   4.41840721,   8.26742458,  15.53846476])
```

Parameters

- **expression** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **binby** – List of expressions for constructing a binned grid
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)
- **progress** – A callable that takes one argument (a floating point value between 0 and 1) indicating the progress, calculations are cancelled when this callable returns False
- **array_type** – Type of output array, possible values are None/"numpy" (ndarray), "xarray" for a xarray.DataArray, or "list" for a Python list

Returns Numpy array with the given shape, or a scalar when no binby argument is given, with the statistic

median_approx(*expression*, *percentage=50.0*, *binby=[]*, *limits=None*, *shape=128*, *percentile_shape=256*, *percentile_limits='minmax'*, *selection=False*, *delay=False*)

Calculate the median, possibly on a grid defined by binby.

NOTE: this value is approximated by calculating the cumulative distribution on a grid defined by percentile_shape and percentile_limits

Parameters

- **expression** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **binby** – List of expressions for constructing a binned grid
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **percentile_limits** – description for the min and max values to use for the cumulative histogram, should currently only be 'minmax'
- **percentile_shape** – shape for the array where the cumulative histogram is calculated on, integer type
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)

Returns Numpy array with the given shape, or a scalar when no binby argument is given, with the statistic

min(*expression*, *binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *progress=None*, *edges=False*, *array_type=None*)

Calculate the minimum for given expressions, possibly on a grid defined by binby.

Example:

```
>>> df.min("x")
array(-128.293991)
>>> df.min(["x", "y"])
array([-128.293991 ,  -71.5523682])
>>> df.min("x", binby="x", shape=5, limits=[-10, 10])
array([-9.99919128, -5.99972439, -1.99991322,  2.0000093 ,  6.0004878 ])
```

Parameters

- **expression** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **binby** – List of expressions for constructing a binned grid
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)
- **progress** – A callable that takes one argument (a floating point value between 0 and 1) indicating the progress, calculations are cancelled when this callable returns False
- **array_type** – Type of output array, possible values are None/"numpy" (ndarray), "xarray" for a xarray.DataArray, or "list" for a Python list

Returns Numpy array with the given shape, or a scalar when no binby argument is given, with the statistic, the last dimension is of shape (2)

minmax(*expression*, *binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *progress=None*)

Calculate the minimum and maximum for expressions, possibly on a grid defined by binby.

Example:

```
>>> df.minmax("x")
array([-128.293991,  271.365997])
>>> df.minmax(["x", "y"])
array([[-128.293991 ,  271.365997 ],
           [ -71.5523682,  146.465836 ]])
>>> df.minmax("x", binby="x", shape=5, limits=[-10, 10])
array([[-9.99919128, -6.00010443],
           [-5.99972439, -2.00002384],
           [-1.99991322,  1.99998057],
           [ 2.0000093 ,  5.99983597],
           [ 6.0004878 ,  9.99984646]])
```

Parameters

- **expression** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **binby** – List of expressions for constructing a binned grid
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)
- **progress** – A callable that takes one argument (a floating point value between 0 and 1) indicating the progress, calculations are cancelled when this callable returns False

Returns Numpy array with the given shape, or a scalar when no binby argument is given, with the statistic, the last dimension is of shape (2)

mode(*expression*, *binby=[]*, *limits=None*, *shape=256*, *mode_shape=64*, *mode_limits=None*, *progressbar=False*, *selection=None*)
Calculate/estimate the mode.

mutual_information(*x*, *y=None*, *mi_limits=None*, *mi_shape=256*, *binby=[]*, *limits=None*, *shape=128*, *sort=False*, *selection=False*, *delay=False*)
Estimate the mutual information between and x and y on a grid with shape mi_shape and mi_limits, possibly on a grid defined by binby.

If sort is True, the mutual information is returned in sorted (descending) order and the list of expressions is returned in the same order.

Example:

```
>>> df.mutual_information("x", "y")
array(0.1511814526380327)
>>> df.mutual_information([["x", "y"], ["x", "z"], ["E", "Lz"]])
array([ 0.15118145,  0.18439181,  1.07067379])
>>> df.mutual_information([["x", "y"], ["x", "z"], ["E", "Lz"]], sort=True)
(array([ 1.07067379,  0.18439181,  0.15118145]),
[['E', 'Lz'], ['x', 'z'], ['x', 'y']])
```

Parameters

- **x** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **y** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **binby** – List of expressions for constructing a binned grid
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']

- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **sort** – return mutual information in sorted (descending) order, and also return the correspond list of expressions when sorted is True
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)

Returns Numpy array with the given shape, or a scalar when no binby argument is given, with the statistic,

nbytes
Alias for *df.byte_size()*, see `DataFrame.byte_size()`.

nop (*expression*, *progress=False*, *delay=False*)
Evaluates expression, and drop the result, usefull for benchmarking, since vaex is usually lazy

percentile_approx (*expression*, *percentage=50.0*, *binby=[]*, *limits=None*, *shape=128*, *percentile_shape=1024*, *percentile_limits='minmax'*, *selection=False*, *delay=False*)
Calculate the percentile given by percentage, possibly on a grid defined by binby.

NOTE: this value is approximated by calculating the cumulative distribution on a grid defined by percentile_shape and percentile_limits.

Example:

```
>>> df.percentile_approx("x", 10), df.percentile_approx("x", 90)
(array([-8.3220355]), array([ 7.92080358]))
>>> df.percentile_approx("x", 50, binby="x", shape=5, limits=[-10, 10])
array([[-7.56462982],
           [-3.61036641],
           [-0.01296306],
           [ 3.56697863],
           [ 7.45838367]])
```

Parameters

- **expression** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **binby** – List of expressions for constructing a binned grid
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **percentile_limits** – description for the min and max values to use for the cumulative histogram, should currently only be 'minmax'
- **percentile_shape** – shape for the array where the cumulative histogram is calculated on, integer type
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections

- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)

Returns Numpy array with the given shape, or a scalar when no binby argument is given, with the statistic

plot (*x=None, y=None, z=None, what='count(*)', vwhat=None, reduce=['colormap'], f=None, normalize='normalize', normalize_axis='what', vmin=None, vmax=None, shape=256, vshape=32, limits=None, grid=None, colormap='afmhot', figsize=None, xlabel=None, ylabel=None, aspect='auto', tight_layout=True, interpolation='nearest', show=False, colorbar=True, colorbar_label=None, selection=None, selection_labels=None, title=None, background_color='white', pre_blend=False, background_alpha=1.0, visual={'column': 'what', 'fade': 'selection', 'layer': 'z', 'row': 'subspace', 'x': 'x', 'y': 'y'}, smooth_pre=None, smooth_post=None, wrap=True, wrap_columns=4, return_extra=False, hardcopy=None*)

Viz data in a 2d histogram/heatmap.

Declarative plotting of statistical plots using matplotlib, supports subplots, selections, layers.

Instead of passing x and y, pass a list as x argument for multiple panels. Give what a list of options to have multiple panels. When both are present then will be origanized in a column/row order.

This methods creates a 6 dimensional 'grid', where each dimension can map the a visual dimension. The grid dimensions are:

- x: shape determined by shape, content by x argument or the first dimension of each space
- y: ,,
- z: related to the z argument
- selection: shape equals length of selection argument
- what: shape equals length of what argument
- space: shape equals length of x argument if multiple values are given

By default, this its shape is (1, 1, 1, 1, shape, shape) (where x is the last dimension)

The visual dimensions are

- x: x coordinate on a plot / image (default maps to grid's x)
- y: y ,, (default maps to grid's y)
- layer: each image in this dimension is blended togeher to one image (default maps to z)
- fade: each image is shown faded after the next image (default mapt to selection)
- row: rows of subplots (default maps to space)
- columns: columns of subplot (default maps to what)

All these mappings can be changes by the visual argument, some examples:

```
>>> df.plot('x', 'y', what=['mean(x)', 'correlation(vx, vy)'])
```

Will plot each 'what' as a column.

```
>>> df.plot('x', 'y', selection=['FeH < -3', '(FeH >= -3) & (FeH < -2)'],
↪visual=dict(column='selection'))
```

Will plot each selection as a column, instead of a faded on top of each other.

Parameters

- **x** – Expression to bin in the x direction (by default maps to x), or list of pairs, like [['x', 'y'], ['x', 'z']], if multiple pairs are given, this dimension maps to rows by default
- **y** – y (by default maps to y)
- **z** – Expression to bin in the z direction, followed by a :start,end,shape signature, like 'FeH:-3,1:5' will produce 5 layers between -10 and 10 (by default maps to layer)
- **what** – What to plot, count(*) will show a N-d histogram, mean('x'), the mean of the x column, sum('x') the sum, std('x') the standard deviation, correlation('vx', 'vy') the correlation coefficient. Can also be a list of values, like ['count(x)', std('vx')], (by default maps to column)
- **reduce** –
- **f** – transform values by: 'identity' does nothing 'log' or 'log10' will show the log of the value
- **normalize** – normalization function, currently only 'normalize' is supported
- **normalize_axis** – which axes to normalize on, None means normalize by the global maximum.
- **vmin** – instead of automatic normalization, (using normalize and normalization_axis) scale the data between vmin and vmax to [0, 1]
- **vmax** – see vmin
- **shape** – shape/size of the n-D histogram grid
- **limits** – list of [[xmin, xmax], [ymin, ymax]], or a description such as 'minmax', '99%'
- **grid** – if the binning is done before by yourself, you can pass it
- **colormap** – matplotlib colormap to use
- **figsize** – (x, y) tuple passed to pylab.figure for setting the figure size
- **xlabel** –
- **ylabel** –
- **aspect** –
- **tight_layout** – call pylab.tight_layout or not
- **colorbar** – plot a colorbar or not
- **interpolation** – interpolation for imshow, possible options are: 'nearest', 'bilinear', 'bicubic', see matplotlib for more
- **return_extra** –

Returns

plot1d(*x=None, what='count(*)', grid=None, shape=64, facet=None, limits=None, figsize=None, f='identity', n=None, normalize_axis=None, xlabel=None, ylabel=None, label=None, selection=None, show=False, tight_layout=True, hardcopy=None, progress=None, **kwargs*)

Viz data in 1d (histograms, running means etc)

Example

```
>>> df.plot1d(df.x)
>>> df.plot1d(df.x, limits=[0, 100], shape=100)
>>> df.plot1d(df.x, what='mean(y)', limits=[0, 100], shape=100)
```

If you want to do a computation yourself, pass the grid argument, but you are responsible for passing the same limits arguments:

```
>>> counts = df.mean(df.y, binby=df.x, limits=[0, 100], shape=100)/100.
>>> df.plot1d(df.x, limits=[0, 100], shape=100, grid=means, label='mean(y)/100
↪')
```

Parameters

- **x** – Expression to bin in the x direction
- **what** – What to plot, count(*) will show a N-d histogram, mean('x'), the mean of the x column, sum('x') the sum
- **grid** – If the binning is done before by yourself, you can pass it
- **facet** – Expression to produce facetted plots (facet='x:0,1,12' will produce 12 plots with x in a range between 0 and 1)
- **limits** – list of [xmin, xmax], or a description such as 'minmax', '99%'
- **figsize** – (x, y) tuple passed to pylab.figure for setting the figure size
- **f** – transform values by: 'identity' does nothing 'log' or 'log10' will show the log of the value
- **n** – normalization function, currently only 'normalize' is supported, or None for no normalization
- **normalize_axis** – which axes to normalize on, None means normalize by the global maximum.
- **normalize_axis** –
- **xlabel** – String for label on x axis (may contain latex)
- **ylabel** – Same for y axis
- **kwargs** – extra argument passed to pylab.plot

Param tight_layout: call pylab.tight_layout or not

Returns

plot2d_contour (*x=None, y=None, what='count(*)', limits=None, shape=256, selection=None, f='identity', figsize=None, xlabel=None, ylabel=None, aspect='auto', levels=None, fill=False, colorbar=False, colorbar_label=None, colormap=None, colors=None, linewidths=None, linestyles=None, vmin=None, vmax=None, grid=None, show=None, **kwargs*)

Plot conting contours on 2D grid.

Parameters

- **x** – {expression}
- **y** – {expression}
- **what** – What to plot, count(*) will show a N-d histogram, mean('x'), the mean of the x column, sum('x') the sum, std('x') the standard deviation, correlation('vx', 'vy') the correlation coefficient. Can also be a list of values, like ['count(x)', std('vx')], (by default maps to column)
- **limits** – {limits}
- **shape** – {shape}

- **selection** – {selection}
- **f** – transform values by: 'identity' does nothing 'log' or 'log10' will show the log of the value
- **figsize** – (x, y) tuple passed to pylab.figure for setting the figure size
- **xlabel** – label of the x-axis (defaults to param x)
- **ylabel** – label of the y-axis (defaults to param y)
- **aspect** – the aspect ratio of the figure
- **levels** – the contour levels to be passed on pylab.contour or pylab.contourf
- **colorbar** – plot a colorbar or not
- **colorbar_label** – the label of the colourbar (defaults to param what)
- **colormap** – matplotlib colormap to pass on to pylab.contour or pylab.contourf
- **colors** – the colours of the contours
- **linewidths** – the widths of the contours
- **linestyles** – the style of the contour lines
- **vmin** – instead of automatic normalization, scale the data between vmin and vmax
- **vmax** – see vmin
- **grid** – {grid}
- **show** –

plot3d(*x, y, z, vx=None, vy=None, vz=None, vwhat=None, limits=None, grid=None, what='count(*)', shape=128, selection=[None, True], f=None, vcount_limits=None, smooth_pre=None, smooth_post=None, grid_limits=None, normalize='normalize', colormap='afmhot', figure_key=None, fig=None, lighting=True, level=[0.1, 0.5, 0.9], opacity=[0.01, 0.05, 0.1], level_width=0.1, show=True, **kwargs*)

Use at own risk, requires ipyvolume

plot_bq(*x, y, grid=None, shape=256, limits=None, what='count(*)', figsize=None, f='identity', figure_key=None, fig=None, axes=None, xlabel=None, ylabel=None, title=None, show=True, selection=[None, True], colormap='afmhot', grid_limits=None, normalize='normalize', grid_before=None, what_kwargs={}, type='default', scales=None, tool_select=False, bq_cleanup=True, **kwargs*)

Deprecated: use plot_widget

plot_widget(*x, y, limits=None, f='identity', **kwargs*)

Deprecated: use df.widget.heatmap

propagate_uncertainties(*columns, depending_variables=None, cov_matrix='auto', covariance_format='{}_{}_covariance', uncertainty_format='{}_uncertainty'*)

Propagates uncertainties (full covariance matrix) for a set of virtual columns.

Covariance matrix of the depending variables is guessed by finding columns prefixed by "e" or "*e_*" or postfixed by "_error", "_uncertainty", "e" and "*_e*". Off diagonals (covariance or correlation) by postfixes with "_correlation" or "_corr" for correlation or "_covariance" or "_cov" for covariances. (Note that x_y_cov = x_e * y_e * x_y_correlation.)

Example

```
>>> df = vaex.from_scalars(x=1, y=2, e_x=0.1, e_y=0.2)
>>> df["u"] = df.x + df.y
>>> df["v"] = np.log10(df.x)
>>> df.propagate_uncertainties([df.u, df.v])
>>> df.u_uncertainty, df.v_uncertainty
```

Parameters

- **columns** – list of columns for which to calculate the covariance matrix.
- **depending_variables** – If not given, it is found out automatically, otherwise a list of columns which have uncertainties.
- **cov_matrix** – List of list with expressions giving the covariance matrix, in the same order as depending_variables. If 'full' or 'auto', the covariance matrix for the depending_variables will be guessed, where 'full' gives an error if an entry was not found.

remove_virtual_meta()

Removes the file with the virtual column etc, it does not change the current virtual columns etc.

rename(*name*, *new_name*, *unique=False*)

Renames a column or variable, and rewrite expressions such that they refer to the new name

sample(*n=None*, *frac=None*, *replace=False*, *weights=None*, *random_state=None*)

Returns a DataFrame with a random set of rows

Note: Note that no copy of the underlying data is made, only a view/reference is made.

Provide either n or frac.

Example:

```
>>> import vaex, numpy as np
>>> df = vaex.from_arrays(s=np.array(['a', 'b', 'c', 'd']), x=np.arange(1,5))
>>> df
  #  s     x
  0  a     1
  1  b     2
  2  c     3
  3  d     4
>>> df.sample(n=2, random_state=42) # 2 random rows, fixed seed
  #  s     x
  0  b     2
  1  d     4
>>> df.sample(frac=1, random_state=42) # 'shuffling'
  #  s     x
  0  c     3
  1  a     1
  2  d     4
  3  b     2
>>> df.sample(frac=1, replace=True, random_state=42) # useful for bootstrap␣
↪(may contain repeated samples)
  #  s     x
  0  d     4
  1  a     1
  2  a     1
  3  d     4
```

Parameters

- **n** (*int*) – number of samples to take (default 1 if frac is None)
- **frac** (*float*) – fractional number of takes to take
- **replace** (*bool*) – If true, a row may be drawn multiple times
- **or expression weights** (*str*) – (unnormalized) probability that a row can be drawn
- **or RandomState** (*int*) – seed or RandomState for reproducability, when None a random seed it chosen

Returns Returns a new DataFrame with a shallow copy/view of the underlying data

Return type *DataFrame*

scatter (*x, y, xerr=None, yerr=None, cov=None, corr=None, s_expr=None, c_expr=None, labels=None, selection=None, length_limit=50000, length_check=True, label=None, xlabel=None, ylabel=None, errorbar_kwargs={}, ellipse_kwargs={}, **kwargs*)

Viz (small amounts) of data in 2d using a scatter plot

Convenience wrapper around pylab.scatter when for working with small DataFrames or selections

Parameters

- **x** – Expression for x axis
- **y** – Idem for y
- **s_expr** – When given, use if for the s (size) argument of pylab.scatter
- **c_expr** – When given, use if for the c (color) argument of pylab.scatter
- **labels** – Annotate the points with these text values
- **selection** – Single selection expression, or None
- **length_limit** – maximum number of rows it will plot
- **length_check** – should we do the maximum row check or not?
- **label** – label for the legend
- **xlabel** – label for x axis, if None .label(x) is used
- **ylabel** – label for y axis, if None .label(y) is used
- **errorbar_kwargs** – extra dict with arguments passed to plt.errorbar
- **kwargs** – extra arguments passed to pylab.scatter

Returns

select (*boolean_expression, mode='replace', name='default', executor=None*)

Perform a selection, defined by the boolean expression, and combined with the previous selection using the given mode.

Selections are recorded in a history tree, per name, undo/redo can be done for them separately.

Parameters

- **boolean_expression** (*str*) – Any valid column expression, with comparison operators
- **mode** (*str*) – Possible boolean operator: replace/and/or/xor/subtract
- **name** (*str*) – history tree or selection 'slot' to use

- **executor** –

Returns

select_box (*spaces*, *limits*, *mode='replace'*, *name='default'*)
Select a n-dimensional rectangular box bounded by limits.

The following examples are equivalent:

```
>>> df.select_box(['x', 'y'], [(0, 10), (0, 1)])
>>> df.select_rectangle('x', 'y', [(0, 10), (0, 1)])
```

Parameters

- **spaces** – list of expressions
- **limits** – sequence of shape [(x1, x2), (y1, y2)]
- **mode** –
- **name** –

Returns

select_circle (*x*, *y*, *xc*, *yc*, *r*, *mode='replace'*, *name='default'*, *inclusive=True*)
Select a circular region centred on xc, yc, with a radius of r.

Example:

```
>>> df.select_circle('x','y',2,3,1)
```

Parameters

- **x** – expression for the x space
- **y** – expression for the y space
- **xc** – location of the centre of the circle in x
- **yc** – location of the centre of the circle in y
- **r** – the radius of the circle
- **name** – name of the selection
- **mode** –

Returns

select_ellipse (*x*, *y*, *xc*, *yc*, *width*, *height*, *angle=0*, *mode='replace'*, *name='default'*, *radians=False*, *inclusive=True*)
Select an elliptical region centred on xc, yc, with a certain width, height and angle.

Example:

```
>>> df.select_ellipse('x','y', 2, -1, 5,1, 30, name='my_ellipse')
```

Parameters

- **x** – expression for the x space
- **y** – expression for the y space
- **xc** – location of the centre of the ellipse in x

- **yc** – location of the centre of the ellipse in y
- **width** – the width of the ellipse (diameter)
- **height** – the width of the ellipse (diameter)
- **angle** – (degrees) orientation of the ellipse, counter-clockwise measured from the y axis
- **name** – name of the selection
- **mode** –

Returns

select_inverse(*name='default'*, *executor=None*)
Invert the selection, i.e. what is selected will not be, and vice versa

Parameters

- **name** (*str*) –
- **executor** –

Returns

select_lasso(*expression_x*, *expression_y*, *xsequence*, *ysequence*, *mode='replace'*, *name='default'*, *executor=None*)
For performance reasons, a lasso selection is handled differently.

Parameters

- **expression_x** (*str*) – Name/expression for the x coordinate
- **expression_y** (*str*) – Name/expression for the y coordinate
- **xsequence** – list of x numbers defining the lasso, together with y
- **ysequence** –
- **mode** (*str*) – Possible boolean operator: replace/and/or/xor/subtract
- **name** (*str*) –
- **executor** –

Returns

select_non_missing(*drop_nan=True*, *drop_masked=True*, *column_names=None*, *mode='replace'*, *name='default'*)
Create a selection that selects rows having non missing values for all columns in column_names.

The name reflects Pandas, no rows are really dropped, but a mask is kept to keep track of the selection

Parameters

- **drop_nan** – drop rows when there is a NaN in any of the columns (will only affect float values)
- **drop_masked** – drop rows when there is a masked value in any of the columns
- **column_names** – The columns to consider, default: all (real, non-virtual) columns
- **mode** (*str*) – Possible boolean operator: replace/and/or/xor/subtract
- **name** (*str*) – history tree or selection 'slot' to use

Returns

select_nothing (*name='default'*)
Select nothing.

select_rectangle (*x, y, limits, mode='replace', name='default'*)
Select a 2d rectangular box in the space given by x and y, bounded by limits.

Example:

```
>>> df.select_box('x', 'y', [(0, 10), (0, 1)])
```

Parameters

- **x** – expression for the x space
- **y** – expression fo the y space
- **limits** – sequence of shape [(x1, x2), (y1, y2)]
- **mode** –

selected_length ()
Returns the number of rows that are selected.

selection_can_redo (*name='default'*)
Can selection name be redone?

selection_can_undo (*name='default'*)
Can selection name be undone?

selection_redo (*name='default', executor=None*)
Redo selection, for the name.

selection_undo (*name='default', executor=None*)
Undo selection, for the name.

set_active_fraction (*value*)
Sets the active_fraction, set picked row to None, and remove selection.

TODO: we may be able to keep the selection, if we keep the expression, and also the picked row

set_active_range (*i1, i2*)
Sets the active_fraction, set picked row to None, and remove selection.

TODO: we may be able to keep the selection, if we keep the expression, and also the picked row

set_current_row (*value*)
Set the current row, and emit the signal signal_pick.

set_selection (*selection, name='default', executor=None*)
Sets the selection object

Parameters

- **selection** – Selection object
- **name** – selection 'slot'
- **executor** –

Returns

set_variable (*name, expression_or_value, write=True*)
Set the variable to an expression or value defined by expression_or_value.

Example

```
>>> df.set_variable("a", 2.)
>>> df.set_variable("b", "a**2")
>>> df.get_variable("b")
'a**2'
>>> df.evaluate_variable("b")
4.0
```

Parameters

- **name** – Name of the variable
- **write** – write variable to meta file
- **expression** – value or expression

sort (*by*, *ascending=True*, *kind='quicksort'*)

Return a sorted DataFrame, sorted by the expression 'by'

The kind keyword is ignored if doing multi-key sorting.

Note: Note that no copy of the underlying data is made, only a view/reference is made.

Note: Note that filtering will be ignored (since they may change), you may want to consider running `extract()` first.

Example:

```
>>> import vaex, numpy as np
>>> df = vaex.from_arrays(s=np.array(['a', 'b', 'c', 'd']), x=np.arange(1,5))
>>> df['y'] = (df.x-1.8)**2
>>> df
  #  s      x     y
  0  a      1  0.64
  1  b      2  0.04
  2  c      3  1.44
  3  d      4  4.84
>>> df.sort('y', ascending=False)  # Note: passing '(x-1.8)**2' gives the␣
↪same result
  #  s      x     y
  0  d      4  4.84
  1  c      3  1.44
  2  a      1  0.64
  3  b      2  0.04
```

Parameters

- **or expression by** (*str*) – expression to sort by
- **ascending** (*bool*) – ascending (default, True) or descending (False)
- **kind** (*str*) – kind of algorithm to use (passed to numpy.argsort)

split (*frac*)

Returns a list containing ordered subsets of the DataFrame.

Note: Note that no copy of the underlying data is made, only a view/reference is made.

Example:

```
>>> import vaex
>>> df = vaex.from_arrays(x = [0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
>>> for dfs in df.split(frac=0.3):
...     print(dfs.x.values)
...
[0 1 3]
[3 4 5 6 7 8 9]
>>> for split in df.split(frac=[0.2, 0.3, 0.5]):
...     print(dfs.x.values)
[0 1]
[2 3 4]
[5 6 7 8 9]
```

Parameters **frac** (*int/list*) – If int will split the DataFrame in two portions, the first of which will have size as specified by this parameter. If list, the generator will generate as many portions as elements in the list, where each element defines the relative fraction of that portion.

Returns A list of DataFrames.

Return type list

split_random(*frac*, *random_state=None*)

Returns a list containing random portions of the DataFrame.

Note: Note that no copy of the underlying data is made, only a view/reference is made.

Example:

```
>>> import vaex, import numpy as np
>>> np.random.seed(111)
>>> df = vaex.from_arrays(x = [0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
>>> for dfs in df.split_random(frac=0.3, random_state=42):
...     print(dfs.x.values)
...
[8 1 5]
[0 7 2 9 4 3 6]
>>> for split in df.split_random(frac=[0.2, 0.3, 0.5], random_state=42):
...     print(dfs.x.values)
[8 1]
[5 0 7]
[2 9 4 3 6]
```

Parameters

- **frac** (*int/list*) – If int will split the DataFrame in two portions, the first of which will have size as specified by this parameter. If list, the generator will generate as many portions as elements in the list, where each element defines the relative fraction of that portion.
- **random_state** (*int*) – (default, None) Random number seed for reproducibility.

Returns A list of DataFrames.

Return type list

state_get()

Return the internal state of the DataFrame in a dictionary

Example:

```
>>> import vaex
>>> df = vaex.from_scalars(x=1, y=2)
>>> df['r'] = (df.x**2 + df.y**2)**0.5
>>> df.state_get()
{'active_range': [0, 1],
'column_names': ['x', 'y', 'r'],
'description': None,
'descriptions': {},
'functions': {},
'renamed_columns': [],
'selections': {'__filter__': None},
'ucds': {},
'units': {},
'variables': {},
'virtual_columns': {'r': '(((x ** 2) + (y ** 2)) ** 0.5)'}}
```

state_load(*f*, *use_active_range=False*)

Load a state previously stored by *DataFrame.state_write()*, see also *DataFrame.state_set()*.

state_set(*state*, *use_active_range=False*, *trusted=True*)

Sets the internal state of the df

Example:

```
>>> import vaex
>>> df = vaex.from_scalars(x=1, y=2)
>>> df
  #    x    y        r
  0    1    2  2.23607
>>> df['r'] = (df.x**2 + df.y**2)**0.5
>>> state = df.state_get()
>>> state
{'active_range': [0, 1],
'column_names': ['x', 'y', 'r'],
'description': None,
'descriptions': {},
'functions': {},
'renamed_columns': [],
'selections': {'__filter__': None},
'ucds': {},
'units': {},
'variables': {},
'virtual_columns': {'r': '(((x ** 2) + (y ** 2)) ** 0.5)'}}
>>> df2 = vaex.from_scalars(x=3, y=4)
>>> df2.state_set(state)  # now the virtual functions are 'copied'
>>> df2
  #    x    y    r
  0    3    4    5
```

Parameters

- **state** – dict as returned by *DataFrame.state_get()*.
- **use_active_range** (*bool*) – Whether to use the active range or not.

state_write(*f*)

Write the internal state to a json or yaml file (see *DataFrame.state_get()*)

Example

```
>>> import vaex
>>> df = vaex.from_scalars(x=1, y=2)
>>> df['r'] = (df.x**2 + df.y**2)**0.5
>>> df.state_write('state.json')
>>> print(open('state.json').read())
{
"virtual_columns": {
    "r": "(((x ** 2) + (y ** 2)) ** 0.5)"
},
"column_names": [
    "x",
    "y",
    "r"
],
"renamed_columns": [],
"variables": {
    "pi": 3.141592653589793,
    "e": 2.718281828459045,
    "km_in_au": 149597870.7,
    "seconds_per_year": 31557600
},
"functions": {},
"selections": {
    "__filter__": null
},
"ucds": {},
"units": {},
"descriptions": {},
"description": null,
"active_range": [
    0,
    1
]
}
>>> df.state_write('state.yaml')
>>> print(open('state.yaml').read())
active_range:
- 0
- 1
column_names:
- x
- y
- r
description: null
descriptions: {}
functions: {}
renamed_columns: []
selections:
```

(continues on next page)

(continued from previous page)

```
__filter__: null
ucds: {}
units: {}
variables:
pi: 3.141592653589793
e: 2.718281828459045
km_in_au: 149597870.7
seconds_per_year: 31557600
virtual_columns:
r: (((x ** 2) + (y ** 2)) ** 0.5)
```

Parameters **f** (*str*) – filename (ending in .json or .yaml)

std(*expression*, *binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *progress=None*, *array_type=None*)

Calculate the standard deviation for the given expression, possible on a grid defined by binby

```
>>> df.std("vz")
110.31773397535071
>>> df.std("vz", binby=["(x**2+y**2)**0.5"], shape=4)
array([ 123.57954851,   85.35190177,   61.14345748,   38.0740619 ])
```

Parameters

- **expression** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **binby** – List of expressions for constructing a binned grid
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)
- **progress** – A callable that takes one argument (a floating point value between 0 and 1) indicating the progress, calculations are cancelled when this callable returns False
- **array_type** – Type of output array, possible values are None/"numpy" (ndarray), "xarray" for a xarray.DataArray, or "list" for a Python list

Returns Numpy array with the given shape, or a scalar when no binby argument is given, with the statistic

sum(*expression*, *binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *progress=None*, *edges=False*, *array_type=None*)

Calculate the sum for the given expression, possible on a grid defined by binby

Example:

```
>>> df.sum("L")
304054882.49378014
>>> df.sum("L", binby="E", shape=4)
```

(continues on next page)

(continued from previous page)

```
array([  8.83517994e+06,   5.92217598e+07,   9.55218726e+07,
         1.40008776e+08])
```

Parameters

- **expression** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **binby** – List of expressions for constructing a binned grid
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)
- **progress** – A callable that takes one argument (a floating point value between 0 and 1) indicating the progress, calculations are cancelled when this callable returns False
- **array_type** – Type of output array, possible values are None/"numpy" (ndarray), "xarray" for a xarray.DataArray, or "list" for a Python list

Returns Numpy array with the given shape, or a scalar when no binby argument is given, with the statistic

tail (*n=10*)
Return a shallow copy a DataFrame with the last n rows.

take (*indices*, *filtered=True*, *dropfilter=True*)
Returns a DataFrame containing only rows indexed by indices

Note: Note that no copy of the underlying data is made, only a view/reference is made.

Example:

```
>>> import vaex, numpy as np
>>> df = vaex.from_arrays(s=np.array(['a', 'b', 'c', 'd']), x=np.arange(1,5))
>>> df.take([0,2])
 #  s      x
 0  a      1
 1  c      3
```

Parameters

- **indices** – sequence (list or numpy array) with row numbers
- **filtered** – (for internal use) The indices refer to the filtered data.
- **dropfilter** – (for internal use) Drop the filter, set to False when indices refer to unfiltered, but may contain rows that still need to be filtered out.

Returns DataFrame which is a shallow copy of the original data.

Return type *DataFrame*

to_arrays(*column_names=None*, *selection=None*, *strings=True*, *virtual=True*, *parallel=True*, *chunk_size=None*, *array_type=None*)
Return a list of ndarrays

Parameters

- **column_names** – list of column names, to export, when None DataFrame.get_column_names(strings=strings, virtual=virtual) is used
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **strings** – argument passed to DataFrame.get_column_names when column_names is None
- **virtual** – argument passed to DataFrame.get_column_names when column_names is None
- **parallel** – Evaluate the (virtual) columns in parallel
- **chunk_size** – Return an iterator with cuts of the object in lenght of this size
- **array_type** – Type of output array, possible values are None/"numpy" (ndarray), "xarray" for a xarray.DataArray, or "list" for a Python list

Returns list of arrays

to_arrow_table(*column_names=None*, *selection=None*, *strings=True*, *virtual=True*, *parallel=True*, *chunk_size=None*)
Returns an arrow Table object containing the arrays corresponding to the evaluated data

Parameters

- **column_names** – list of column names, to export, when None DataFrame.get_column_names(strings=strings, virtual=virtual) is used
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **strings** – argument passed to DataFrame.get_column_names when column_names is None
- **virtual** – argument passed to DataFrame.get_column_names when column_names is None
- **parallel** – Evaluate the (virtual) columns in parallel
- **chunk_size** – Return an iterator with cuts of the object in lenght of this size

Returns pyarrow.Table object or iterator of

to_astropy_table(*column_names=None*, *selection=None*, *strings=True*, *virtual=True*, *index=None*, *parallel=True*)
Returns a astropy table object containing the ndarrays corresponding to the evaluated data

Parameters

- **column_names** – list of column names, to export, when None DataFrame.get_column_names(strings=strings, virtual=virtual) is used
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **strings** – argument passed to DataFrame.get_column_names when column_names is None

- **virtual** – argument passed to DataFrame.get_column_names when column_names is None
- **index** – if this column is given it is used for the index of the DataFrame

Returns astropy.table.Table object

to_copy (*column_names=None*, *selection=None*, *strings=True*, *virtual=True*, *selections=True*)
Return a copy of the DataFrame, if selection is None, it does not copy the data, it just has a reference

Parameters

- **column_names** – list of column names, to copy, when None DataFrame.get_column_names(strings=strings, virtual=virtual) is used
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **strings** – argument passed to DataFrame.get_column_names when column_names is None
- **virtual** – argument passed to DataFrame.get_column_names when column_names is None
- **selections** – copy selections to a new DataFrame

Returns dict

to_dask_array (*chunks='auto'*)
Lazily expose the DataFrame as a dask.array

Example

```
>>> df = vaex.example()
>>> A = df[['x', 'y', 'z']].to_dask_array()
>>> A
dask.array<vaex-df-1f048b40-10ec-11ea-9553, shape=(330000, 3), dtype=float64,␣
↪chunksize=(330000, 3), chunktype=numpy.ndarray>
>>> A+1
dask.array<add, shape=(330000, 3), dtype=float64, chunksize=(330000, 3),␣
↪chunktype=numpy.ndarray>
```

Parameters **chunks** – How to chunk the array, similar to `dask.array.from_array()`.

Returns `dask.array.Array` object.

to_dict (*column_names=None*, *selection=None*, *strings=True*, *virtual=True*, *parallel=True*, *chunk_size=None*, *array_type=None*)
Return a dict containing the ndarray corresponding to the evaluated data

Parameters

- **column_names** – list of column names, to export, when None DataFrame.get_column_names(strings=strings, virtual=virtual) is used
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **strings** – argument passed to DataFrame.get_column_names when column_names is None
- **virtual** – argument passed to DataFrame.get_column_names when column_names is None

- **parallel** – Evaluate the (virtual) columns in parallel
- **chunk_size** – Return an iterator with cuts of the object in lenght of this size
- **array_type** – Type of output array, possible values are None/"numpy" (ndarray), "xarray" for a xarray.DataArray, or "list" for a Python list

Returns dict

to_items(*column_names=None*, *selection=None*, *strings=True*, *virtual=True*, *parallel=True*, *chunk_size=None*, *array_type=None*)

Return a list of [(column_name, ndarray), . . .)] pairs where the ndarray corresponds to the evaluated data

Parameters

- **column_names** – list of column names, to export, when None DataFrame.get_column_names(strings=strings, virtual=virtual) is used
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **strings** – argument passed to DataFrame.get_column_names when column_names is None
- **virtual** – argument passed to DataFrame.get_column_names when column_names is None
- **parallel** – Evaluate the (virtual) columns in parallel
- **chunk_size** – Return an iterator with cuts of the object in lenght of this size
- **array_type** – Type of output array, possible values are None/"numpy" (ndarray), "xarray" for a xarray.DataArray, or "list" for a Python list

Returns list of (name, ndarray) pairs or iterator of

to_pandas_df(*column_names=None*, *selection=None*, *strings=True*, *virtual=True*, *index_name=None*, *parallel=True*, *chunk_size=None*)

Return a pandas DataFrame containing the ndarray corresponding to the evaluated data

If index is given, that column is used for the index of the dataframe.

Example

```
>>> df_pandas = df.to_pandas_df(["x", "y", "z"])
>>> df_copy = vaex.from_pandas(df_pandas)
```

Parameters

- **column_names** – list of column names, to export, when None DataFrame.get_column_names(strings=strings, virtual=virtual) is used
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **strings** – argument passed to DataFrame.get_column_names when column_names is None
- **virtual** – argument passed to DataFrame.get_column_names when column_names is None
- **index_column** – if this column is given it is used for the index of the DataFrame
- **parallel** – Evaluate the (virtual) columns in parallel
- **chunk_size** – Return an iterator with cuts of the object in lenght of this size

Returns pandas.DataFrame object or iterator of

trim (*inplace=False*)
Return a DataFrame, where all columns are 'trimmed' by the active range.

For the returned DataFrame, df.get_active_range() returns (0, df.length_original()).

Note: Note that no copy of the underlying data is made, only a view/reference is made.

Parameters **inplace** – Make modifications to self or return a new DataFrame

Return type *DataFrame*

ucd_find (*ucds, exclude=[]*)
Find a set of columns (names) which have the ucd, or part of the ucd.

Prefixed with a ^, it will only match the first part of the ucd.

Example

```
>>> df.ucd_find('pos.eq.ra', 'pos.eq.dec')
['RA', 'DEC']
>>> df.ucd_find('pos.eq.ra', 'doesnotexist')
>>> df.ucds[df.ucd_find('pos.eq.ra')]
'pos.eq.ra;meta.main'
>>> df.ucd_find('meta.main')]
'dec'
>>> df.ucd_find('^meta.main')]
```

unit (*expression, default=None*)
Returns the unit (an astropy.unit.Units object) for the expression.

Example

```
>>> import vaex
>>> ds = vaex.example()
>>> df.unit("x")
Unit("kpc")
>>> df.unit("x*L")
Unit("km kpc2 / s")
```

Parameters

- **expression** – Expression, which can be a column name
- **default** – if no unit is known, it will return this

Returns The resulting unit of the expression

Return type astropy.units.Unit

validate_expression (*expression*)
Validate an expression (may throw Exceptions)

var (*expression, binby=[], limits=None, shape=128, selection=False, delay=False, progress=None, array_type=None*)
Calculate the sample variance for the given expression, possible on a grid defined by binby

Example:

```
>>> df.var("vz")
12170.002429456246
>>> df.var("vz", binby=["(x**2+y**2)**0.5"], shape=4)
array([ 15271.90481083,   7284.94713504,   3738.52239232,   1449.63418988])
>>> df.var("vz", binby=["(x**2+y**2)**0.5"], shape=4)**0.5
array([ 123.57954851,   85.35190177,   61.14345748,   38.0740619 ])
>>> df.std("vz", binby=["(x**2+y**2)**0.5"], shape=4)
array([ 123.57954851,   85.35190177,   61.14345748,   38.0740619 ])
```

Parameters

- **expression** – expression or list of expressions, e.g. df.x, 'x', or ['x, 'y']
- **binby** – List of expressions for constructing a binned grid
- **limits** – description for the min and max values for the expressions, e.g. 'minmax' (default), '99.7%', [0, 10], or a list of, e.g. [[0, 10], [0, 20], 'minmax']
- **shape** – shape for the array where the statistic is calculated on, if only an integer is given, it is used for all dimensions, e.g. shape=128, shape=[128, 256]
- **selection** – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False), or a list of selections
- **delay** – Do not return the result, but a proxy for delayhronous calculations (currently only for internal use)
- **progress** – A callable that takes one argument (a floating point value between 0 and 1) indicating the progress, calculations are cancelled when this callable returns False
- **array_type** – Type of output array, possible values are None/"numpy" (ndarray), "xarray" for a xarray.DataArray, or "list" for a Python list

Returns Numpy array with the given shape, or a scalar when no binby argument is given, with the statistic

7.2.2 DataFrameLocal class

class vaex.dataframe.**DataFrameLocal**(*name*, *path*, *column_names*)

Bases: `vaex.dataframe.DataFrame`

Base class for DataFrames that work with local file/data

__array__(*dtype=None*, *parallel=True*)

Gives a full memory copy of the DataFrame into a 2d numpy array of shape (n_rows, n_columns). Note that the memory order is fortran, so all values of 1 column are contiguous in memory for performance reasons.

Note this returns the same result as:

```
>>> np.array(ds)
```

If any of the columns contain masked arrays, the masks are ignored (i.e. the masked elements are returned as well).

__call__(**expressions*, ***kwargs*)

The local implementation of `DataFrame.__call__()`

__init__(*name*, *path*, *column_names*)

Initialize self. See help(type(self)) for accurate signature.

binby (*by=None*, *agg=None*)

Return a `BinBy` or `DataArray` object when agg is not None

The binby operation does not return a 'flat' DataFrame, instead it returns an N-d grid in the form of an xarray.

Parameters list or agg agg (*dict*,) – Aggregate operation in the form of a string, vaex.agg object, a dictionary where the keys indicate the target column names, and the values the operations, or the a list of aggregates. When not given, it will return the binby object.

Returns `DataArray` or `BinBy` object.

categorize (*column*, *min_value=0*, *max_value=None*, *labels=None*, *inplace=False*)

Mark column as categorical.

This may help speed up calculations using integer columns between a range of [min_value, max_value].

If max_value is not given, the [min_value and max_value] are calcuated from the data.

Example:

```
>>> import vaex
>>> df = vaex.from_arrays(year=[2012, 2015, 2019], weekday=[0, 4, 6])
>>> df.categorize('year', min_value=2020, max_value=2019)
>>> df.categorize('weekday', labels=['Mon', 'Tue', 'Wed', 'Thu', 'Fri', 'Sat',
↪ 'Sun'])
```

Parameters

- **column** – column to assume is categorical.
- **labels** – labels to associate to the values between min_value and max_value
- **min_value** – minimum integer value (if max_value is not given, this is calculated)
- **max_value** – maximum integer value (if max_value is not given, this is calculated)
- **labels** – Labels to associate to each value, list(range(min_value, max_value+1)) by default
- **inplace** – Make modifications to self or return a new DataFrame

compare (*other*, *report_missing=True*, *report_difference=False*, *show=10*, *orderby=None*, *column_names=None*)

Compare two DataFrames and report their difference, use with care for large DataFrames

concat (*other*)

Concatenates two DataFrames, adding the rows of the other DataFrame to the current, returned in a new DataFrame.

No copy of the data is made.

Parameters other – The other DataFrame that is concatenated with this DataFrame

Returns New DataFrame with the rows concatenated

Return type DataFrameConcatenated

data

Gives direct access to the data as numpy arrays.

Convenient when working with IPython in combination with small DataFrames, since this gives tab-completion. Only real columns (i.e. no virtual) columns can be accessed, for getting the data from virtual columns, use DataFrame.evaluate(. . .).

Columns can be accessed by their names, which are attributes. The attributes are of type numpy.ndarray.

Example:

```
>>> df = vaex.example()
>>> r = np.sqrt(df.data.x**2 + df.data.y**2)
```

export (*path*, *column_names=None*, *byteorder='='*, *shuffle=False*, *selection=False*, *progress=None*, *virtual=True*, *sort=None*, *ascending=True*)
Exports the DataFrame to a file written with arrow

Parameters

- **df** (DataFrameLocal) – DataFrame to export
- **path** (*str*) – path for file
- **column_names** (*lis[str]*) – list of column names to export or None for all columns
- **byteorder** (*str*) – = for native, < for little endian and > for big endian (not supported for fits)
- **shuffle** (*bool*) – export rows in random order
- **selection** (*bool*) – export selection or not
- **progress** – progress callback that gets a progress fraction as argument and should return True to continue, or a default progress bar when progress=True
- **sort** (*str*) – expression used for sorting the output
- **ascending** (*bool*) – sort ascending (True) or descending

Param bool virtual: When True, export virtual columns

Returns

export_arrow (*path*, *column_names=None*, *byteorder='='*, *shuffle=False*, *selection=False*, *progress=None*, *virtual=True*, *sort=None*, *ascending=True*)
Exports the DataFrame to a file written with arrow

Parameters

- **df** (DataFrameLocal) – DataFrame to export
- **path** (*str*) – path for file
- **column_names** (*lis[str]*) – list of column names to export or None for all columns
- **byteorder** (*str*) – = for native, < for little endian and > for big endian
- **shuffle** (*bool*) – export rows in random order
- **selection** (*bool*) – export selection or not
- **progress** – progress callback that gets a progress fraction as argument and should return True to continue, or a default progress bar when progress=True
- **sort** (*str*) – expression used for sorting the output
- **ascending** (*bool*) – sort ascending (True) or descending

Param bool virtual: When True, export virtual columns

Returns

export_csv (*path*, *virtual=True*, *selection=False*, *progress=None*, *chunk_size=1000000*, ***kwargs*)
Exports the DataFrame to a CSV file.

Parameters

- **path** (*str*) – Path for file
- **virtual** (*bool*) – If True, export virtual columns as well
- **selection** (*bool*) – Name of selection to use (or True for the 'default'), or all the data (when selection is None or False)
- **progress** – A callable that takes one argument (a floating point value between 0 and 1) indicating the progress, calculations are cancelled when this callable returns False
- **chunk_size** (*int*) – Number of rows to be written to disk in a single iteration
- ****kwargs** – Extra keyword arguments to be passed on pandas.DataFrame.to_csv()

Returns

export_fits(*path*, *column_names=None*, *shuffle=False*, *selection=False*, *progress=None*, *virtual=True*, *sort=None*, *ascending=True*)

Exports the DataFrame to a fits file that is compatible with TOPCAT colfits format

Parameters

- **df** (*DataFrameLocal*) – DataFrame to export
- **path** (*str*) – path for file
- **column_names** (*lis[str]*) – list of column names to export or None for all columns
- **shuffle** (*bool*) – export rows in random order
- **selection** (*bool*) – export selection or not
- **progress** – progress callback that gets a progress fraction as argument and should return True to continue, or a default progress bar when progress=True
- **sort** (*str*) – expression used for sorting the output
- **ascending** (*bool*) – sort ascending (True) or descending

Param bool virtual: When True, export virtual columns

Returns

export_hdf5(*path*, *column_names=None*, *byteorder='='*, *shuffle=False*, *selection=False*, *progress=None*, *virtual=True*, *sort=None*, *ascending=True*)

Exports the DataFrame to a vaex hdf5 file

Parameters

- **df** (*DataFrameLocal*) – DataFrame to export
- **path** (*str*) – path for file
- **column_names** (*lis[str]*) – list of column names to export or None for all columns
- **byteorder** (*str*) – = for native, < for little endian and > for big endian
- **shuffle** (*bool*) – export rows in random order
- **selection** (*bool*) – export selection or not
- **progress** – progress callback that gets a progress fraction as argument and should return True to continue, or a default progress bar when progress=True
- **sort** (*str*) – expression used for sorting the output
- **ascending** (*bool*) – sort ascending (True) or descending

Param bool virtual: When True, export virtual columns

Returns

export_parquet (*path*, *column_names=None*, *byteorder='='*, *shuffle=False*, *selection=False*, *progress=None*, *virtual=True*, *sort=None*, *ascending=True*)
Exports the DataFrame to a parquet file

Parameters

- **df** (`DataFrameLocal`) – DataFrame to export
- **path** (`str`) – path for file
- **column_names** (`lis[str]`) – list of column names to export or None for all columns
- **byteorder** (`str`) – = for native, < for little endian and > for big endian
- **shuffle** (`bool`) – export rows in random order
- **selection** (`bool`) – export selection or not
- **progress** – progress callback that gets a progress fraction as argument and should return True to continue, or a default progress bar when progress=True
- **sort** (`str`) – expression used for sorting the output
- **ascending** (`bool`) – sort ascending (True) or descending

Param bool virtual: When True, export virtual columns

Returns

groupby (*by=None*, *agg=None*)
Return a `GroupBy` or `DataFrame` object when agg is not None

Examples:

```
>>> import vaex
>>> import numpy as np
>>> np.random.seed(42)
>>> x = np.random.randint(1, 5, 10)
>>> y = x**2
>>> df = vaex.from_arrays(x=x, y=y)
>>> df.groupby(df.x, agg='count')
#    x    y_count
0    3          4
1    4          2
2    1          3
3    2          1
>>> df.groupby(df.x, agg=[vaex.agg.count('y'), vaex.agg.mean('y')])
#    x    y_count    y_mean
0    3          4         9
1    4          2        16
2    1          3         1
3    2          1         4
>>> df.groupby(df.x, agg={'z': [vaex.agg.count('y'), vaex.agg.mean('y')]})
#    x    z_count    z_mean
0    3          4         9
1    4          2        16
2    1          3         1
3    2          1         4
```

Example using datetime:

```
>>> import vaex
>>> import numpy as np
>>> t = np.arange('2015-01-01', '2015-02-01', dtype=np.datetime64)
>>> y = np.arange(len(t))
>>> df = vaex.from_arrays(t=t, y=y)
>>> df.groupby(vaex.BinnerTime.per_week(df.t)).agg({'y' : 'sum'})
#  t                      y
0  2015-01-01 00:00:00   21
1  2015-01-08 00:00:00   70
2  2015-01-15 00:00:00  119
3  2015-01-22 00:00:00  168
4  2015-01-29 00:00:00   87
```

Parameters **list or agg agg** (*dict,*) – Aggregate operation in the form of a string, vaex.agg object, a dictionary where the keys indicate the target column names, and the values the operations, or the a list of aggregates. When not given, it will return the groupby object.

Returns *DataFrame* or GroupBy object.

is_local()
The local implementation of *DataFrame.evaluate()*, always returns True.

join(*other*, *on=None*, *left_on=None*, *right_on=None*, *lprefix=''*, *rprefix=''*, *lsuffix=''*, *rsuffix=''*, *how='left'*, *allow_duplication=False*, *inplace=False*)
Return a DataFrame joined with other DataFrames, matched by columns/expression on/left_on/right_on

If neither on/left_on/right_on is given, the join is done by simply adding the columns (i.e. on the implicit row index).

Note: The filters will be ignored when joining, the full DataFrame will be joined (since filters may change). If either DataFrame is heavily filtered (contains just a small number of rows) consider running *DataFrame.extract()* first.

Example:

```
>>> a = np.array(['a', 'b', 'c'])
>>> x = np.arange(1,4)
>>> ds1 = vaex.from_arrays(a=a, x=x)
>>> b = np.array(['a', 'b', 'd'])
>>> y = x**2
>>> ds2 = vaex.from_arrays(b=b, y=y)
>>> ds1.join(ds2, left_on='a', right_on='b')
```

Parameters

- **other** – Other DataFrame to join with (the right side)
- **on** – default key for the left table (self)
- **left_on** – key for the left table (self), overrides on
- **right_on** – default key for the right table (other), overrides on
- **lprefix** – prefix to add to the left column names in case of a name collision
- **rprefix** – similar for the right
- **lsuffix** – suffix to add to the left column names in case of a name collision
- **rsuffix** – similar for the right

- **how** – how to join, 'left' keeps all rows on the left, and adds columns (with possible missing values) 'right' is similar with self and other swapped. 'inner' will only return rows which overlap.
- **allow_duplication** (*bool*) – Allow duplication of rows when the joined column contains non-unique values.
- **inplace** – Make modifications to self or return a new DataFrame

Returns

label_encode(*column*, *values=None*, *inplace=False*)
Deprecated: use is_category

Encode column as ordinal values and mark it as categorical.

The existing column is renamed to a hidden column and replaced by a numerical columns with values between [0, len(values)-1].

length(*selection=False*)
Get the length of the DataFrames, for the selection of the whole DataFrame.

If selection is False, it returns len(df).

TODO: Implement this in DataFrameRemote, and move the method up in `DataFrame.length()`

Parameters selection – When True, will return the number of selected rows

Returns

ordinal_encode(*column*, *values=None*, *inplace=False*)
Deprecated: use is_category

Encode column as ordinal values and mark it as categorical.

The existing column is renamed to a hidden column and replaced by a numerical columns with values between [0, len(values)-1].

selected_length(*selection='default'*)
The local implementation of `DataFrame.selected_length()`

shallow_copy(*virtual=True*, *variables=True*)
Creates a (shallow) copy of the DataFrame.

It will link to the same data, but will have its own state, e.g. virtual columns, variables, selection etc.

7.2.3 Expression class

class vaex.expression.**Expression**(*ds*, *expression*, *ast=None*)
Bases: `object`

Expression class

__abs__()
Returns the absolute value of the expression

__bool__()
Cast expression to boolean. Only supports (<expr1> == <expr2> and <expr1> != <expr2>)

The main use case for this is to support assigning to traitlets. e.g.:

```
>>> bool(expr1 == expr2)
```

This will return True when expr1 and expr2 are exactly the same (in string representation). And similarly for:

```
>>> bool(expr != expr2)
```

All other cases will return True.

__init__(*ds*, *expression*, *ast=None*)
Initialize self. See help(type(self)) for accurate signature.

__repr__()
Return repr(self).

__str__()
Return str(self).

__weakref__
list of weak references to the object (if defined)

abs(***kwargs*)
Lazy wrapper around `numpy.abs`

apply(*f*)
Apply a function along all values of an Expression.

Example:

```
>>> df = vaex.example()
>>> df.x
Expression = x
Length: 330,000 dtype: float64 (column)
---------------------------------------
     0  -0.777471
     1    3.77427
     2    1.37576
     3   -7.06738
     4   0.243441
```

```
>>> def func(x):
...     return x**2
```

```
>>> df.x.apply(func)
Expression = lambda_function(x)
Length: 330,000 dtype: float64 (expression)
-------------------------------------------
     0   0.604461
     1    14.2451
     2    1.89272
     3    49.9478
     4  0.0592637
```

Parameters **f** – A function to be applied on the Expression values

Returns A function that is lazily evaluated when called.

arccos(***kwargs*)
Lazy wrapper around `numpy.arccos`

arccosh(***kwargs*)
Lazy wrapper around `numpy.arccosh`

arcsin(***kwargs*)
Lazy wrapper around `numpy.arcsin`

arcsinh(***kwargs*)
Lazy wrapper around `numpy.arcsinh`

arctan(***kwargs*)
Lazy wrapper around `numpy.arctan`

arctan2(***kwargs*)
Lazy wrapper around `numpy.arctan2`

arctanh(***kwargs*)
Lazy wrapper around `numpy.arctanh`

ast
Returns the abstract syntax tree (AST) of the expression

clip(***kwargs*)
Lazy wrapper around `numpy.clip`

copy(*df=None*)
Efficiently copies an expression.

Expression objects have both a string and AST representation. Creating the AST representation involves parsing the expression, which is expensive.

Using copy will deepcopy the AST when the expression was already parsed.

Parameters **df** – DataFrame for which the expression will be evaluated (self.df if None)

cos(***kwargs*)
Lazy wrapper around `numpy.cos`

cosh(***kwargs*)
Lazy wrapper around `numpy.cosh`

count(*binby=[], limits=None, shape=128, selection=False, delay=False, edges=False, progress=None*)
Shortcut for ds.count(expression, . . .), see *Dataset.count*

countmissing()
Returns the number of missing values in the expression.

countna()
Returns the number of Not Availiable (N/A) values in the expression. This includes missing values and np.nan values.

countnan()
Returns the number of NaN values in the expression.

data_type()
Alias to df.data_type(self.expression)

deg2rad(***kwargs*)
Lazy wrapper around `numpy.deg2rad`

digitize(***kwargs*)
Lazy wrapper around `numpy.digitize`

dt
Gives access to datetime operations via *`DateTime`*

exp(***kwargs*)
Lazy wrapper around `numpy.exp`

expand (*stop=[]*)
Expand the expression such that no virtual columns occurs, only normal columns.

Example:

```
>>> df = vaex.example()
>>> r = np.sqrt(df.data.x**2 + df.data.y**2)
>>> r.expand().expression
'sqrt(((x ** 2) + (y ** 2)))'
```

expm1 (***kwargs*)
Lazy wrapper around `numpy.expm1`

fillmissing (*value*)
Returns an array where missing values are replaced by value. See *:ismissing* for the definition of missing values.

fillna (*value*)
Returns an array where NA values are replaced by value. See *:isna* for the definition of missing values.

fillnan (*value*)
Returns an array where nan values are replaced by value. See *:isnan* for the definition of missing values.

format (*format*)
Uses http://www.cplusplus.com/reference/string/to_string/ for formatting

isfinite (***kwargs*)
Lazy wrapper around `numpy.isfinite`

isin (*values*)
Lazily tests if each value in the expression is present in values.

Parameters **values** – List/array of values to check

Returns *Expression* with the lazy expression.

ismissing ()
Returns True where there are missing values (masked arrays), missing strings or None

isna ()
Returns a boolean expression indicating if the values are Not Availiable (missing or NaN).

isnan ()
Returns an array where there are NaN values

log (***kwargs*)
Lazy wrapper around `numpy.log`

log10 (***kwargs*)
Lazy wrapper around `numpy.log10`

log1p (***kwargs*)
Lazy wrapper around `numpy.log1p`

map (*mapper, nan_value=None, missing_value=None, default_value=None, allow_missing=False*)
Map values of an expression or in memory column according to an input dictionary or a custom callable function.

Example:

```
>>> import vaex
>>> df = vaex.from_arrays(color=['red', 'red', 'blue', 'red', 'green'])
>>> mapper = {'red': 1, 'blue': 2, 'green': 3}
```

(continues on next page)

(continued from previous page)

```
>>> df['color_mapped'] = df.color.map(mapper)
>>> df
#  color      color_mapped
0  red                   1
1  red                   1
2  blue                  2
3  red                   1
4  green                 3
>>> import numpy as np
>>> df = vaex.from_arrays(type=[0, 1, 2, 2, 2, np.nan])
>>> df['role'] = df['type'].map({0: 'admin', 1: 'maintainer', 2: 'user', np.
↪nan: 'unknown'})
>>> df
#    type  role
0       0  admin
1       1  maintainer
2       2  user
3       2  user
4       2  user
5     nan  unknown
>>> import vaex
>>> import numpy as np
>>> df = vaex.from_arrays(type=[0, 1, 2, 2, 2, 4])
>>> df['role'] = df['type'].map({0: 'admin', 1: 'maintainer', 2: 'user'},
↪default_value='unknown')
>>> df
#    type  role
0       0  admin
1       1  maintainer
2       2  user
3       2  user
4       2  user
5       4  unknown
:param mapper: dict like object used to map the values from keys to values
:param nan_value: value to be used when a nan is present (and not in the
↪mapper)
:param missing_value: value to use used when there is a missing value
:param default_value: value to be used when a value is not in the mapper
↪(like dict.get(key, default))
:param allow_missing: used to signal that values in the mapper should map to
↪a masked array with missing values,
    assumed True when default_value is not None.
:return: A vaex expression
:rtype: vaex.expression.Expression
```

masked
Alias to df.is_masked(expression)

max (*binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *progress=None*)
Shortcut for ds.max(expression, . . .), see *Dataset.max*

maximum (***kwargs*)
Lazy wrapper around `numpy.maximum`

mean (*binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *progress=None*)
Shortcut for ds.mean(expression, . . .), see *Dataset.mean*

min (*binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *progress=None*)

Shortcut for ds.min(expression, …), see *Dataset.min*

minimum(***kwargs*)
Lazy wrapper around `numpy.minimum`

minmax(*binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *progress=None*)
Shortcut for ds.minmax(expression, …), see *Dataset.minmax*

nop()
Evaluates expression, and drop the result, usefull for benchmarking, since vaex is usually lazy

notna()
Opposite of isna

nunique(*dropna=False*, *dropnan=False*, *dropmissing=False*, *selection=None*, *delay=False*)
Counts number of unique values, i.e. *len(df.x.unique()) == df.x.nunique()*.

Parameters

- **dropmissing** – do not count missing values
- **dropnan** – do not count nan values
- **dropna** – short for any of the above, (see `Expression.isna()`)

rad2deg(***kwargs*)
Lazy wrapper around `numpy.rad2deg`

searchsorted(***kwargs*)
Lazy wrapper around `numpy.searchsorted`

sin(***kwargs*)
Lazy wrapper around `numpy.sin`

sinc(***kwargs*)
Lazy wrapper around `numpy.sinc`

sinh(***kwargs*)
Lazy wrapper around `numpy.sinh`

sqrt(***kwargs*)
Lazy wrapper around `numpy.sqrt`

std(*binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *progress=None*)
Shortcut for ds.std(expression, …), see *Dataset.std*

str
Gives access to string operations via `StringOperations`

str_pandas
Gives access to string operations via `StringOperationsPandas` (using Pandas Series)

sum(*binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *progress=None*)
Shortcut for ds.sum(expression, …), see *Dataset.sum*

tan(***kwargs*)
Lazy wrapper around `numpy.tan`

tanh(***kwargs*)
Lazy wrapper around `numpy.tanh`

td
Gives access to timedelta operations via `TimeDelta`

to_numpy()
Return a numpy representation of the data

to_pandas_series()
Return a pandas.Series representation of the expression.

Note: Pandas is likely to make a memory copy of the data.

tolist()
Short for expr.evaluate().tolist()

transient
If this expression is not transient (e.g. on disk) optimizations can be made

unique(*dropna=False*, *dropnan=False*, *dropmissing=False*, *selection=None*, *delay=False*)
Returns all unique values.

Parameters

- **dropmissing** – do not count missing values
- **dropnan** – do not count nan values
- **dropna** – short for any of the above, (see *Expression.isna()*)

value_counts(*dropna=False*, *dropnan=False*, *dropmissing=False*, *ascending=False*, *progress=False*)
Computes counts of unique values.

WARNING:

- If the expression/column is not categorical, it will be converted on the fly
- dropna is False by default, it is True by default in pandas

Parameters

- **dropna** – when True, it will not report the NA (see *Expression.isna()*)
- **dropnan** – when True, it will not report the nans(see *Expression.isnan()*)
- **dropmissing** – when True, it will not report the missing values (see *Expression.ismissing()*)
- **ascending** – when False (default) it will report the most frequent occuring item first

Returns Pandas series containing the counts

var(*binby=[]*, *limits=None*, *shape=128*, *selection=False*, *delay=False*, *progress=None*)
Shortcut for ds.std(expression, . . .), see *Dataset.var*

variables(*ourself=False*, *expand_virtual=True*, *include_virtual=True*)
Return a set of variables this expression depends on.

Example:

```
>>> df = vaex.example()
>>> r = np.sqrt(df.data.x**2 + df.data.y**2)
>>> r.variables()
{'x', 'y'}
```

where(***kwargs*)
Lazy wrapper around `numpy.where`

7.2.4 Aggregation and statistics

class vaex.stat.**Expression**

Bases: object

Describes an expression for a statistic

calculate(*ds*, *binby=[]*, *shape=256*, *limits=None*, *selection=None*)

Calculate the statistic for a Dataset

vaex.stat.**correlation**(*x*, *y*)

Creates a standard deviation statistic

vaex.stat.**count**(*expression='*'*)

Creates a count statistic

vaex.stat.**covar**(*x*, *y*)

Creates a standard deviation statistic

vaex.stat.**mean**(*expression*)

Creates a mean statistic

vaex.stat.**std**(*expression*)

Creates a standard deviation statistic

vaex.stat.**sum**(*expression*)

Creates a sum statistic

class vaex.agg.**AggregatorDescriptorMean**(*name*, *expression*, *short_name='mean'*, *selection=None*, *edges=False*)

Bases: *vaex.agg.AggregatorDescriptorMulti*

class vaex.agg.**AggregatorDescriptorMulti**(*name*, *expression*, *short_name*, *selection=None*, *edges=False*)

Bases: vaex.agg.AggregatorDescriptor

Uses multiple operations/aggregation to calculate the final aggretation

class vaex.agg.**AggregatorDescriptorStd**(*name*, *expression*, *short_name='var'*, *ddof=0*, *selection=None*, *edges=False*)

Bases: *vaex.agg.AggregatorDescriptorVar*

class vaex.agg.**AggregatorDescriptorVar**(*name*, *expression*, *short_name='var'*, *ddof=0*, *selection=None*, *edges=False*)

Bases: *vaex.agg.AggregatorDescriptorMulti*

vaex.agg.**count**(*expression='*'*, *selection=None*, *edges=False*)

Creates a count aggregation

vaex.agg.**first**(*expression*, *order_expression*, *selection=None*, *edges=False*)

Creates a max aggregation

vaex.agg.**max**(*expression*, *selection=None*, *edges=False*)

Creates a max aggregation

vaex.agg.**mean**(*expression*, *selection=None*, *edges=False*)

Creates a mean aggregation

vaex.agg.**min**(*expression*, *selection=None*, *edges=False*)

Creates a min aggregation

vaex.agg.**nunique**(*expression*, *dropna=False*, *dropnan=False*, *dropmissing=False*, *selection=None*, *edges=False*)

Aggregator that calculates the number of unique items per bin.

Parameters

- **expression** – Expression for which to calculate the unique items
- **dropmissing** – do not count missing values
- **dropnan** – do not count nan values
- **dropna** – short for any of the above, (see `Expression.isna()`)

`vaex.agg.`**`std`**(*expression*, *ddof=0*, *selection=None*, *edges=False*)
Creates a standard deviation aggregation

`vaex.agg.`**`sum`**(*expression*, *selection=None*, *edges=False*)
Creates a sum aggregation

`vaex.agg.`**`var`**(*expression*, *ddof=0*, *selection=None*, *edges=False*)
Creates a variance aggregation

7.3 Extensions

7.3.1 String operations

class `vaex.expression.`**`StringOperations`**(*expression*)
Bases: `object`

String operations.

Usually accessed using e.g. *df.name.str.lower()*

`__init__`(*expression*)
Initialize self. See help(type(self)) for accurate signature.

`__weakref__`
list of weak references to the object (if defined)

`byte_length`()
Returns the number of bytes in a string sample.

Returns an expression contains the number of bytes in each sample of a string column.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.byte_length()
Expression = str_byte_length(text)
Length: 5 dtype: int64 (expression)
-----------------------------------
0   9
```

(continues on next page)

(continued from previous page)

```
1   11
2    9
3    3
4    4
```

capitalize()

Capitalize the first letter of a string sample.

Returns an expression containing the capitalized strings.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.capitalize()
Expression = str_capitalize(text)
Length: 5 dtype: str (expression)
---------------------------------
0    Something
1  Very pretty
2    Is coming
3          Our
4         Way.
```

cat(*other*)

Concatenate two string columns on a row-by-row basis.

Parameters **other** (*expression*) – The expression of the other column to be concatenated.

Returns an expression containing the concatenated columns.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.cat(df.text)
Expression = str_cat(text, text)
Length: 5 dtype: str (expression)
---------------------------------
```

(continues on next page)

(continued from previous page)

```
0      SomethingSomething
1   very prettyvery pretty
2       is comingis coming
3                   ourour
4                 way.way.
```

center (*width*, *fillchar=' '*)

Fills the left and right side of the strings with additional characters, such that the sample has a total of *width* characters.

Parameters

- **width** (*int*) – The total number of characters of the resulting string sample.
- **fillchar** (*str*) – The character used for filling.

Returns an expression containing the filled strings.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.center(width=11, fillchar='!')
Expression = str_center(text, width=11, fillchar='!')
Length: 5 dtype: str (expression)
---------------------------------
0  !Something!
1  very pretty
2  !is coming!
3  !!!!our!!!!
4  !!!!way.!!!
```

contains (*pattern*, *regex=True*)

Check if a string pattern or regex is contained within a sample of a string column.

Parameters

- **pattern** (*str*) – A string or regex pattern
- **regex** (*bool*) – If True,

Returns an expression which is evaluated to True if the pattern is found in a given sample, and it is False otherwise.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
```

(continues on next page)

(continued from previous page)

```
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.contains('very')
Expression = str_contains(text, 'very')
Length: 5 dtype: bool (expression)
----------------------------------
0  False
1   True
2  False
3  False
4  False
```

count (*pat*, *regex=False*)

Count the occurences of a pattern in sample of a string column.

Parameters

- **pat** (*str*) – A string or regex pattern
- **regex** (*bool*) – If True,

Returns an expression containing the number of times a pattern is found in each sample.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.count(pat="et", regex=False)
Expression = str_count(text, pat='et', regex=False)
Length: 5 dtype: int64 (expression)
-----------------------------------
0  1
1  1
2  0
3  0
4  0
```

endswith (*pat*)

Check if the end of each string sample matches the specified pattern.

Parameters **pat** (*str*) – A string pattern or a regex

Returns an expression evaluated to True if the pattern is found at the end of a given sample, False otherwise.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.endswith(pat="ing")
Expression = str_endswith(text, pat='ing')
Length: 5 dtype: bool (expression)
----------------------------------
0   True
1  False
2   True
3  False
4  False
```

equals (*y*)

Tests if strings x and y are the same

Returns a boolean expression

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.equals(df.text)
Expression = str_equals(text, text)
Length: 5 dtype: bool (expression)
----------------------------------
0  True
1  True
2  True
3  True
4  True
```

```
>>> df.text.str.equals('our')
Expression = str_equals(text, 'our')
Length: 5 dtype: bool (expression)
----------------------------------
0  False
1  False
```

(continues on next page)

(continued from previous page)

```
2   False
3    True
4   False
```

find (*sub*, *start=0*, *end=None*)

Returns the lowest indices in each string in a column, where the provided substring is fully contained between within a sample. If the substring is not found, -1 is returned.

Parameters

- **sub** (*str*) – A substring to be found in the samples
- **start** (*int*) –
- **end** (*int*) –

Returns an expression containing the lowest indices specifying the start of the substring.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.find(sub="et")
Expression = str_find(text, sub='et')
Length: 5 dtype: int64 (expression)
-----------------------------------
0   3
1   7
2  -1
3  -1
4  -1
```

get (*i*)

Extract a character from each sample at the specified position from a string column. Note that if the specified position is out of bound of the string sample, this method returns '', while pandas retunrs nan.

Parameters **i** (*int*) – The index location, at which to extract the character.

Returns an expression containing the extracted characters.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
```

(continues on next page)

(continued from previous page)

```
  3  our
  4  way.
```

```
>>> df.text.str.get(5)
Expression = str_get(text, 5)
Length: 5 dtype: str (expression)
---------------------------------
0    h
1    p
2    m
3
4
```

index (*sub*, *start=0*, *end=None*)

Returns the lowest indices in each string in a column, where the provided substring is fully contained between within a sample. If the substring is not found, -1 is returned. It is the same as *str.find*.

Parameters

- **sub** (*str*) – A substring to be found in the samples
- **start** (*int*) –
- **end** (*int*) –

Returns an expression containing the lowest indices specifying the start of the substring.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.index(sub="et")
Expression = str_find(text, sub='et')
Length: 5 dtype: int64 (expression)
-----------------------------------
0   3
1   7
2  -1
3  -1
4  -1
```

isalnum ()

Check if all characters in a string sample are alphanumeric.

Returns an expression evaluated to True if a sample contains only alphanumeric characters, otherwise False.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.isalnum()
Expression = str_isalnum(text)
Length: 5 dtype: bool (expression)
----------------------------------
0   True
1  False
2  False
3   True
4  False
```

isalpha()

Check if all characters in a string sample are alphabetic.

Returns an expression evaluated to True if a sample contains only alphabetic characters, otherwise False.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.isalpha()
Expression = str_isalpha(text)
Length: 5 dtype: bool (expression)
----------------------------------
0   True
1  False
2  False
3   True
4  False
```

isdigit()

Check if all characters in a string sample are digits.

Returns an expression evaluated to True if a sample contains only digits, otherwise False.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', '6']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  6
```

```
>>> df.text.str.isdigit()
Expression = str_isdigit(text)
Length: 5 dtype: bool (expression)
----------------------------------
0  False
1  False
2  False
3  False
4   True
```

islower()

Check if all characters in a string sample are lowercase characters.

Returns an expression evaluated to True if a sample contains only lowercase characters, otherwise False.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.islower()
Expression = str_islower(text)
Length: 5 dtype: bool (expression)
----------------------------------
0  False
1   True
2   True
3   True
4   True
```

isspace()

Check if all characters in a string sample are whitespaces.

Returns an expression evaluated to True if a sample contains only whitespaces, otherwise False.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', '       ', ' ']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3
  4
```

```
>>> df.text.str.isspace()
Expression = str_isspace(text)
Length: 5 dtype: bool (expression)
----------------------------------
0  False
1  False
2  False
3   True
4   True
```

isupper()

Check if all characters in a string sample are lowercase characters.

Returns an expression evaluated to True if a sample contains only lowercase characters, otherwise False.

Example:

```
>>> import vaex
>>> text = ['SOMETHING', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  SOMETHING
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.isupper()
Expression = str_isupper(text)
Length: 5 dtype: bool (expression)
----------------------------------
0   True
1  False
2  False
3  False
4  False
```

join(*sep*)

Same as find (difference with pandas is that it does not raise a ValueError)

len()

Returns the length of a string sample.

Returns an expression contains the length of each sample of a string column.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.len()
Expression = str_len(text)
Length: 5 dtype: int64 (expression)
-----------------------------------
0   9
1  11
2   9
3   3
4   4
```

ljust (*width*, *fillchar=' '*)

Fills the right side of string samples with a specified character such that the strings are right-hand justified.

Parameters

- **width** (*int*) – The minimal width of the strings.
- **fillchar** (*str*) – The character used for filling.

Returns an expression containing the filled strings.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.ljust(width=10, fillchar='!')
Expression = str_ljust(text, width=10, fillchar='!')
Length: 5 dtype: str (expression)
---------------------------------
0   Something!
1  very pretty
2   is coming!
3   our!!!!!!!
4   way.!!!!!!
```

lower ()

Converts string samples to lower case.

Returns an expression containing the converted strings.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.lower()
Expression = str_lower(text)
Length: 5 dtype: str (expression)
---------------------------------
0    something
1  very pretty
2    is coming
3          our
4         way.
```

lstrip(*to_strip=None*)

Remove leading characters from a string sample.

Parameters **to_strip** (*str*) – The string to be removed

Returns an expression containing the modified string column.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.lstrip(to_strip='very ')
Expression = str_lstrip(text, to_strip='very ')
Length: 5 dtype: str (expression)
---------------------------------
0  Something
1     pretty
2  is coming
3        our
4       way.
```

match(*pattern*)

Check if a string sample matches a given regular expression.

Parameters **pattern** (*str*) – a string or regex to match to a string sample.

Returns an expression which is evaluated to True if a match is found, False otherwise.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.match(pattern='our')
Expression = str_match(text, pattern='our')
Length: 5 dtype: bool (expression)
----------------------------------
0  False
1  False
2  False
3   True
4  False
```

pad(*width*, *side='left'*, *fillchar=' '*)
Pad strings in a given column.

Parameters

- **width** (*int*) – The total width of the string
- **side** (*str*) – If 'left' than pad on the left, if 'right' than pad on the right side the string.
- **fillchar** (*str*) – The character used for padding.

Returns an expression containing the padded strings.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.pad(width=10, side='left', fillchar='!')
Expression = str_pad(text, width=10, side='left', fillchar='!')
Length: 5 dtype: str (expression)
---------------------------------
0   !Something
1  very pretty
2   !is coming
3   !!!!!!!our
4   !!!!!!way.
```

repeat (*repeats*)
Duplicate each string in a column.

Parameters **repeats** (*int*) – number of times each string sample is to be duplicated.

Returns an expression containing the duplicated strings

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.repeat(3)
Expression = str_repeat(text, 3)
Length: 5 dtype: str (expression)
---------------------------------
0         SomethingSomethingSomething
1   very prettyvery prettyvery pretty
2         is comingis comingis coming
3                           ourourour
4                        way.way.way.
```

replace (*pat*, *repl*, *n=-1*, *flags=0*, *regex=False*)
Replace occurences of a pattern/regex in a column with some other string.

Parameters

- **pattern** (*str*) – string or a regex pattern
- **replace** (*str*) – a replacement string
- **n** (*int*) – number of replacements to be made from the start. If -1 make all replacements.
- **flags** (*int*) – ??
- **regex** (*bool*) – If True, . . . ?

Returns an expression containing the string replacements.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.replace(pat='et', repl='__')
Expression = str_replace(text, pat='et', repl='__')
Length: 5 dtype: str (expression)
---------------------------------
0    Som__hing
1  very pr__ty
2    is coming
3          our
4         way.
```

rfind (*sub*, *start=0*, *end=None*)

Returns the highest indices in each string in a column, where the provided substring is fully contained between within a sample. If the substring is not found, -1 is returned.

Parameters

- **sub** (*str*) – A substring to be found in the samples
- **start** (*int*) –
- **end** (*int*) –

Returns an expression containing the highest indices specifying the start of the substring.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.rfind(sub="et")
Expression = str_rfind(text, sub='et')
Length: 5 dtype: int64 (expression)
-----------------------------------
0   3
1   7
2  -1
3  -1
4  -1
```

rindex (*sub*, *start=0*, *end=None*)

Returns the highest indices in each string in a column, where the provided substring is fully contained between within a sample. If the substring is not found, -1 is returned. Same as *str.rfind*.

Parameters

- **sub** (*str*) – A substring to be found in the samples
- **start** (*int*) –
- **end** (*int*) –

Returns an expression containing the highest indices specifying the start of the substring.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.rindex(sub="et")
Expression = str_rindex(text, sub='et')
Length: 5 dtype: int64 (expression)
-----------------------------------
0   3
1   7
2  -1
3  -1
4  -1
```

rjust (*width*, *fillchar=' '*)

Fills the left side of string samples with a specified character such that the strings are left-hand justified.

Parameters

- **width** (*int*) – The minimal width of the strings.
- **fillchar** (*str*) – The character used for filling.

Returns an expression containing the filled strings.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.rjust(width=10, fillchar='!')
Expression = str_rjust(text, width=10, fillchar='!')
Length: 5 dtype: str (expression)
---------------------------------
0   !Something
1  very pretty
2   !is coming
3   !!!!!!!our
4   !!!!!!way.
```

rstrip (*to_strip=None*)

Remove trailing characters from a string sample.

Parameters **to_strip** (*str*) – The string to be removed

Returns an expression containing the modified string column.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.rstrip(to_strip='ing')
Expression = str_rstrip(text, to_strip='ing')
Length: 5 dtype: str (expression)
---------------------------------
0       Someth
1  very pretty
2       is com
3          our
4         way.
```

slice (*start=0*, *stop=None*)

Slice substrings from each string element in a column.

Parameters

- **start** (*int*) – The start position for the slice operation.
- **end** (*int*) – The stop position for the slice operation.

Returns an expression containing the sliced substrings.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.slice(start=2, stop=5)
Expression = str_pandas_slice(text, start=2, stop=5)
Length: 5 dtype: str (expression)
---------------------------------
0  met
1   ry
2   co
3    r
4   y.
```

startswith (*pat*)

Check if a start of a string matches a pattern.

Parameters **pat** (*str*) – A string pattern. Regular expressions are not supported.

Returns an expression which is evaluated to True if the pattern is found at the start of a string sample, False otherwise.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.startswith(pat='is')
Expression = str_startswith(text, pat='is')
Length: 5 dtype: bool (expression)
----------------------------------
0  False
1  False
2   True
3  False
4  False
```

strip (*to_strip=None*)

Removes leading and trailing characters.

Strips whitespaces (including new lines), or a set of specified characters from each string saple in a column, both from the left right sides.

Parameters

- **to_strip** (*str*) – The characters to be removed. All combinations of the characters will be removed. If None, it removes whitespaces.
- **returns** – an expression containing the modified string samples.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.strip(to_strip='very')
Expression = str_strip(text, to_strip='very')
Length: 5 dtype: str (expression)
```

(continues on next page)

(continued from previous page)

```
--------------------------------
0  Something
1      prett
2  is coming
3         ou
4       way.
```

title()

Converts all string samples to titlecase.

Returns an expression containing the converted strings.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.title()
Expression = str_title(text)
Length: 5 dtype: str (expression)
---------------------------------
0    Something
1  Very Pretty
2    Is Coming
3          Our
4         Way.
```

upper()

Converts all strings in a column to uppercase.

Returns an expression containing the converted strings.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.upper()
Expression = str_upper(text)
Length: 5 dtype: str (expression)
---------------------------------
```

(continues on next page)

(continued from previous page)

```
0    SOMETHING
1  VERY PRETTY
2    IS COMING
3          OUR
4         WAY.
```

zfill (*width*)

Pad strings in a column by prepanding "0" characters.

Parameters **width** (*int*) – The minimum length of the resulting string. Strings shorter less than *width* will be prepended with zeros.

Returns an expression containing the modified strings.

Example:

```
>>> import vaex
>>> text = ['Something', 'very pretty', 'is coming', 'our', 'way.']
>>> df = vaex.from_arrays(text=text)
>>> df
  #  text
  0  Something
  1  very pretty
  2  is coming
  3  our
  4  way.
```

```
>>> df.text.str.zfill(width=12)
Expression = str_zfill(text, width=12)
Length: 5 dtype: str (expression)
---------------------------------
0  000Something
1  0very pretty
2  000is coming
3  000000000our
4  00000000way.
```

7.3.2 String (pandas) operations

class vaex.expression.**StringOperationsPandas** (*expression*)

Bases: object

String operations using Pandas Series (much slower)

__init__ (*expression*)

Initialize self. See help(type(self)) for accurate signature.

__weakref__

list of weak references to the object (if defined)

byte_length (***kwargs*)

Wrapper around pandas.Series.byte_length

capitalize (***kwargs*)

Wrapper around pandas.Series.capitalize

cat (***kwargs*)

Wrapper around pandas.Series.cat

center (***kwargs*)
Wrapper around pandas.Series.center

contains (***kwargs*)
Wrapper around pandas.Series.contains

count (***kwargs*)
Wrapper around pandas.Series.count

endswith (***kwargs*)
Wrapper around pandas.Series.endswith

equals (***kwargs*)
Wrapper around pandas.Series.equals

find (***kwargs*)
Wrapper around pandas.Series.find

get (***kwargs*)
Wrapper around pandas.Series.get

index (***kwargs*)
Wrapper around pandas.Series.index

isalnum (***kwargs*)
Wrapper around pandas.Series.isalnum

isalpha (***kwargs*)
Wrapper around pandas.Series.isalpha

isdigit (***kwargs*)
Wrapper around pandas.Series.isdigit

islower (***kwargs*)
Wrapper around pandas.Series.islower

isspace (***kwargs*)
Wrapper around pandas.Series.isspace

isupper (***kwargs*)
Wrapper around pandas.Series.isupper

join (***kwargs*)
Wrapper around pandas.Series.join

len (***kwargs*)
Wrapper around pandas.Series.len

ljust (***kwargs*)
Wrapper around pandas.Series.ljust

lower (***kwargs*)
Wrapper around pandas.Series.lower

lstrip (***kwargs*)
Wrapper around pandas.Series.lstrip

match (***kwargs*)
Wrapper around pandas.Series.match

pad (***kwargs*)
Wrapper around pandas.Series.pad

repeat (***kwargs*)
Wrapper around pandas.Series.repeat

replace (***kwargs*)
Wrapper around pandas.Series.replace

rfind (***kwargs*)
Wrapper around pandas.Series.rfind

rindex (***kwargs*)
Wrapper around pandas.Series.rindex

rjust (***kwargs*)
Wrapper around pandas.Series.rjust

rstrip (***kwargs*)
Wrapper around pandas.Series.rstrip

slice (***kwargs*)
Wrapper around pandas.Series.slice

split (***kwargs*)
Wrapper around pandas.Series.split

startswith (***kwargs*)
Wrapper around pandas.Series.startswith

strip (***kwargs*)
Wrapper around pandas.Series.strip

title (***kwargs*)
Wrapper around pandas.Series.title

upper (***kwargs*)
Wrapper around pandas.Series.upper

zfill (***kwargs*)
Wrapper around pandas.Series.zfill

7.3.3 Date/time operations

class vaex.expression.**DateTime** (*expression*)
Bases: object

DateTime operations

Usually accessed using e.g. *df.birthday.dt.dayofweek*

__init__ (*expression*)
Initialize self. See help(type(self)) for accurate signature.

__weakref__
list of weak references to the object (if defined)

day
Extracts the day from a datetime sample.

Returns an expression containing the day extracted from a datetime column.

Example:

```
>>> import vaex
>>> import numpy as np
>>> date = np.array(['2009-10-12T03:31:00', '2016-02-11T10:17:34', '2015-11-
↪12T11:34:22'], dtype=np.datetime64)
>>> df = vaex.from_arrays(date=date)
>>> df
  #  date
  0  2009-10-12 03:31:00
  1  2016-02-11 10:17:34
  2  2015-11-12 11:34:22
```

```
>>> df.date.dt.day
Expression = dt_day(date)
Length: 3 dtype: int64 (expression)
-----------------------------------
0  12
1  11
2  12
```

day_name

Returns the day names of a datetime sample in English.

Returns an expression containing the day names extracted from a datetime column.

Example:

```
>>> import vaex
>>> import numpy as np
>>> date = np.array(['2009-10-12T03:31:00', '2016-02-11T10:17:34', '2015-11-
↪12T11:34:22'], dtype=np.datetime64)
>>> df = vaex.from_arrays(date=date)
>>> df
  #  date
  0  2009-10-12 03:31:00
  1  2016-02-11 10:17:34
  2  2015-11-12 11:34:22
```

```
>>> df.date.dt.day_name
Expression = dt_day_name(date)
Length: 3 dtype: str (expression)
---------------------------------
0    Monday
1  Thursday
2  Thursday
```

dayofweek

Obtain the day of the week with Monday=0 and Sunday=6

Returns an expression containing the day of week.

Example:

```
>>> import vaex
>>> import numpy as np
>>> date = np.array(['2009-10-12T03:31:00', '2016-02-11T10:17:34', '2015-11-
↪12T11:34:22'], dtype=np.datetime64)
>>> df = vaex.from_arrays(date=date)
>>> df
```

(continues on next page)

(continued from previous page)

```
  #  date
  0  2009-10-12 03:31:00
  1  2016-02-11 10:17:34
  2  2015-11-12 11:34:22
```

```
>>> df.date.dt.dayofweek
Expression = dt_dayofweek(date)
Length: 3 dtype: int64 (expression)
-----------------------------------
0  0
1  3
2  3
```

dayofyear

The ordinal day of the year.

Returns an expression containing the ordinal day of the year.

Example:

```
>>> import vaex
>>> import numpy as np
>>> date = np.array(['2009-10-12T03:31:00', '2016-02-11T10:17:34', '2015-11-
↪12T11:34:22'], dtype=np.datetime64)
>>> df = vaex.from_arrays(date=date)
>>> df
  #  date
  0  2009-10-12 03:31:00
  1  2016-02-11 10:17:34
  2  2015-11-12 11:34:22
```

```
>>> df.date.dt.dayofyear
Expression = dt_dayofyear(date)
Length: 3 dtype: int64 (expression)
-----------------------------------
0  285
1   42
2  316
```

hour

Extracts the hour out of a datetime samples.

Returns an expression containing the hour extracted from a datetime column.

Example:

```
>>> import vaex
>>> import numpy as np
>>> date = np.array(['2009-10-12T03:31:00', '2016-02-11T10:17:34', '2015-11-
↪12T11:34:22'], dtype=np.datetime64)
>>> df = vaex.from_arrays(date=date)
>>> df
  #  date
  0  2009-10-12 03:31:00
  1  2016-02-11 10:17:34
  2  2015-11-12 11:34:22
```

```
>>> df.date.dt.hour
Expression = dt_hour(date)
Length: 3 dtype: int64 (expression)
-----------------------------------
0   3
1  10
2  11
```

is_leap_year

Check whether a year is a leap year.

Returns an expression which evaluates to True if a year is a leap year, and to False otherwise.

Example:

```
>>> import vaex
>>> import numpy as np
>>> date = np.array(['2009-10-12T03:31:00', '2016-02-11T10:17:34', '2015-11-
↪12T11:34:22'], dtype=np.datetime64)
>>> df = vaex.from_arrays(date=date)
>>> df
  #  date
  0  2009-10-12 03:31:00
  1  2016-02-11 10:17:34
  2  2015-11-12 11:34:22
```

```
>>> df.date.dt.is_leap_year
Expression = dt_is_leap_year(date)
Length: 3 dtype: bool (expression)
----------------------------------
0  False
1   True
2  False
```

minute

Extracts the minute out of a datetime samples.

Returns an expression containing the minute extracted from a datetime column.

Example:

```
>>> import vaex
>>> import numpy as np
>>> date = np.array(['2009-10-12T03:31:00', '2016-02-11T10:17:34', '2015-11-
↪12T11:34:22'], dtype=np.datetime64)
>>> df = vaex.from_arrays(date=date)
>>> df
  #  date
  0  2009-10-12 03:31:00
  1  2016-02-11 10:17:34
  2  2015-11-12 11:34:22
```

```
>>> df.date.dt.minute
Expression = dt_minute(date)
Length: 3 dtype: int64 (expression)
-----------------------------------
0  31
```

(continues on next page)

(continued from previous page)

```
1   17
2   34
```

month

Extracts the month out of a datetime sample.

Returns an expression containing the month extracted from a datetime column.

Example:

```
>>> import vaex
>>> import numpy as np
>>> date = np.array(['2009-10-12T03:31:00', '2016-02-11T10:17:34', '2015-11-
↪12T11:34:22'], dtype=np.datetime64)
>>> df = vaex.from_arrays(date=date)
>>> df
  #  date
  0  2009-10-12 03:31:00
  1  2016-02-11 10:17:34
  2  2015-11-12 11:34:22
```

```
>>> df.date.dt.month
Expression = dt_month(date)
Length: 3 dtype: int64 (expression)
-----------------------------------
0  10
1   2
2  11
```

month_name

Returns the month names of a datetime sample in English.

Returns an expression containing the month names extracted from a datetime column.

Example:

```
>>> import vaex
>>> import numpy as np
>>> date = np.array(['2009-10-12T03:31:00', '2016-02-11T10:17:34', '2015-11-
↪12T11:34:22'], dtype=np.datetime64)
>>> df = vaex.from_arrays(date=date)
>>> df
  #  date
  0  2009-10-12 03:31:00
  1  2016-02-11 10:17:34
  2  2015-11-12 11:34:22
```

```
>>> df.date.dt.month_name
Expression = dt_month_name(date)
Length: 3 dtype: str (expression)
---------------------------------
0   October
1  February
2  November
```

quarter

Extracts the quarter from a datetime sample.

Returns an expression containing the number of the quarter extracted from a datetime column.

Example:

```
>>> import vaex
>>> import numpy as np
>>> date = np.array(['2009-10-12T03:31:00', '2016-02-11T10:17:34', '2015-11-
↪12T11:34:22'], dtype=np.datetime64)
>>> df = vaex.from_arrays(date=date)
>>> df
  #  date
  0  2009-10-12 03:31:00
  1  2016-02-11 10:17:34
  2  2015-11-12 11:34:22
```

```
>>> df.date.dt.quarter
Expression = dt_quarter(date)
Length: 3 dtype: int64 (expression)
-----------------------------------
0  4
1  1
2  4
```

second

Extracts the second out of a datetime samples.

Returns an expression containing the second extracted from a datetime column.

Example:

```
>>> import vaex
>>> import numpy as np
>>> date = np.array(['2009-10-12T03:31:00', '2016-02-11T10:17:34', '2015-11-
↪12T11:34:22'], dtype=np.datetime64)
>>> df = vaex.from_arrays(date=date)
>>> df
  #  date
  0  2009-10-12 03:31:00
  1  2016-02-11 10:17:34
  2  2015-11-12 11:34:22
```

```
>>> df.date.dt.second
Expression = dt_second(date)
Length: 3 dtype: int64 (expression)
-----------------------------------
0   0
1  34
2  22
```

strftime(*date_format*)

Returns a formatted string from a datetime sample.

Returns an expression containing a formatted string extracted from a datetime column.

Example:

```
>>> import vaex
>>> import numpy as np
>>> date = np.array(['2009-10-12T03:31:00', '2016-02-11T10:17:34', '2015-11-
↪12T11:34:22'], dtype=np.datetime64)
```

(continues on next page)

(continued from previous page)

```
>>> df = vaex.from_arrays(date=date)
>>> df
  #  date
  0  2009-10-12 03:31:00
  1  2016-02-11 10:17:34
  2  2015-11-12 11:34:22
```

```
>>> df.date.dt.strftime("%Y-%m")
Expression = dt_strftime(date, '%Y-%m')
Length: 3 dtype: object (expression)
------------------------------------
0  2009-10
1  2016-02
2  2015-11
```

weekofyear

Returns the week ordinal of the year.

Returns an expression containing the week ordinal of the year, extracted from a datetime column.

Example:

```
>>> import vaex
>>> import numpy as np
>>> date = np.array(['2009-10-12T03:31:00', '2016-02-11T10:17:34', '2015-11-
↪12T11:34:22'], dtype=np.datetime64)
>>> df = vaex.from_arrays(date=date)
>>> df
  #  date
  0  2009-10-12 03:31:00
  1  2016-02-11 10:17:34
  2  2015-11-12 11:34:22
```

```
>>> df.date.dt.weekofyear
Expression = dt_weekofyear(date)
Length: 3 dtype: int64 (expression)
-----------------------------------
0  42
1   6
2  46
```

year

Extracts the year out of a datetime sample.

Returns an expression containing the year extracted from a datetime column.

Example:

```
>>> import vaex
>>> import numpy as np
>>> date = np.array(['2009-10-12T03:31:00', '2016-02-11T10:17:34', '2015-11-
↪12T11:34:22'], dtype=np.datetime64)
>>> df = vaex.from_arrays(date=date)
>>> df
  #  date
  0  2009-10-12 03:31:00
```

(continues on next page)

(continued from previous page)

```
  1  2016-02-11 10:17:34
  2  2015-11-12 11:34:22
```

```
>>> df.date.dt.year
Expression = dt_year(date)
Length: 3 dtype: int64 (expression)
-----------------------------------
0  2009
1  2016
2  2015
```

7.3.4 Timedelta operations

class vaex.expression.**TimeDelta**(*expression*)

Bases: object

TimeDelta operations

Usually accessed using e.g. *df.delay.td.days*

__init__(*expression*)

Initialize self. See help(type(self)) for accurate signature.

__weakref__

list of weak references to the object (if defined)

days

Number of days in each timedelta sample.

Returns an expression containing the number of days in a timedelta sample.

Example:

```
>>> import vaex
>>> import numpy as np
>>> delta = np.array([17658720110,   11047049384039, 40712636304958, -
↪18161254954], dtype='timedelta64[s]')
>>> df = vaex.from_arrays(delta=delta)
>>> df
  #  delta
  0  204 days +9:12:00
  1  1 days +6:41:10
  2  471 days +5:03:56
  3  -22 days +23:31:15
```

```
>>> df.delta.td.days
Expression = td_days(delta)
Length: 4 dtype: int64 (expression)
-----------------------------------
0  204
1    1
2  471
3  -22
```

microseconds

Number of microseconds (>= 0 and less than 1 second) in each timedelta sample.

Returns an expression containing the number of microseconds in a timedelta sample.

Example:

```
>>> import vaex
>>> import numpy as np
>>> delta = np.array([17658720110,   11047049384039, 40712636304958, -
↪18161254954], dtype='timedelta64[s]')
>>> df = vaex.from_arrays(delta=delta)
>>> df
  #  delta
  0  204 days +9:12:00
  1  1 days +6:41:10
  2  471 days +5:03:56
  3  -22 days +23:31:15
```

```
>>> df.delta.td.microseconds
Expression = td_microseconds(delta)
Length: 4 dtype: int64 (expression)
-----------------------------------
0  290448
1  978582
2   19583
3  709551
```

nanoseconds

Number of nanoseconds (>= 0 and less than 1 microsecond) in each timedelta sample.

Returns an expression containing the number of nanoseconds in a timedelta sample.

Example:

```
>>> import vaex
>>> import numpy as np
>>> delta = np.array([17658720110,   11047049384039, 40712636304958, -
↪18161254954], dtype='timedelta64[s]')
>>> df = vaex.from_arrays(delta=delta)
>>> df
  #  delta
  0  204 days +9:12:00
  1  1 days +6:41:10
  2  471 days +5:03:56
  3  -22 days +23:31:15
```

```
>>> df.delta.td.nanoseconds
Expression = td_nanoseconds(delta)
Length: 4 dtype: int64 (expression)
-----------------------------------
0  384
1   16
2  488
3  616
```

seconds

Number of seconds (>= 0 and less than 1 day) in each timedelta sample.

Returns an expression containing the number of seconds in a timedelta sample.

Example:

```
>>> import vaex
>>> import numpy as np
>>> delta = np.array([17658720110,   11047049384039, 40712636304958, -
↪18161254954], dtype='timedelta64[s]')
>>> df = vaex.from_arrays(delta=delta)
>>> df
  #  delta
  0  204 days +9:12:00
  1  1 days +6:41:10
  2  471 days +5:03:56
  3  -22 days +23:31:15
```

```
>>> df.delta.td.seconds
Expression = td_seconds(delta)
Length: 4 dtype: int64 (expression)
-----------------------------------
0  30436
1  39086
2  28681
3  23519
```

total_seconds()

Total duration of each timedelta sample expressed in seconds.

Returns an expression containing the total number of seconds in a timedelta sample.

Example: >>> import vaex >>> import numpy as np >>> delta = np.array([17658720110, 11047049384039, 40712636304958, -18161254954], dtype='timedelta64[s]') >>> df = vaex.from_arrays(delta=delta) >>> df

delta 0 204 days +9:12:00 1 1 days +6:41:10 2 471 days +5:03:56 3 -22 days +23:31:15

```
>>> df.delta.td.total_seconds()
Expression = td_total_seconds(delta)
Length: 4 dtype: float64 (expression)
-------------------------------------
0  -7.88024e+08
1  -2.55032e+09
2   6.72134e+08
3   2.85489e+08
```

7.3.5 Geo operations

class vaex.geo.**DataFrameAccessorGeo**(*df*)

Bases: object

Geometry/geographic helper methods

Example:

```
>>> df_xyz = df.geo.spherical2cartesian(df.longitude, df.latitude, df.distance)
>>> df_xyz.x.mean()
```

__init__(*df*)

Initialize self. See help(type(self)) for accurate signature.

__weakref__

list of weak references to the object (if defined)

bearing (*lon1*, *lat1*, *lon2*, *lat2*, *bearing='bearing'*, *inplace=False*)
Calculates a bearing, based on http://www.movable-type.co.uk/scripts/latlong.html

cartesian2spherical (*x='x'*, *y='y'*, *z='z'*, *alpha='l'*, *delta='b'*, *distance='distance'*, *radians=False*, *center=None*, *center_name='solar_position'*, *inplace=False*)
Convert cartesian to spherical coordinates.

Parameters

- **x** –
- **y** –
- **z** –
- **alpha** –
- **delta** – name for polar angle, ranges from -90 to 90 (or -pi to pi when radians is True).
- **distance** –
- **radians** –
- **center** –
- **center_name** –

Returns

cartesian_to_polar (*x='x'*, *y='y'*, *radius_out='r_polar'*, *azimuth_out='phi_polar'*, *propagate_uncertainties=False*, *radians=False*, *inplace=False*)
Convert cartesian to polar coordinates

Parameters

- **x** – expression for x
- **y** – expression for y
- **radius_out** – name for the virtual column for the radius
- **azimuth_out** – name for the virtual column for the azimuth angle
- **propagate_uncertainties** – {propagate_uncertainties}
- **radians** – if True, azimuth is in radians, defaults to degrees

Returns

inside_polygon (*y*, *px*, *py*)
Test if points defined by x and y are inside the polygon px, py

Example:

```
>>> import vaex
>>> import numpy as np
>>> df = vaex.from_arrays(x=[1, 2, 3], y=[2, 3, 4])
>>> px = np.array([1.5, 2.5, 2.5, 1.5])
>>> py = np.array([2.5, 2.5, 3.5, 3.5])
>>> df['inside'] = df.geo.inside_polygon(df.x, df.y, px, py)
>>> df
#    x    y  inside
0    1    2  False
1    2    3  True
2    3    4  False
```

Parameters

- **x** – {expression_one}
- **y** – {expression_one}
- **px** – list of x coordinates for the polygon
- **px** – list of y coordinates for the polygon

Returns Expression, which is true if point is inside, else false.

inside_polygons (*y*, *pxs*, *pys*, *any=True*)

Test if points defined by x and y are inside all or any of the the polygons px, py

Example:

```
>>> import vaex
>>> import numpy as np
>>> df = vaex.from_arrays(x=[1, 2, 3], y=[2, 3, 4])
>>> px = np.array([1.5, 2.5, 2.5, 1.5])
>>> py = np.array([2.5, 2.5, 3.5, 3.5])
>>> df['inside'] = df.geo.inside_polygons(df.x, df.y, [px, px + 1], [py, py +
↪1], any=True)
>>> df
#    x    y  inside
0    1    2  False
1    2    3  True
2    3    4  True
```

Parameters

- **x** – {expression_one}
- **y** – {expression_one}
- **pxs** – list of N ndarrays with x coordinates for the polygon, N is the number of polygons
- **pxs** – list of N ndarrays with y coordinates for the polygon
- **any** – return true if in any polygon, or all polygons

Returns Expression , which is true if point is inside, else false.

inside_which_polygon (*y*, *pxs*, *pys*)

Find in which polygon (0 based index) a point resides

Example:

```
>>> import vaex
>>> import numpy as np
>>> df = vaex.from_arrays(x=[1, 2, 3], y=[2, 3, 4])
>>> px = np.array([1.5, 2.5, 2.5, 1.5])
>>> py = np.array([2.5, 2.5, 3.5, 3.5])
>>> df['polygon_index'] = df.geo.inside_which_polygon(df.x, df.y, [px, px +
↪1], [py, py + 1])
>>> df
#    x    y  polygon_index
0    1    2  --
1    2    3  0
2    3    4  1
```

Parameters

- **x** – {expression_one}
- **y** – {expression_one}
- **px** – list of N ndarrays with x coordinates for the polygon, N is the number of polygons
- **px** – list of N ndarrays with y coordinates for the polygon

Returns Expression, 0 based index to which polygon the point belongs (or missing/masked value)

inside_which_polygons (*x*, *y*, *pxss*, *pyss=None*, *any=True*)

Find in which set of polygons (0 based index) a point resides.

If any=True, it will be the first matching polygon set index, if any=False, it will be the first index that matches all polygons in the set.

```
>>> import vaex
>>> import numpy as np
>>> df = vaex.from_arrays(x=[1, 2, 3], y=[2, 3, 4])
>>> px = np.array([1.5, 2.5, 2.5, 1.5])
>>> py = np.array([2.5, 2.5, 3.5, 3.5])
>>> polygonA = [px, py]
>>> polygonB = [px + 1, py + 1]
>>> pxs = [[polygonA, polygonB], [polygonA]]
>>> df['polygon_index'] = df.geo.inside_which_polygons(df.x, df.y, pxs,␣
↪any=True)
>>> df
#    x    y  polygon_index
0    1    2  --
1    2    3  0
2    3    4  0
>>> df['polygon_index'] = df.geo.inside_which_polygons(df.x, df.y, pxs,␣
↪any=False)
>>> df
#    x    y  polygon_index
0    1    2  --
1    2    3  1
2    3    4  --
```

Parameters

- **x** – expression in the form of a string, e.g. 'x' or 'x+y' or vaex expression object, e.g. df.x or df.x+df.y
- **y** – expression in the form of a string, e.g. 'x' or 'x+y' or vaex expression object, e.g. df.x or df.x+df.y
- **px** – list of N ndarrays with x coordinates for the polygon, N is the number of polygons
- **px** – list of N ndarrays with y coordinates for the polygon, if None, the shape of the ndarrays of the last dimention of the x arrays should be 2 (i.e. have the x and y coordinates)
- **any** – test if point it in any polygon (logically or), or all polygons (logically and)

Returns Expression, 0 based index to which polygon the point belongs (or missing/masked value)

project_aitoff (*alpha*, *delta*, *x*, *y*, *radians=True*, *inplace=False*)
Add aitoff (https://en.wikipedia.org/wiki/Aitoff_projection) projection

Parameters

- **alpha** – azimuth angle
- **delta** – polar angle
- **x** – output name for x coordinate
- **y** – output name for y coordinate
- **radians** – input and output in radians (True), or degrees (False)

Returns

project_gnomic (*alpha*, *delta*, *alpha0=0*, *delta0=0*, *x='x'*, *y='y'*, *radians=False*, *postfix="*, *inplace=False*)
Adds a gnomic projection to the DataFrame

rotation_2d (*x*, *y*, *xnew*, *ynew*, *angle_degrees*, *propagate_uncertainties=False*, *inplace=False*)
Rotation in 2d.

Parameters

- **x** (*str*) – Name/expression of x column
- **y** (*str*) – idem for y
- **xnew** (*str*) – name of transformed x column
- **ynew** (*str*) –
- **angle_degrees** (*float*) – rotation in degrees, anti clockwise

Returns

spherical2cartesian (*alpha, delta, distance, xname='x', yname='y', zname='z', propagate_uncertainties=False, center=[0, 0, 0], radians=False, inplace=False*)
Convert spherical to cartesian coordinates.

Parameters

- **alpha** –
- **delta** – polar angle, ranging from the -90 (south pole) to 90 (north pole)
- **distance** – radial distance, determines the units of x, y and z
- **xname** –
- **yname** –
- **zname** –
- **propagate_uncertainties** – If true, will propagate errors for the new virtual columns, see `propagate_uncertainties()` for details
- **center** –
- **radians** –

Returns New dataframe (in inplace is False) with new x,y,z columns

velocity_cartesian2polar (*x='x'*, *y='y'*, *vx='vx'*, *radius_polar=None*, *vy='vy'*, *vr_out='vr_polar'*, *vazimuth_out='vphi_polar'*, *propagate_uncertainties=False*, *inplace=False*)
Convert cartesian to polar velocities.

Parameters

- **x** –
- **y** –
- **vx** –
- **radius_polar** – Optional expression for the radius, may lead to a better performance when given.
- **vy** –
- **vr_out** –
- **vazimuth_out** –
- **propagate_uncertainties** – If true, will propagate errors for the new virtual columns, see `propagate_uncertainties()` for details

Returns

velocity_cartesian2spherical(*x='x'*, *y='y'*, *z='z'*, *vx='vx'*, *vy='vy'*, *vz='vz'*, *vr='vr'*, *vlong='vlong'*, *vlat='vlat'*, *distance=None*, *inplace=False*)

Convert velocities from a cartesian to a spherical coordinate system

TODO: uncertainty propagation

Parameters

- **x** – name of x column (input)
- **y** – y
- **z** – z
- **vx** – vx
- **vy** – vy
- **vz** – vz
- **vr** – name of the column for the radial velocity in the r direction (output)
- **vlong** – name of the column for the velocity component in the longitude direction (output)
- **vlat** – name of the column for the velocity component in the latitude direction, positive points to the north pole (output)
- **distance** – Expression for distance, if not given defaults to sqrt(x**2+y**2+z**2), but if this column already exists, passing this expression may lead to a better performance

Returns

velocity_polar2cartesian(*x='x'*, *y='y'*, *azimuth=None*, *vr='vr_polar'*, *vazimuth='vphi_polar'*, *vx_out='vx'*, *vy_out='vy'*, *propagate_uncertainties=False*, *inplace=False*)

Convert cylindrical polar velocities to Cartesian.

Parameters

- **x** –
- **y** –
- **azimuth** – Optional expression for the azimuth in degrees , may lead to a better performance when given.

- **vr** –
- **vazimuth** –
- **vx_out** –
- **vy_out** –
- **propagate_uncertainties** – If true, will propagate errors for the new virtual columns, see `propagate_uncertainties()` for details

7.3.6 GraphQL operations

class vaex.graphql.**DataFrameAccessorGraphQL**(*df*)

Bases: `object`

Exposes a GraphQL layer to a DataFrame

See the GraphQL example for more usage.

The easiest way to learn to use the GraphQL language/vaex interface is to launch a server, and play with the GraphiQL graphical interface, its autocomplete, and the schema explorer.

We try to stay close to the Hasura API: https://docs.hasura.io/1.0/graphql/manual/api-reference/graphql-api/query.html

__init__(*df*)
Initialize self. See help(type(self)) for accurate signature.

__weakref__
list of weak references to the object (if defined)

execute(**args*, ***kwargs*)
Creates a schema, and execute the query (first argument)

query(*name='df'*)
Creates a graphene query object exposing this DataFrame named *name*

schema(*name='df'*, *auto_camelcase=False*, ***kwargs*)
Creates a graphene schema for this DataFrame

serve(*port=9001*, *address="*, *name='df'*, *verbose=True*)
Serve the DataFrame via a http server

7.3.7 Jupyter widgets accessor

class vaex.jupyter.**DataFrameAccessorWidget**(*df*)

Bases: `object`

__init__(*df*)
Initialize self. See help(type(self)) for accurate signature.

__weakref__
list of weak references to the object (if defined)

data_array(*axes=[]*, *selection=None*, *shared=False*, *display_function=<function display>*, ***kwargs*)
Create a `vaex.jupyter.model.DataArray()` model and `vaex.jupyter.view.DataArray()` widget and links them.

This is a convenience method to create the model and view, and hook them up.

execute_debounced
Schedules an execution of dataframe tasks in the near future (debounced).

expression (*value=None*, *label='Custom expression'*)
Create a widget to edit a vaex expression.

If value is an **:py:'vaex.jupyter.model.Axis'** object, its expression will be (bi-directionally) linked to the widget.

Parameters value – Valid expression (string or Expression object), or Axis

7.4 vaex-jupyter

vaex.jupyter.**debounced** (*delay_seconds=0.5*, *skip_gather=False*, *on_error=None*, *reentrant=True*)
A decorator to debounce many method/function call into 1 call.

Note: this only works in an async environment, such as a Jupyter notebook context. Outside of this context, calling *flush()* will execute pending calls.

Parameters

- **delay_seconds** (*float*) – The amount of seconds that should pass without any call, before the (final) call will be executed.
- **method** (*bool*) – The decorator should know if the callable is a a method or not, otherwise the debounced is on a per-class basis.
- **skip_gather** (*bool*) – The decorated function will be be waited for when calling vaex.jupyter.gather()
- **on_error** – callback function that takes an exception as argument.
- **reentrant** (*bool*) – reentrant function or not

vaex.jupyter.**flush** (*recursive_counts=-1*, *ignore_exceptions=False*, *all=False*)
Run all non-executed debounced functions.

If execution of debounced calls lead to scheduling of new calls, they will be recursively executed, with a limit or recursive_counts calls. recursive_counts=-1 means infinite.

vaex.jupyter.**interactive_selection** (*df*)

7.4.1 vaex.jupyter.model

7.4.2 vaex.jupyter.view

7.4.3 vaex.jupyter.widgets

class vaex.jupyter.widgets.**ColumnExpressionAdder** (**args*, ***kwargs*)
Bases: *vaex.jupyter.widgets.ColumnPicker*

component
A trait which allows any value.

target
A trait for unicode strings.

vue_menu_click (*data*)

class `vaex.jupyter.widgets.`**`ColumnList`**(*df*, ***kwargs*)
Bases: `ipyvuetify.VuetifyTemplate.VuetifyTemplate`, `vaex.jupyter.traitlets.ColumnsMixin`

`column_filter`
A trait for unicode strings.

`dialog_open`
A boolean (True, False) trait.

`editor`
A trait which allows any value.

`editor_open`
A boolean (True, False) trait.

`template`
A trait for unicode strings.

`tooltip`
A trait for unicode strings.

`valid_expression`
A boolean (True, False) trait.

`vue_add_virtual_column`(*data*)

`vue_column_click`(*data*)

`vue_save_column`(*data*)

class `vaex.jupyter.widgets.`**`ColumnPicker`**(**args*, ***kwargs*)
Bases: `ipyvuetify.VuetifyTemplate.VuetifyTemplate`, `vaex.jupyter.traitlets.ColumnsMixin`

`label`
A trait for unicode strings.

`template`
A trait for unicode strings.

`value`
A trait for unicode strings.

class `vaex.jupyter.widgets.`**`ColumnSelectionAdder`**(**args*, ***kwargs*)
Bases: *`vaex.jupyter.widgets.ColumnPicker`*

`component`
A trait which allows any value.

`target`
A trait for unicode strings.

`vue_menu_click`(*data*)

class `vaex.jupyter.widgets.`**`ContainerCard`**(**args*, ***kwargs*)
Bases: `ipyvuetify.VuetifyTemplate.VuetifyTemplate`

`card_props`
An instance of a Python dict.

`controls`
An instance of a Python list.

main
A trait which allows any value.

main_props
An instance of a Python dict.

show_controls
A boolean (True, False) trait.

subtitle
A trait for unicode strings.

text
A trait for unicode strings.

title
A trait for unicode strings.

class vaex.jupyter.widgets.**Counter**(**args*, ***kwargs*)
Bases: ipyvuetify.VuetifyTemplate.VuetifyTemplate

characters
An instance of a Python list.

format
A trait for unicode strings.

postfix
A trait for unicode strings.

prefix
A trait for unicode strings.

template
A trait for unicode strings.

value
An int trait.

class vaex.jupyter.widgets.**Expression**(***kwargs*)
Bases: ipyvuetify.generated.TextField.TextField

Public constructor

check_expression()

df
A trait which allows any value.

valid
A boolean (True, False) trait.

value

class vaex.jupyter.widgets.**ExpressionSelectionTextArea**(***kwargs*)
Bases: *vaex.jupyter.widgets.Expression*

selection_name
A trait which allows any value.

update_custom_selection

update_selection()

`vaex.jupyter.widgets.`**`ExpressionTextArea`**
alias of `vaex.jupyter.widgets.Expression`

`class` `vaex.jupyter.widgets.`**`Html`**(***kwargs*)
Bases: `ipyvuetify.Html.Html`

Public constructor

`class` `vaex.jupyter.widgets.`**`LinkList`**(**args*, ***kwargs*)
Bases: `vaex.jupyter.widgets.VuetifyTemplate`

`items`
An instance of a Python list.

`class` `vaex.jupyter.widgets.`**`PlotTemplate`**(**args*, ***kwargs*)
Bases: `ipyvuetify.VuetifyTemplate.VuetifyTemplate`

`button_text`
A trait for unicode strings.

`clipped`
A boolean (True, False) trait.

`components`
An instance of a Python dict.

`dark`
A boolean (True, False) trait.

`drawer`
A boolean (True, False) trait.

`drawers`
A trait which allows any value.

`floating`
A boolean (True, False) trait.

`items`
An instance of a Python list.

`mini`
A boolean (True, False) trait.

`model`
A trait which allows any value.

`new_output`
A boolean (True, False) trait.

`show_output`
A boolean (True, False) trait.

`template`
A trait for unicode strings.

`title`
A trait for unicode strings.

`type`
A trait for unicode strings.

`class` `vaex.jupyter.widgets.`**`ProgressCircularNoAnimation`**(**args*, ***kwargs*)
Bases: `ipyvuetify.VuetifyTemplate.VuetifyTemplate`

v-progress-circular that avoids animations

color
A trait for unicode strings.

hidden
A boolean (True, False) trait.

parts
An instance of a Python list.

size
An int trait.

template
A trait for unicode strings.

text
A trait for unicode strings.

value
A float trait.

width
An int trait.

class vaex.jupyter.widgets.**Selection**(**args*, ***kwargs*)
Bases: ipyvuetify.VuetifyTemplate.VuetifyTemplate

df
A trait which allows any value.

name
A trait for unicode strings.

value
A trait for unicode strings.

class vaex.jupyter.widgets.**SelectionEditor**(**args*, ***kwargs*)
Bases: ipyvuetify.VuetifyTemplate.VuetifyTemplate

adder
A trait which allows any value.

components
An instance of a Python dict.

df
A trait which allows any value.

input
A trait which allows any value.

on_close
A trait which allows any value.

template
A trait for unicode strings.

class vaex.jupyter.widgets.**Status**(**args*, ***kwargs*)
Bases: ipyvuetify.VuetifyTemplate.VuetifyTemplate

template
A trait for unicode strings.

value
A trait for unicode strings.

class vaex.jupyter.widgets.**ToolsSpeedDial**(**args*, ***kwargs*)
Bases: ipyvuetify.VuetifyTemplate.VuetifyTemplate

children
An instance of a Python list.

expand
A boolean (True, False) trait.

items
A trait which allows any value.

template
A trait for unicode strings.

value
A trait for unicode strings.

vue_action(*data*)

class vaex.jupyter.widgets.**ToolsToolbar**(**args*, ***kwargs*)
Bases: ipyvuetify.VuetifyTemplate.VuetifyTemplate

interact_items
A trait which allows any value.

interact_value
A trait for unicode strings.

supports_normalize
A boolean (True, False) trait.

supports_transforms
A boolean (True, False) trait.

transform_items
An instance of a Python list.

transform_value
A trait for unicode strings.

class vaex.jupyter.widgets.**UsesVaexComponents**(**args*, ***kwargs*)
Bases: traitlets.traitlets.HasTraits

class vaex.jupyter.widgets.**VirtualColumnEditor**(**args*, ***kwargs*)
Bases: ipyvuetify.VuetifyTemplate.VuetifyTemplate

adder
A trait which allows any value.

column_name
A trait for unicode strings.

components
An instance of a Python dict.

df
A trait which allows any value.

editor
A trait which allows any value.

on_close
A trait which allows any value.

save_column()

template
A trait for unicode strings.

class vaex.jupyter.widgets.**VuetifyTemplate**(**args*, ***kwargs*)
Bases: ipyvuetify.VuetifyTemplate.VuetifyTemplate

vaex.jupyter.widgets.**component**(*name*)

vaex.jupyter.widgets.**load_template**(*filename*)

7.5 Machine learning with vaex.ml

See the *ML tutorial* an introduction, and the *ML examples* for more advanced usage.

7.5.1 Scikit-learn

vaex.ml.sklearn.IncrementalPredictor([. . .])	This class wraps any scikit-learn estimator (a.k.a predictions) that has a *.partial_fit* method, and makes it a vaex pipeline object.
vaex.ml.sklearn.Predictor([features, model, . . .])	This class wraps any scikit-learn estimator (a.k.a predictor) making it a vaex pipeline object.

class vaex.ml.sklearn.**IncrementalPredictor**(*batch_size=1000000*, *features=traitlets.Undefined*, *model=None*, *num_epochs=1*, *partial_fit_kwargs=traitlets.Undefined*, *prediction_name='prediction'*, *shuffle=False*, *target=''*)
Bases: vaex.ml.state.HasState

This class wraps any scikit-learn estimator (a.k.a predictions) that has a *.partial_fit* method, and makes it a vaex pipeline object.

By wrapping "on-line" scikit-learn estimators with this class, they become a vaex pipeline object. Thus, they can take full advantage of the serialization and pipeline system of vaex. While the underlying estimator need to call the *.partial_fit* method, this class contains the standard *.fit* method, and the rest happens behind the scenes. One can also iterate over the data multiple times (epochs), and optionally shuffle each batch before it is sent to the estimator. The *predict* method returns a numpy array, while the *transform* method adds the prediction as a virtual column to a vaex DataFrame.

Note: the *.fit* method will use as much memory as needed to copy one batch of data, while the *.predict* method will require as much memory as needed to output the predictions as a numpy array. The *transform* method is evaluated lazily, and no memory copies are made.

Note: we are using normal sklearn without modifications here.

Example:

```
>>> import vaex
>>> import vaex.ml
```

(continues on next page)

(continued from previous page)

```
>>> from vaex.ml.sklearn import IncrementalPredictor
>>> from sklearn.linear_model import SGDRegressor
>>>
>>> df = vaex.example()
>>>
>>> features = df.column_names[:6]
>>> target = 'FeH'
>>>
>>> standard_scaler = vaex.ml.StandardScaler(features=features)
>>> df = standard_scaler.fit_transform(df)
>>>
>>> features = df.get_column_names(regex='^standard')
>>> model = SGDRegressor(learning_rate='constant', eta0=0.01, random_state=42)
>>>
>>> incremental = IncrementalPredictor(model=model,
...                                    features=features,
...                                    target=target,
...                                    batch_size=10_000,
...                                    num_epochs=3,
...                                    shuffle=True,
...                                    prediction_name='pred_FeH')
>>> incremental.fit(df=df)
>>> df = incremental.transform(df)
>>> df.head(5)[['FeH', 'pred_FeH']]
  #        FeH    pred_FeH
  0  -2.30923     -1.66226
  1  -1.78874     -1.68218
  2  -0.761811    -1.59562
  3  -1.52088     -1.62225
  4  -2.65534     -1.61991
```

Parameters

- **batch_size** – Number of samples to be sent to the model in each batch.
- **features** – List of features to use.
- **model** – A scikit-learn estimator with a *.fit_predict* method.
- **num_epochs** – Number of times each batch is sent to the model.
- **partial_fit_kwargs** – A dictionary of key word arguments to be passed on to the *fit_predict* method of the *model*.
- **prediction_name** – The name of the virtual column housing the predictions.
- **shuffle** – If True, shuffle the samples before sending them to the model.
- **target** – The name of the target column.

batch_size
An int trait.

features
An instance of a Python list.

fit (*df*, *progress=None*)
Fit the IncrementalPredictor to the DataFrame.

Parameters

- **df** – A vaex DataFrame containing the features and target on which to train the model.
- **progress** – If True, display a progressbar which tracks the training progress.

model
A trait which allows any value.

num_epochs
An int trait.

partial_fit_kwargs
An instance of a Python dict.

predict (*df*)
Get an in-memory numpy array with the predictions of the SKLearnPredictor.self

Parameters df – A vaex DataFrame, containing the input features.

Returns A in-memory numpy array containing the SKLearnPredictor predictions.

Return type numpy.array

prediction_name
A trait for unicode strings.

shuffle
A boolean (True, False) trait.

target
A trait for unicode strings.

transform (*df*)
Transform a DataFrame such that it contains the predictions of the IncrementalPredictor. in form of a virtual column.

Parameters df – A vaex DataFrame.

Return copy A shallow copy of the DataFrame that includes the IncrementalPredictor prediction as a virtual column.

Return type *DataFrame*

class vaex.ml.sklearn.**Predictor** (*features=traitlets.Undefined, model=None, prediction_name='prediction', target=''*)
Bases: vaex.ml.state.HasState

This class wraps any scikit-learn estimator (a.k.a predictor) making it a vaex pipeline object.

By wrapping any scikit-learn estimators with this class, it becomes a vaex pipeline object. Thus, it can take full advantage of the serialization and pipeline system of vaex. One can use the *predict* method to get a numpy array as an output of a fitted estimator, or the *transform* method do add such a prediction to a vaex DataFrame as a virtual column.

Note that a full memory copy of the data used is created when the *fit* and *predict* are called. The *transform* method is evaluated lazily.

The scikit-learn estimators themselves are not modified at all, they are taken from your local installation of scikit-learn.

Example:

```
>>> import vaex.ml
>>> from vaex.ml.sklearn import Predictor
>>> from sklearn.linear_model import LinearRegression
```

(continues on next page)

(continued from previous page)

```
>>> df = vaex.ml.datasets.load_iris()
>>> features = ['sepal_width', 'petal_length', 'sepal_length']
>>> df_train, df_test = df.ml.train_test_split()
>>> model = Predictor(model=LinearRegression(), features=features, target='petal_
↪width', prediction_name='pred')
>>> model.fit(df_train)
>>> df_train = model.transform(df_train)
>>> df_train.head(3)
 #    sepal_length    sepal_width    petal_length    petal_width    class_      ␣
↪pred
 0             5.4              3             4.5            1.5         1  1.
↪64701
 1             4.8            3.4             1.6            0.2         0  0.
↪352236
 2             6.9            3.1             4.9            1.5         1  1.
↪59336
>>> df_test = model.transform(df_test)
>>> df_test.head(3)
 #    sepal_length    sepal_width    petal_length    petal_width    class_     ␣
↪pred
 0             5.9              3             4.2            1.5         1  1.
↪39437
 1             6.1              3             4.6            1.4         1  1.
↪56469
 2             6.6            2.9             4.6            1.3         1  1.
↪44276
```

Parameters

- **features** – List of features to use.
- **model** – A scikit-learn estimator.
- **prediction_name** – The name of the virtual column housing the predictions.
- **target** – The name of the target column.

features
An instance of a Python list.

fit (*df*, ***kwargs*)
Fit the SKLearnPredictor to the DataFrame.

Parameters df – A vaex DataFrame containing the features and target on which to train the model.

model
A trait which allows any value.

predict (*df*)
Get an in-memory numpy array with the predictions of the SKLearnPredictor.self

Parameters df – A vaex DataFrame, containing the input features.

Returns A in-memory numpy array containing the SKLearnPredictor predictions.

Return type numpy.array

prediction_name
A trait for unicode strings.

target
A trait for unicode strings.

transform (*df*)
Transform a DataFrame such that it contains the predictions of the SKLearnPredictor. in form of a virtual column.

Parameters **df** – A vaex DataFrame.

Return copy A shallow copy of the DataFrame that includes the SKLearnPredictor prediction as a virtual column.

Return type *DataFrame*

class vaex.ml.sklearn.**SKLearnPredictor** (*features=traitlets.Undefined*, *model=None*, *prediction_name='prediction'*, *target=''*)
Bases: *vaex.ml.sklearn.Predictor*

Parameters

- **features** – List of features to use.
- **model** – A scikit-learn estimator.
- **prediction_name** – The name of the virtual column housing the predictions.
- **target** – The name of the target column.

7.5.2 Clustering

vaex.ml.cluster.KMeans([cluster_centers, ...])	The KMeans clustering algorithm.

class vaex.ml.cluster.**KMeans** (*cluster_centers=traitlets.Undefined*, *features=traitlets.Undefined*, *inertia=None*, *init='random'*, *max_iter=300*, *n_clusters=2*, *n_init=1*, *prediction_label='prediction_kmeans'*, *random_state=None*, *verbose=False*)
Bases: vaex.ml.state.HasState

The KMeans clustering algorithm.

Example:

```
>>> import vaex.ml
>>> import vaex.ml.cluster
>>> df = vaex.ml.datasets.load_iris()
>>> features = ['sepal_width', 'petal_length', 'sepal_length', 'petal_width']
>>> cls = vaex.ml.cluster.KMeans(n_clusters=3, features=features, init='random',
↪max_iter=10)
>>> cls.fit(df)
>>> df = cls.transform(df)
>>> df.head(5)
 #    sepal_width    petal_length    sepal_length    petal_width    class_
↪prediction_kmeans
 0              3             4.2             5.9            1.5         1
↪              2
 1              3             4.6             6.1            1.4         1
↪              2
 2            2.9             4.6             6.6            1.3         1
↪              2
```

(continues on next page)

(continued from previous page)

```
3          3.3          5.7          6.7          2.1          2          ␣
↪          0
4          4.2          1.4          5.5          0.2          0          ␣
↪          1
```

Parameters

- **cluster_centers** – Coordinates of cluster centers.
- **features** – List of features to cluster.
- **inertia** – Sum of squared distances of samples to their closest cluster center.
- **init** – Method for initializing the centroids.
- **max_iter** – Maximum number of iterations of the KMeans algorithm for a single run.
- **n_clusters** – Number of clusters to form.
- **n_init** – Number of centroid initializations. The KMeans algorithm will be run for each initialization, and the final results will be the best output of the n_init consecutive runs in terms of inertia.
- **prediction_label** – The name of the virtual column that houses the cluster labels for each point.
- **random_state** – Random number generation for centroid initialization. If an int is specified, the randomness becomes deterministic.
- **verbose** – If True, enable verbosity mode.

fit (*dataframe*)

Fit the KMeans model to the dataframe.

Parameters dataframe – A vaex DataFrame.

transform (*dataframe*)

Label a DataFrame with a fitted KMeans model.

Parameters dataframe – A vaex DataFrame.

Returns copy A shallow copy of the DataFrame that includes the cluster labels.

Return type *DataFrame*

7.5.3 Transformers/encoders

vaex.ml.transformations.FrequencyEncoder([…])	Encode categorical columns by the frequency of their respective samples.
vaex.ml.transformations.LabelEncoder([…])	Encode categorical columns with integer values between 0 and num_classes-1.
vaex.ml.transformations.MaxAbsScaler([…])	Scale features by their maximum absolute value.
vaex.ml.transformations.MinMaxScaler([…])	Will scale a set of features to a given range.
vaex.ml.transformations.OneHotEncoder([…])	Encode categorical columns according ot the One-Hot scheme.

Continued on next page

Table 6 – continued from previous page

`vaex.ml.transformations.PCA`([features, ...])	Transform a set of features using a Principal Component Analysis.
`vaex.ml.transformations.RobustScaler`([...])	The RobustScaler removes the median and scales the data according to a given percentile range.
`vaex.ml.transformations.StandardScaler`([...])	Standardize features by removing thir mean and scaling them to unit variance.
`vaex.ml.transformations.CycleTransformer`([...])	A strategy for transforming cyclical features (e.g.
`vaex.ml.transformations.BayesianTargetEncoder`(...)	Encode categorical variables with a Bayesian Target Encoder.
`vaex.ml.transformations.WeightOfEvidenceEncoder`(...)	Encode categorical variables with a Weight of Evidence Encoder.

class `vaex.ml.transformations.`**`FrequencyEncoder`**(*features=traitlets.Undefined, mappings_=traitlets.Undefined, prefix='frequency_encoded_', unseen='nan'*)

Bases: `vaex.ml.transformations.Transformer`

Encode categorical columns by the frequency of their respective samples.

Example:

```
>>> import vaex
>>> df = vaex.from_arrays(color=['red', 'green', 'green', 'blue', 'red', 'green'])
>>> df
 #  color
 0  red
 1  green
 2  green
 3  blue
 4  red
>>> encoder = vaex.ml.FrequencyEncoder(features=['color'])
>>> encoder.fit_transform(df)
 #  color      frequency_encoded_color
 0  red                       0.333333
 1  green                     0.5
 2  green                     0.5
 3  blue                      0.166667
 4  red                       0.333333
 5  green                     0.5
```

Parameters

- **`features`** – List of features to transform.
- **`prefix`** – Prefix for the names of the transformed features.
- **`unseen`** – Strategy to deal with unseen values.

`fit`(*df*)

Fit FrequencyEncoder to the DataFrame.

Parameters **`df`** – A vaex DataFrame.

`transform`(*df*)

Transform a DataFrame with a fitted FrequencyEncoder.

Parameters **df** – A vaex DataFrame.

Returns A shallow copy of the DataFrame that includes the encodings.

Return type *DataFrame*

class vaex.ml.transformations.**LabelEncoder**(*allow_unseen=False*, *features=traitlets.Undefined*, *prefix='label_encoded_'*)

Bases: vaex.ml.transformations.Transformer

Encode categorical columns with integer values between 0 and num_classes-1.

Example:

```
>>> import vaex
>>> df = vaex.from_arrays(color=['red', 'green', 'green', 'blue', 'red'])
>>> df
 #  color
 0  red
 1  green
 2  green
 3  blue
 4  red
>>> encoder = vaex.ml.LabelEncoder(features=['color'])
>>> encoder.fit_transform(df)
 #  color      label_encoded_color
 0  red                          2
 1  green                        1
 2  green                        1
 3  blue                         0
 4  red                          2
```

Parameters

- **allow_unseen** – If True, unseen values will be encoded with -1, otherwise an error is raised
- **features** – List of features to transform.
- **prefix** – Prefix for the names of the transformed features.

fit(*df*)

Fit LabelEncoder to the DataFrame.

Parameters **df** – A vaex DataFrame.

transform(*df*)

Transform a DataFrame with a fitted LabelEncoder.

Parameters **df** – A vaex DataFrame.

Returns: :return copy: A shallow copy of the DataFrame that includes the encodings. :rtype: DataFrame

class vaex.ml.transformations.**MaxAbsScaler**(*features=traitlets.Undefined*, *prefix='absmax_scaled_'*)

Bases: vaex.ml.transformations.Transformer

Scale features by their maximum absolute value.

Example:

```
>>> import vaex
>>> df = vaex.from_arrays(x=[2,5,7,2,15], y=[-2,3,0,0,10])
>>> df
 #    x    y
 0    2   -2
 1    5    3
 2    7    0
 3    2    0
 4   15   10
>>> scaler = vaex.ml.MaxAbsScaler(features=['x', 'y'])
>>> scaler.fit_transform(df)
 #    x    y    absmax_scaled_x    absmax_scaled_y
 0    2   -2           0.133333               -0.2
 1    5    3           0.333333                0.3
 2    7    0           0.466667                0
 3    2    0           0.133333                0
 4   15   10           1                       1
```

Parameters

- **features** – List of features to transform.
- **prefix** – Prefix for the names of the transformed features.

fit (*df*)

Fit MinMaxScaler to the DataFrame.

Parameters **df** – A vaex DataFrame.

transform (*df*)

Transform a DataFrame with a fitted MaxAbsScaler.

Parameters **df** – A vaex DataFrame.

Return copy a shallow copy of the DataFrame that includes the scaled features.

Return type *DataFrame*

class vaex.ml.transformations.**MinMaxScaler** (*feature_range=traitlets.Undefined, features=traitlets.Undefined, prefix='minmax_scaled_'*)

Bases: vaex.ml.transformations.Transformer

Will scale a set of features to a given range.

Example:

```
>>> import vaex
>>> df = vaex.from_arrays(x=[2,5,7,2,15], y=[-2,3,0,0,10])
>>> df
 #    x    y
 0    2   -2
 1    5    3
 2    7    0
 3    2    0
 4   15   10
>>> scaler = vaex.ml.MinMaxScaler(features=['x', 'y'])
>>> scaler.fit_transform(df)
 #    x    y    minmax_scaled_x    minmax_scaled_y
 0    2   -2           0                    0
```

(continues on next page)

(continued from previous page)

```
1    5    3            0.230769             0.416667
2    7    0            0.384615             0.166667
3    2    0            0                    0.166667
4   15   10            1                    1
```

Parameters

- **feature_range** – The range the features are scaled to.
- **features** – List of features to transform.
- **prefix** – Prefix for the names of the transformed features.

fit (*df*)

Fit MinMaxScaler to the DataFrame.

Parameters **df** – A vaex DataFrame.

transform (*df*)

Transform a DataFrame with a fitted MinMaxScaler.

Parameters **df** – A vaex DataFrame.

Return copy a shallow copy of the DataFrame that includes the scaled features.

Return type *DataFrame*

class vaex.ml.transformations.**OneHotEncoder** (*features=traitlets.Undefined*, *one=1*, *prefix=''*, *zero=0*)

Bases: vaex.ml.transformations.Transformer

Encode categorical columns according ot the One-Hot scheme.

Example:

```
>>> import vaex
>>> df = vaex.from_arrays(color=['red', 'green', 'green', 'blue', 'red'])
>>> df
 #  color
 0  red
 1  green
 2  green
 3  blue
 4  red
>>> encoder = vaex.ml.OneHotEncoder(features=['color'])
>>> encoder.fit_transform(df)
 #  color      color_blue    color_green    color_red
 0  red                 0              0            1
 1  green               0              1            0
 2  green               0              1            0
 3  blue                1              0            0
 4  red                 0              0            1
```

Parameters

- **features** – List of features to transform.
- **one** – Value to encode when a category is present.
- **prefix** – Prefix for the names of the transformed features.

- **zero** – Value to encode when category is absent.

fit (*df*)
Fit OneHotEncoder to the DataFrame.

Parameters df – A vaex DataFrame.

transform (*df*)
Transform a DataFrame with a fitted OneHotEncoder.

Parameters df – A vaex DataFrame.

Returns A shallow copy of the DataFrame that includes the encodings.

Return type *DataFrame*

class vaex.ml.transformations.**PCA** (*features=traitlets.Undefined, n_components=0, prefix='PCA_', progress=False*)
Bases: vaex.ml.transformations.Transformer

Transform a set of features using a Principal Component Analysis.

Example:

```
>>> import vaex
>>> df = vaex.from_arrays(x=[2,5,7,2,15], y=[-2,3,0,0,10])
>>> df
 #    x    y
 0    2   -2
 1    5    3
 2    7    0
 3    2    0
 4   15   10
>>> pca = vaex.ml.PCA(n_components=2, features=['x', 'y'])
>>> pca.fit_transform(df)
 #     x     y        PCA_0       PCA_1
 0     2    -2     5.92532     0.413011
 1     5     3     0.380494   -1.39112
 2     7     0     0.840049    2.18502
 3     2     0     4.61287    -1.09612
 4    15    10   -11.7587     -0.110794
```

Parameters

- **features** – List of features to transform.
- **n_components** – Number of components to retain. If None, all the components will be retained.
- **prefix** – Prefix for the names of the transformed features.
- **progress** – If True, display a progressbar of the PCA fitting process.

fit (*df*)
Fit the PCA model to the DataFrame.

Parameters df – A vaex DataFrame.

transform (*df, n_components=None*)
Apply the PCA transformation to the DataFrame.

Parameters

- **df** – A vaex DataFrame.
- **n_components** – The number of PCA components to retain.

Return copy A shallow copy of the DataFrame that includes the PCA components.

Return type *DataFrame*

class vaex.ml.transformations.**RobustScaler**(*features=traitlets.Undefined, percentile_range=traitlets.Undefined, prefix='robust_scaled_', with_centering=True, with_scaling=True*)

Bases: vaex.ml.transformations.Transformer

The RobustScaler removes the median and scales the data according to a given percentile range. By default, the scaling is done between the 25th and the 75th percentile. Centering and scaling happens independently for each feature (column).

Example:

```
>>> import vaex
>>> df = vaex.from_arrays(x=[2,5,7,2,15], y=[-2,3,0,0,10])
>>> df
 #    x    y
 0    2   -2
 1    5    3
 2    7    0
 3    2    0
 4   15   10
>>> scaler = vaex.ml.MaxAbsScaler(features=['x', 'y'])
>>> scaler.fit_transform(df)
 #    x    y    robust_scaled_x    robust_scaled_y
 0    2   -2       -0.333686              -0.266302
 1    5    3       -0.000596934            0.399453
 2    7    0        0.221462               0
 3    2    0       -0.333686               0
 4   15   10        1.1097                 1.33151
```

Parameters

- **features** – List of features to transform.
- **percentile_range** – The percentile range to which to scale each feature to.
- **prefix** – Prefix for the names of the transformed features.
- **with_centering** – If True, remove the median.
- **with_scaling** – If True, scale each feature between the specified percentile range.

fit(*df*)

Fit RobustScaler to the DataFrame.

Parameters **df** – A vaex DataFrame.

transform(*df*)

Transform a DataFrame with a fitted RobustScaler.

Parameters **df** – A vaex DataFrame.

Returns copy a shallow copy of the DataFrame that includes the scaled features.

Return type *DataFrame*

class vaex.ml.transformations.**StandardScaler**(*features=traitlets.Undefined, prefix='standard_scaled_', with_mean=True, with_std=True*)

Bases: `vaex.ml.transformations.Transformer`

Standardize features by removing thir mean and scaling them to unit variance.

Example:

```
>>> import vaex
>>> df = vaex.from_arrays(x=[2,5,7,2,15], y=[-2,3,0,0,10])
>>> df
 #    x    y
 0    2   -2
 1    5    3
 2    7    0
 3    2    0
 4   15   10
>>> scaler = vaex.ml.StandardScaler(features=['x', 'y'])
>>> scaler.fit_transform(df)
 #    x    y    standard_scaled_x    standard_scaled_y
 0    2   -2            -0.876523            -0.996616
 1    5    3            -0.250435             0.189832
 2    7    0             0.166957            -0.522037
 3    2    0            -0.876523            -0.522037
 4   15   10              1.83652              1.85086
```

Parameters

- **features** – List of features to transform.
- **prefix** – Prefix for the names of the transformed features.
- **with_mean** – If True, remove the mean from each feature.
- **with_std** – If True, scale each feature to unit variance.

fit(*df*)

Fit StandardScaler to the DataFrame.

Parameters df – A vaex DataFrame.

transform(*df*)

Transform a DataFrame with a fitted StandardScaler.

Parameters df – A vaex DataFrame.

Returns copy a shallow copy of the DataFrame that includes the scaled features.

Return type *DataFrame*

class vaex.ml.transformations.**CycleTransformer**(*features=traitlets.Undefined, n=0, prefix_x='', prefix_y='', suffix_x='_x', suffix_y='_y'*)

Bases: `vaex.ml.transformations.Transformer`

A strategy for transforming cyclical features (e.g. angles, time).

Think of each feature as an angle of a unit circle in polar coordinates, and then and then obtaining the x and y coordinate projections, or the cos and sin components respectively.

Suitable for a variaty of machine learning tasks. It preserves the cyclical continuity of the feature. Inspired by: http://blog.davidkaleko.com/feature-engineering-cyclical-features.html

Example:

```
>>> import vaex
>>> import vaex.ml
>>> df = vaex.from_arrays(days=[0, 1, 2, 3, 4, 5, 6])
>>> cyctrans = vaex.ml.CycleTransformer(n=7, features=['days'])
>>> cyctrans.fit_transform(df)
  #    days      days_x      days_y
  0       0    1           0
  1       1    0.62349     0.781831
  2       2   -0.222521    0.974928
  3       3   -0.900969    0.433884
  4       4   -0.900969   -0.433884
  5       5   -0.222521   -0.974928
  6       6    0.62349    -0.781831
```

Parameters

- **features** – List of features to transform.
- **n** – The number of elements in one cycle.
- **prefix_x** – Prefix for the x-component of the transformed features.
- **prefix_y** – Prefix for the y-component of the transformed features.
- **suffix_x** – Suffix for the x-component of the transformed features.
- **suffix_y** – Suffix for the y-component of the transformed features.

fit(*df*)

Fit a CycleTransformer to the DataFrame.

This is a dummy method, as it is not needed for the transformation to be applied.

Parameters **df** – A vaex DataFrame.

transform(*df*)

Transform a DataFrame with a CycleTransformer.

Parameters **df** – A vaex DataFrame.

class vaex.ml.transformations.**BayesianTargetEncoder**(**args*, ***kwargs*)

Bases: vaex.ml.transformations.Transformer

Encode categorical variables with a Bayesian Target Encoder.

The categories are encoded by the mean of their target value, which is adjusted by the global mean value of the target variable using a Bayesian schema. For a larger *weight* value, the target encodings are smoothed toward the global mean, while for a *weight* of 0, the encodings are just the mean target value per class.

Reference: https://www.wikiwand.com/en/Bayes_estimator#/Practical_example_of_Bayes_estimators

Example:

```
>>> import vaex
>>> import vaex.ml
>>> df = vaex.from_arrays(x=['a', 'a', 'a', 'a', 'b', 'b', 'b', 'b'],
...                       y=[1, 1, 1, 0, 0, 0, 0, 1])
>>> target_encoder = vaex.ml.BayesianTargetEncoder(features=['x'], weight=4)
>>> target_encoder.fit_transform(df, 'y')
  #  x       y    mean_encoded_x
```

(continues on next page)

(continued from previous page)

```
 0   a       1             0.625
 1   a       1             0.625
 2   a       1             0.625
 3   a       0             0.625
 4   b       0             0.375
 5   b       0             0.375
 6   b       0             0.375
 7   b       1             0.375
```

fit (*df*)
Fit a BayesianTargetEncoder to the DataFrame.

Parameters **df** – A vaex DataFrame

transform (*df*)
Transform a DataFrame with a fitted BayesianTargetEncoder.

Parameters **df** – A vaex DataFrame.

Returns A shallow copy of the DataFrame that includes the encodings.

Return type *DataFrame*

class vaex.ml.transformations.**WeightOfEvidenceEncoder** (**args*, ***kwargs*)
Bases: vaex.ml.transformations.Transformer

Encode categorical variables with a Weight of Evidence Encoder.

Weight of Evidence measures how well a particular feature supports the given hypothesis (i.e. the target variable). With this encoder, each category in a categorical feature is encoded by its "strength" i.e. Weight of Evidence value. The target feature can be a boolean or numerical column, where True/1 is seen as 'Good', and False/0 is seen as 'Bad'

Reference: https://www.listendata.com/2015/03/weight-of-evidence-woe-and-information.html

Example:

```
>>> import vaex
>>> import vaex.ml
>>> df = vaex.from_arrays(x=['a', 'a', 'b', 'b', 'b', 'c', 'c'],
...                       y=[1, 1, 0, 0, 1, 1, 0])
>>> woe_encoder = vaex.ml.WeightOfEvidenceEncoder(target='y', features=['x'])
>>> woe_encoder.fit_transform(df)
 #   x       y     mean_encoded_x
 0   a       1          13.8155
 1   a       1          13.8155
 2   b       0          -0.693147
 3   b       0          -0.693147
 4   b       1          -0.693147
 5   c       1           0
 6   c       0           0
```

fit (*df*)
Fit a WeightOfEvidenceEncoder to the DataFrame.

Parameters **df** – A vaex DataFrame

transform (*df*)
Transform a DataFrame with a fitted WeightOfEvidenceEncoder.

Parameters **df** – A vaex DataFrame.

Returns A shallow copy of the DataFrame that includes the encodings.

Return type *DataFrame*

7.5.4 Boosted trees

`vaex.ml.lightgbm.LightGBMModel`([features, ...])	The LightGBM algorithm.
`vaex.ml.xgboost.XGBoostModel`([features, ...])	The XGBoost algorithm.

class vaex.ml.lightgbm.**LightGBMModel**(*features=traitlets.Undefined, num_boost_round=0, params=traitlets.Undefined, prediction_name='lightgbm_prediction', target=''*)

Bases: vaex.ml.state.HasState

The LightGBM algorithm.

This class provides an interface to the LightGBM algorithm, with some optimizations for better memory efficiency when training large datasets. The algorithm itself is not modified at all.

LightGBM is a fast gradient boosting algorithm based on decision trees and is mainly used for classification, regression and ranking tasks. It is under the umbrella of the Distributed Machine Learning Toolkit (DMTK) project of Microsoft. For more information, please visit https://github.com/Microsoft/LightGBM/.

Example:

```
>>> import vaex.ml
>>> import vaex.ml.lightgbm
>>> df = vaex.ml.datasets.load_iris()
>>> features = ['sepal_width', 'petal_length', 'sepal_length', 'petal_width']
>>> df_train, df_test = df.ml.train_test_split()
>>> params = {
    'boosting': 'gbdt',
    'max_depth': 5,
    'learning_rate': 0.1,
    'application': 'multiclass',
    'num_class': 3,
    'subsample': 0.80,
    'colsample_bytree': 0.80}
>>> booster = vaex.ml.lightgbm.LightGBMModel(features=features, target='class_',␣
↪num_boost_round=100, params=params)
>>> booster.fit(df_train)
>>> df_train = booster.transform(df_train)
>>> df_train.head(3)
 #    sepal_width    petal_length    sepal_length    petal_width    class_    ␣
↪lightgbm_prediction
 0              3             4.5             5.4            1.5         1    [0.
↪00165619 0.98097899 0.01736482]
 1            3.4             1.6             4.8            0.2         0    [9.
↪99803930e-01 1.17346471e-04 7.87235133e-05]
 2            3.1             4.9             6.9            1.5         1    [0.
↪00107541 0.9848717  0.01405289]
>>> df_test = booster.transform(df_test)
>>> df_test.head(3)
 #    sepal_width    petal_length    sepal_length    petal_width    class_    ␣
↪lightgbm_prediction
```

(continues on next page)

(continued from previous page)

```
0           3              4.2              5.9            1.5          1    [0.
↪00208904 0.9821348  0.01577616]
1           3              4.6              6.1            1.4          1    [0.
↪00182039 0.98491357 0.01326604]
2           2.9            4.6              6.6            1.3          1    [2.
↪50915444e-04 9.98431777e-01 1.31730785e-03]
```

Parameters

- **features** – List of features to use when fitting the LightGBMModel.
- **num_boost_round** – Number of boosting iterations.
- **params** – parameters to be passed on the to the LightGBM model.
- **prediction_name** – The name of the virtual column housing the predictions.
- **target** – The name of the target column.

fit (*df*, *valid_sets=None*, *valid_names=None*, *early_stopping_rounds=None*, *evals_result=None*, *verbose_eval=None*, *copy=False*, ***kwargs*)

Fit the LightGBMModel to the DataFrame.

The model will train until the validation score stops improving. Validation score needs to improve at least every *early_stopping_rounds* rounds to continue training. Requires at least one validation DataFrame, metric specified. If there's more than one, will check all of them, but the training data is ignored anyway. If early stopping occurs, the model will add `best_iteration` field to the booster object.

Parameters

- **df** – A vaex DataFrame containing the features and target on which to train the model.
- **valid_sets** (*list*) – A list of DataFrames to be used for validation.
- **valid_names** (*list*) – A list of strings to label the validation sets.
- **int** (*early_stopping_rounds*) – Activates early stopping.
- **evals_result** (*dict*) – A dictionary storing the evaluation results of all *valid_sets*.
- **verbose_eval** (*bool*) – Requires at least one item in *valid_sets*. If *verbose_eval* is True then the evaluation metric on the validation set is printed at each boosting stage.
- **copy** (*bool*) – (default, False) If True, make an in memory copy of the data before passing it to LightGBMModel.

predict (*df*, ***kwargs*)

Get an in-memory numpy array with the predictions of the LightGBMModel on a vaex DataFrame. This method accepts the key word arguments of the predict method from LightGBM.

Parameters **df** – A vaex DataFrame.

Returns A in-memory numpy array containing the LightGBMModel predictions.

Return type numpy.array

transform (*df*)

Transform a DataFrame such that it contains the predictions of the LightGBMModel in form of a virtual column.

Parameters **df** – A vaex DataFrame.

Return copy A shallow copy of the DataFrame that includes the LightGBMModel prediction as a virtual column.

Return type *DataFrame*

class vaex.ml.xgboost.**XGBoostModel** (*features=traitlets.Undefined, num_boost_round=0, params=traitlets.Undefined, prediction_name='xgboost_prediction', target=''*)

Bases: vaex.ml.state.HasState

The XGBoost algorithm.

XGBoost is an optimized distributed gradient boosting library designed to be highly efficient, flexible and portable. It implements machine learning algorithms under the Gradient Boosting framework. XGBoost provides a parallel tree boosting (also known as GBDT, GBM) that solves many data science problems in a fast and accurate way. (https://github.com/dmlc/xgboost)

Example:

```
>>> import vaex
>>> import vaex.ml.xgboost
>>> df = vaex.ml.datasets.load_iris()
>>> features = ['sepal_width', 'petal_length', 'sepal_length', 'petal_width']
>>> df_train, df_test = df.ml.train_test_split()
>>> params = {
    'max_depth': 5,
    'learning_rate': 0.1,
    'objective': 'multi:softmax',
    'num_class': 3,
    'subsample': 0.80,
    'colsample_bytree': 0.80,
    'silent': 1}
>>> booster = vaex.ml.xgboost.XGBoostModel(features=features, target='class_',␣
↪num_boost_round=100, params=params)
>>> booster.fit(df_train)
>>> df_train = booster.transform(df_train)
>>> df_train.head(3)
#    sepal_length    sepal_width    petal_length    petal_width    class_    ␣
↪xgboost_prediction
0             5.4            3             4.5            1.5         1         ␣
↪             1
1             4.8            3.4           1.6            0.2         0         ␣
↪             0
2             6.9            3.1           4.9            1.5         1         ␣
↪             1
>>> df_test = booster.transform(df_test)
>>> df_test.head(3)
#    sepal_length    sepal_width    petal_length    petal_width    class_    ␣
↪xgboost_prediction
0             5.9            3             4.2            1.5         1         ␣
↪             1
1             6.1            3             4.6            1.4         1         ␣
↪             1
2             6.6            2.9           4.6            1.3         1         ␣
↪             1
```

Parameters

- **features** – List of features to use when fitting the XGBoostModel.

- **num_boost_round** – Number of boosting iterations.
- **params** – A dictionary of parameters to be passed on to the XGBoost model.
- **prediction_name** – The name of the virtual column housing the predictions.
- **target** – The name of the target column.

fit (*df*, *evals=()*, *early_stopping_rounds=None*, *evals_result=None*, *verbose_eval=False*, ***kwargs*)

Fit the XGBoost model given a DataFrame.

This method accepts all key word arguments for the xgboost.train method.

Parameters

- **df** – A vaex DataFrame containing the features and target on which to train the model.
- **evals** – A list of pairs (DataFrame, string). List of items to be evaluated during training, this allows user to watch performance on the validation set.
- **early_stopping_rounds** (*int*) – Activates early stopping. Validation error needs to decrease at least every *early_stopping_rounds* round(s) to continue training. Requires at least one item in *evals*. If there's more than one, will use the last. Returns the model from the last iteration (not the best one).
- **evals_result** (*dict*) – A dictionary storing the evaluation results of all the items in *evals*.
- **verbose_eval** (*bool*) – Requires at least one item in *evals*. If *verbose_eval* is True then the evaluation metric on the validation set is printed at each boosting stage.

predict (*df*, ***kwargs*)

Provided a vaex DataFrame, get an in-memory numpy array with the predictions from the XGBoost model. This method accepts the key word arguments of the predict method from XGBoost.

Returns A in-memory numpy array containing the XGBoostModel predictions.

Return type numpy.array

transform (*df*)

Transform a DataFrame such that it contains the predictions of the XGBoostModel in form of a virtual column.

Parameters **df** – A vaex DataFrame. It should have the same columns as the DataFrame used to train the model.

Return copy A shallow copy of the DataFrame that includes the XGBoostModel prediction as a virtual column.

Return type *DataFrame*

7.5.5 Incubator/experimental

These models are in the incubator phase and may disappear in the future

class vaex.ml.incubator.annoy.**ANNOYModel** (*features=traitlets.Undefined*, *metric='euclidean'*, *n_neighbours=10*, *n_trees=10*, *predcition_name='annoy_prediction'*, *prediction_name='annoy_prediction'*, *search_k=-1*)

Bases: vaex.ml.state.HasState

Parameters

- **features** – List of features to use.
- **metric** – Metric to use for distance calculations
- **n_neighbours** – Now many neighbours
- **n_trees** – Number of trees to build.
- **predcition_name** – Output column name for the neighbours when transforming a DataFrame
- **prediction_name** – Output column name for the neighbours when transforming a DataFrame
- **search_k** – Jovan?

CHAPTER 8

Datasets to download

Here we list a few datasets, that might be interesting to explore with vaex

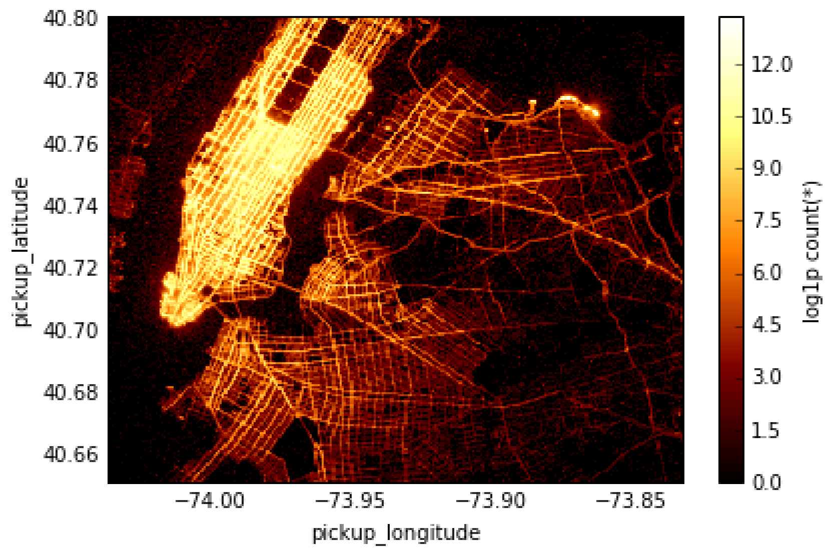
8.1 New york taxi dataset

See for instance Analyzing 1.1 Billion NYC Taxi and Uber Trips, with a Vengeance for some ideas.

- Year: 2015 - 146 million rows - 23GB
- Year 2009-2015 - 1 billion rows - 135GB

```
[2]: import vaex
```

```
[12]: df = vaex.open("/Users/users/breddels/.vaex/data/nyc_taxi/nyc_taxi2015.hdf5")
df.plot(df.col.pickup_longitude, df.col.pickup_latitude, f="log1p", show=True, limits=
↪"96%");
```



8.2 SDSS - dereddened

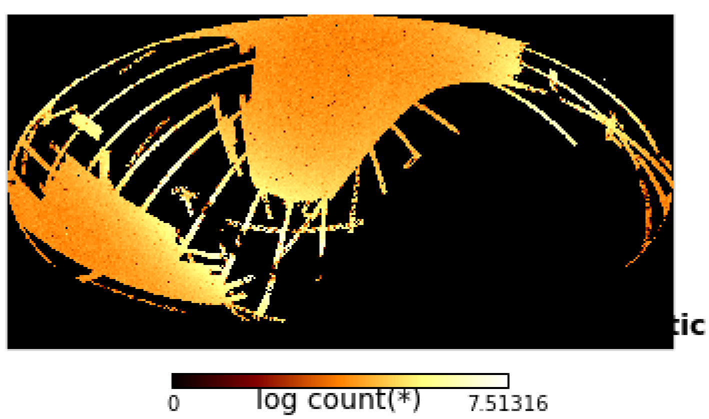
Only: `ra`, `dec`, `g`, `r`, `g_r` (deredenned using Schlegel maps).

The original query at SDSS archive was (although split in small parts):

```
SELECT ra, dec, g, r from PhotoObjAll WHERE type = 6 and  clean = 1 and r>=10.0 and r
↪<23.5;
```

- 162 million rows - 10GB

```
[22]: sdss = vaex.open("/Users/maartenbreddels/vaex/data/sdss/sdss_dereddened.hdf5")
      sdss.healpix_plot(sdss.col.healpix, show=True, f="log", healpix_max_level=9, healpix_
      ↪level=9,
                        healpix_input='galactic', healpix_output='galactic', rotation=(0,45)
                       )
```

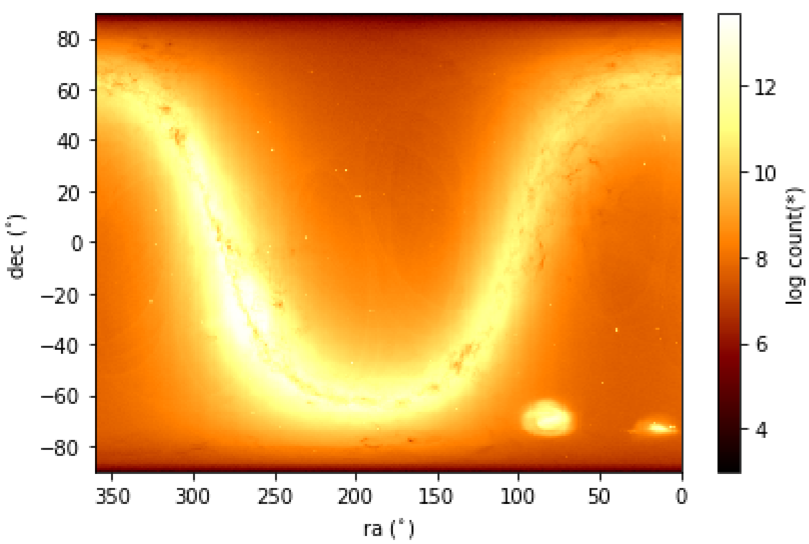


8.3 Gaia

See the Gaia Science Homepage for details, and you may want to try the Gaia Archive for ADQL (SQL like) queries.

- Gaia data release 2 (DR2)
  - Full Gaia DR2 - 1.7 billion rows 1.2TB
  - Split in two sets of columns:
  - All astrometry and errors (without covariances), radial velocity and basic photometry - 253 GB
  - Everything not contained in the above - 1 TB
  - Only with radial velocities - 7 million - 5.2GB
- Gaia data release 1 (DR1)
  - Full Gaia DR1 - 1 billion row - 351GB
  - A few columns of Gaia DR1 - 1 billion row - 88GB
  - 10% of Gaia DR1 - 1 billion row - 35GB
  - TGAS (subset of DR1 with proper motions) - 662MB

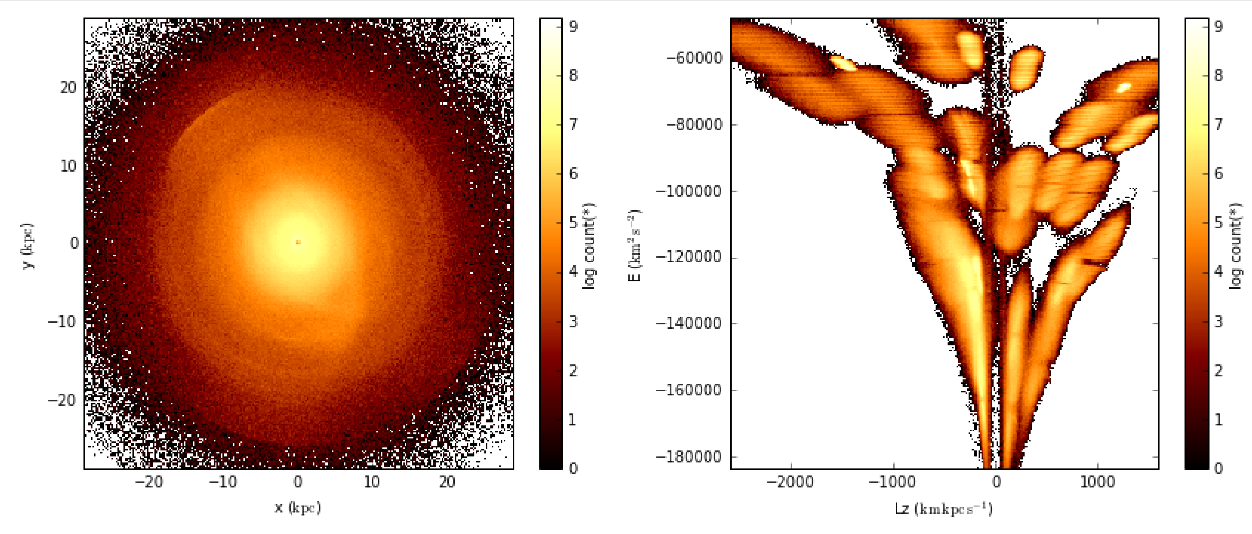
[3]:
```
gaia = vaex.open("/data/users/gaia/gaia-dr2/gaia-dr2-sort-by-source_id.hdf5")
gaia.plot("ra", "dec", f="log", limits=[[360, 0], [-90, 90]], show=True);
```



8.4 Helmi & de Zeeuw 2000

Result of an N-body simulation of the accretion of 33 satellite galaxies into a Milky Way dark matter halo * 3 million rows - 252MB

[26]:
```
hdz = vaex.datasets.helmi_de_zeeuw.fetch() # this will download it on the fly
hdz.plot([["x", "y"], ["Lz", "E"]], f="log", figsize=(12,5), show=True);
```


y (kpc)
x (kpc)
log count(*)
E (km²s⁻²)
Lz (kmkpcs⁻¹)
log count(*)

CHAPTER 9

Frequently Asked Questions

9.1 I have a massive CSV file which I can not fit all into memory at one time. How do I convert it to HDF5?

Such an operation is a one-liner in Vaex:

```
df = vaex.from_csv('./my_data/my_big_file.csv', convert=True, chunk_size=5_000_000)
```

When the above line is executed, Vaex will read the CSV in chunks, and convert each chunk to a temporary HDF5 file on disk. All temporary will files are then concatenated into a single HDF5, and the temporary files deleted. The size of the individual chunks to be read can be specified via the `chunk_size` argument.

For more information on importing and exporting data with Vaex, please refer to please refer to the I/O example page.

9.2 Why can't I open a HDF5 file that was exported from a `pandas` DataFrame using `.to_hdf`?

When one uses the `pandas .to_hdf` method, the output HDF5 file has a row based format. `Vaex` on the other hand expects column based HDF5 files. This allows for more efficient reading of data columns, which is much more commonly required for data science applications.

One can easily export a `pandas` DataFrame to a `vaex` friendly HDF5 file:

```
vaex_df = vaex.from_pandas(pandas_df, copy_index=False)
vaex_df.export_hdf5('my_data.hdf5')
```

CHAPTER 10

What is Vaex?

Vaex is a python library for lazy **Out-of-Core DataFrames** (similar to Pandas), to visualize and explore big tabular datasets. It can calculate *statistics* such as mean, sum, count, standard deviation etc, on an *N-dimensional grid* up to **a billion** (10^9) objects/rows **per second**. Visualization is done using **histograms**, **density plots** and **3d volume rendering**, allowing interactive exploration of big data. Vaex uses memory mapping, a zero memory copy policy, and lazy computations for best performance (no memory wasted).

10.1 Why vaex

- **Performance:** works with huge tabular data, processes 10^9 rows/second
- **Lazy / Virtual columns:** compute on the fly, without wasting ram
- **Memory efficient** no memory copies when doing filtering/selections/subsets.
- **Visualization:** directly supported, a one-liner is often enough.
- **User friendly API:** you will only need to deal with the DataFrame object, and tab completion + docstring will help you out: `ds.mean<tab>`, feels very similar to Pandas.
- **Lean:** separated into multiple packages
  - `vaex-core`: DataFrame and core algorithms, takes numpy arrays as input columns.
  - `vaex-hdf5`: Provides memory mapped numpy arrays to a DataFrame.
  - `vaex-arrow`: Arrow support for cross language data sharing.
  - `vaex-viz`: Visualization based on matplotlib.
  - `vaex-jupyter`: Interactive visualization based on Jupyter widgets / ipywidgets, bqplot, ipyvolume and ipyleaflet.
  - `vaex-astro`: Astronomy related transformations and FITS file support.
  - `vaex-server`: Provides a server to access a DataFrame remotely.

  - `vaex-distributed`: (Proof of concept) combined multiple servers / cluster into a single DataFrame for distributed computations.
  - `vaex-qt`: Program written using Qt GUI.
  - `vaex`: Meta package that installs all of the above.
  - `vaex-ml`: Machine learning
- **Jupyter integration**: vaex-jupyter will give you interactive visualization and selection in the Jupyter notebook and Jupyter lab.

CHAPTER 11

Installation

Using conda:

- `conda install -c conda-forge vaex`

Using pip:

- `pip install --upgrade vaex`

Or read the *detailed instructions*

11.1 Getting started

We assume that you have installed vaex, and are running a Jupyter notebook server. We start by importing vaex and asking it to give us an example dataset.

[1]:
```
import vaex
df = vaex.example()   # open the example dataset provided with vaex
```

Instead, you can *download some larger datasets*, or *read in your csv file*.

[2]:
```
df  # will pretty print the DataFrame
```

[2]:
```
#        x             y             z             vx            vy            vz       ␣
↪    E                L                  Lz                  FeH
0        -0.777470767  2.10626292    1.93743467    53.276722     288.386047    -95.
↪2649078  -121238.171875   831.0799560546875   -336.426513671875    -2.
↪309227609164518
1        3.77427316    2.23387194    3.76209331    252.810791    -69.9498444   -56.
↪3121033  -100819.9140625  1435.1839599609375  -828.7567749023438   -1.
↪788735491591229
2        1.3757627     -6.3283844    2.63250017    96.276474     226.440201    -34.
↪7527161  -100559.9609375  1039.2989501953125  920.802490234375     -0.
↪7618109022478798
3        -7.06737804   1.31737781    -6.10543537   204.968842    -205.679016   -58.
↪9777031  -70174.8515625   2441.724853515625   1183.5899658203125   -1.
↪5208778422936413
```

(continues on next page)

(continued from previous page)

```
4        0.243441463   -0.822781682  -0.206593871  -311.742371  -238.41217   186.
↪824127   -144138.75       374.8164367675781   -314.5353088378906   -2.
↪655341358427361
...      ...           ...           ...           ...          ...          ...     ␣
↪    ...            ...            ...                ...
329,995  3.76883793    4.66251659    -4.42904139   107.432999   -2.13771296  17.
↪5130272   -119687.3203125  746.8833618164062   -508.96484375        -1.
↪6499842518381402
329,996  9.17409325    -8.87091351   -8.61707687   32.0         108.089264   179.
↪060638   -68933.8046875   2395.633056640625   1275.490234375       -1.
↪4336036247720836
329,997  -1.14041007   -8.4957695    2.25749826    8.46711349   -38.2765236  -127.
↪541473  -112580.359375   1182.436279296875   115.58557891845703   -1.
↪9306227597361942
329,998  -14.2985935   -5.51750422   -8.65472317   110.221558   -31.3925591  86.
↪2726822   -74862.90625     1324.5926513671875  1057.017333984375    -1.
↪225019818838568
329,999  10.5450506    -8.86106777   -4.65835428   -2.10541415  -27.6108856  3.
↪80799961   -95361.765625    351.0955505371094   -309.81439208984375  -2.
↪5689636894079477
```

Using **'square brackets[] <api.rst#vaex.dataframe.DataFrame.__getitem__>'__**, we can easily filter or get different views on the DataFrame.

[3]:
```
df_negative = df[df.x < 0]  # easily filter your DataFrame, without making a copy
df_negative[:5][['x', 'y']]  # take the first five rows, and only the 'x' and 'y'␣
↪column (no memory copy!)
```

[3]:

#	x	y
0	-0.777471	2.10626
1	-7.06738	1.31738
2	-5.17174	7.82915
3	-15.9539	5.77126
4	-12.3995	13.9182

When dealing with huge datasets, say a billion rows (10^9), computations with the data can waste memory, up to 8 GB for a new column. Instead, vaex uses lazy computation, storing only a representation of the computation, and computations are done on the fly when needed. You can just use many of the numpy functions, as if it was a normal array.

[4]:
```
import numpy as np
# creates an expression (nothing is computed)
some_expression = df.x + df.z
some_expression  # for convenience, we print out some values
```

[4]:
```
<vaex.expression.Expression(expressions='(x + z)')> instance at 0x118f71550 values=[1.
↪159963903, 7.53636647, 4.00826287, -13.17281341, 0.0368475919999985 ... (total␣
↪330000 values) ... -0.66020346, 0.5570163800000003, 1.1170881900000003, -22.
↪95331667, 5.8866963199999995]
```

These expressions can be added to a DataFrame, creating what we call a *virtual column*. These virtual columns are similar to normal columns, except they do not waste memory.

[5]:
```
df['r'] = some_expression  # add a (virtual) column that will be computed on the fly
df.mean(df.x), df.mean(df.r)  # calculate statistics on normal and virtual columns
```

[5]:
```
(-0.06713149126400597, -0.0501732470530304)
```

One of the core features of vaex is its ability to calculate statistics on a regular (N-dimensional) grid. The dimensions of the grid are specified by the binby argument (analogous to SQL's grouby), and the shape and limits.

[6]:
```
df.mean(df.r, binby=df.x, shape=32, limits=[-10, 10]) # create statistics on a␣
↪regular grid (1d)
```

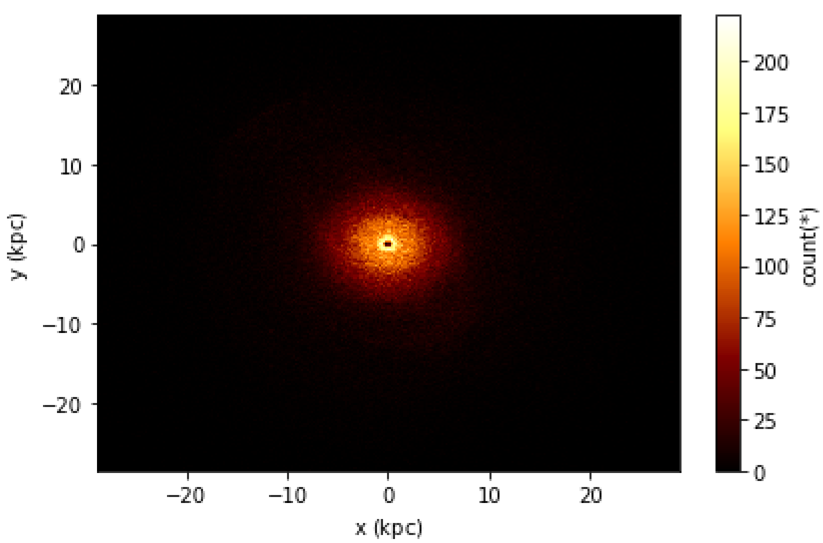
[6]:
```
array([-9.67777315, -8.99466731, -8.17042477, -7.57122871, -6.98273954,
       -6.28362848, -5.70005784, -5.14022306, -4.52820368, -3.96953423,
       -3.3362477 , -2.7801045 , -2.20162243, -1.57910621, -0.92856689,
       -0.35964342,  0.30367721,  0.85684123,  1.53564551,  2.1274488 ,
        2.69235585,  3.37746363,  4.04648274,  4.59580105,  5.20540601,
        5.73475069,  6.28384101,  6.67880226,  7.46059303,  8.13480148,
        8.90738265,  9.6117928 ])
```

[7]:
```
df.mean(df.r, binby=[df.x, df.y], shape=32, limits=[-10, 10]) # or 2d
df.count(df.r, binby=[df.x, df.y], shape=32, limits=[-10, 10]) # or 2d counts/
↪histogram
```

[7]:
```
array([[22., 33., 37., ..., 58., 38., 45.],
       [37., 36., 47., ..., 52., 36., 53.],
       [34., 42., 47., ..., 59., 44., 56.],
       ...,
       [73., 73., 84., ..., 41., 40., 37.],
       [53., 58., 63., ..., 34., 35., 28.],
       [51., 32., 46., ..., 47., 33., 36.]])
```

These one and two dimensional grids can be visualized using any plotting library, such as matplotlib, but the setup can be tedious. For convenience we can use *plot1d*, *plot*, or see the *list of plotting commands*

[8]:
```
df.plot(df.x, df.y, show=True);  # make a plot quickly
```



CHAPTER 12

Continue

Continue the tutorial here or check the *examples*

Python Module Index

V

Index

Symbols

A

B

C

D

E

F

G

H

I

J

K

L

T

U

V

W

X

Y

Z