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# **Streamz Documentation**

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Streamz helps you build pipelines to manage continuous streams of data. It is simple to use in simple cases, but also supports complex pipelines that involve branching, joining, flow control, feedback, back pressure, and so on.

Optionally, Streamz can also work with both [Pandas](#) and [cuDF](#) dataframes, to provide sensible streaming operations on continuous tabular data.

To learn more about how to use streams, visit [Core documentation](#).



Continuous data streams arise in many applications like the following:

1. Log processing from web servers
2. Scientific instrument data like telemetry or image processing pipelines
3. Financial time series
4. Machine learning pipelines for real-time and on-line learning
5. ...

Sometimes these pipelines are very simple, with a linear sequence of processing steps:

And sometimes these pipelines are more complex, involving branching, look-back periods, feedback into earlier stages, and more.

Streamz endeavors to be simple in simple cases, while also being powerful enough to let you define custom and powerful pipelines for your application.

## 1.1 Why not Python generator expressions?

Python users often manage continuous sequences of data with iterators or generator expressions.

```
def fib():
    a, b = 0, 1
    while True:
        yield a
        a, b = b, a + b

sequence = (f(n) for n in fib())
```

However iterators become challenging when you want to fork them or control the flow of data. Typically people rely on tools like `itertools.tee`, and `zip`.

```
x1, x2 = itertools.tee(x, 2)
y1 = map(f, x1)
y2 = map(g, x2)
```

However this quickly become cumbersome, especially when building complex pipelines.



## CHAPTER 2

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### Installation

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To install either use:

- **conda-forge:** `conda install streamz -c conda-forge`
- **pip:** `pip install streamz`
- **dev:** `git clone https://github.com/python-streamz/streamz` followed by `pip install -e streamz/`



Streamz is similar to reactive programming systems like [RxPY](#) or big data streaming systems like [Apache Flink](#), [Apache Beam](#) or [Apache Spark Streaming](#).

## 3.1 Core Streams

This document takes you through how to build basic streams and push data through them. We start with `map` and `accumulate`, talk about emitting data, then discuss flow control and finally back pressure. Examples are used throughout.

### 3.1.1 Map, emit, and sink

<code>Stream.emit(self, x[, asynchronous, metadata])</code>	Push data into the stream at this point
<code>map(upstream, func, *args, **kwargs)</code>	Apply a function to every element in the stream
<code>sink(upstream, func, *args, **kwargs)</code>	Apply a function on every element

You can create a basic pipeline by instantiating the `Streamz` object and then using methods like `map`, `accumulate`, and `sink`.

```
from streamz import Stream

def increment(x):
    return x + 1

source = Stream()
source.map(increment).sink(print)
```

The `map` and `sink` methods both take a function and apply that function to every element in the stream. The `map` method returns a new stream with the modified elements while `sink` is typically used at the end of a stream for final actions.

To push data through our pipeline we call `emit`

```
>>> source.emit(1)
2
>>> source.emit(2)
3
>>> source.emit(10)
11
```

As we can see, whenever we push data in at the source, our pipeline calls `increment` on that data, and then calls `print` on that data, resulting in incremented results being printed to the screen.

Often we call `emit` from some other continuous process, like reading lines from a file

```
import json

data = []

source = Stream()
source.map(json.loads).sink(data.append)

for line in open('myfile.json'):
    source.emit(line)
```

### 3.1.2 Accumulating State

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`accumulate(upstream, func[, start, ...])`

Accumulate results with previous state

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Map and sink both pass data directly through a stream. One piece of data comes in, either one or zero pieces go out. Accumulate allows you to track some state within the pipeline. It takes an accumulation function that takes the previous state, the new element, and then returns a new state and a new element to emit. In the following example we make an accumulator that keeps a running total of the elements seen so far.

```
def add(x, y):
    return x + y

source = Stream()
source.accumulate(add).sink(print)
```

```
>>> source.emit(1)
1
>>> source.emit(2)
3
>>> source.emit(3)
6
>>> source.emit(4)
10
```

The accumulation function above is particularly simple, the state that we store and the value that we emit are the same. In more complex situations we might want to keep around different state than we emit. For example lets count the number of distinct elements that we have seen so far.

```
def num_distinct(state, new):
    state.add(new)
    return state, len(state)
```

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```

source = Stream()
source.accumulate(num_distinct, returns_state=True, start=set()).sink(print)

>>> source.emit('cat')
1
>>> source.emit('dog')
2
>>> source.emit('cat')
2
>>> source.emit('mouse')
3

```

Accumulators allow us to build many interesting operations.

### 3.1.3 Flow Control

<code>buffer(upstream, n, **kwargs)</code>	Allow results to pile up at this point in the stream
<code>flatten([upstream, upstreams, stream_name, ...])</code>	Flatten streams of lists or iterables into a stream of elements
<code>partition(upstream, n, **kwargs)</code>	Partition stream into tuples of equal size
<code>sliding_window(upstream, n[, return_partial])</code>	Produce overlapping tuples of size n
<code>union(*upstreams, **kwargs)</code>	Combine multiple streams into one
<code>unique(upstream[, maxsize, key, hashable])</code>	Avoid sending through repeated elements

You can batch and slice streams into streams of batches in various ways with operations like `partition`, `buffer`, and `sliding_window`

```

source = Stream()
source.sliding_window(3, return_partial=False).sink(print)

>>> source.emit(1)
>>> source.emit(2)
>>> source.emit(3)
(1, 2, 3)
>>> source.emit(4)
(2, 3, 4)
>>> source.emit(5)
(3, 4, 5)

```

### 3.1.4 Branching and Joining

<code>combine_latest(*upstreams, **kwargs)</code>	Combine multiple streams together to a stream of tuples
<code>zip(*upstreams, **kwargs)</code>	Combine streams together into a stream of tuples
<code>zip_latest(lossless, *upstreams, **kwargs)</code>	Combine multiple streams together to a stream of tuples

You can branch multiple streams off of a single stream. Elements that go into the input will pass through to both output streams. Note: `graphviz` and `networkx` need to be installed to visualize the stream graph.

```

def increment(x):
    return x + 1

```

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```
def decrement(x):
    return x - 1

source = Stream()
a = source.map(increment).sink(print)
b = source.map(decrement).sink(print)
b.visualize(rankdir='LR')
```

```
>>> source.emit(1)
0
2
>>> source.emit(10)
9
11
```

Similarly you can also combine multiple streams together with operations like `zip`, which emits once both streams have provided a new element, or `combine_latest` which emits when either stream has provided a new element.

```
source = Stream()
a = source.map(increment)
b = source.map(decrement)
c = a.zip(b).map(sum).sink(print)

>>> source.emit(10)
20 # 9 + 11
```

This branching and combining is where Python iterators break down, and projects like `streamz` start becoming valuable.

### 3.1.5 Processing Time and Back Pressure

<code>delay(upstream, interval, **kwargs)</code>	Add a time delay to results
<code>rate_limit(upstream, interval, **kwargs)</code>	Limit the flow of data
<code>timed_window(upstream, interval, **kwargs)</code>	Emit a tuple of collected results every interval

Time-based flow control depends on having an active `Tornado` event loop. `Tornado` is active by default within a Jupyter notebook, but otherwise you will need to learn at least a little about asynchronous programming in Python to use these features. Learning async programming is not mandatory, the rest of the project will work fine without `Tornado`.

You can control the flow of data through your stream over time. For example you may want to batch all elements that have arrived in the last minute, or slow down the flow of data through sensitive parts of the pipeline, particularly when they may be writing to slow resources like databases.

`Streamz` helps you do these operations both with operations like `delay`, `rate_limit`, and `timed_window`, and also by passing `Tornado` futures back through the pipeline. As data moves forward through the pipeline, futures that signal work completed move backwards. In this way you can reliably avoid buildup of data in slower parts of your pipeline.

Lets consider the following example that reads JSON data from a file and inserts it into a database using an async-aware insertion function.

```

async def write_to_database(...):
    ...

# build pipeline
source = Source()
source.map(json.loads).sink(write_to_database)

async def process_file(fn):
    with open(fn) as f:
        for line in f:
            await source.emit(line) # wait for pipeline to clear

```

As we call the `write_to_database` function on our parsed JSON data it produces a future for us to signal that the writing process has finished. Streamz will ensure that this future is passed all the way back to the `source.emit` call, so that user code at the start of our pipeline can await on it. This allows us to avoid buildup even in very large and complex streams. We always pass futures back to ensure responsiveness.

But wait, maybe we don't mind having a few messages in memory at once, this will help steady the flow of data so that we can continue to work even if our sources or sinks become less productive for brief periods. We might add a buffer just before writing to the database.

```
source.map(json.loads).buffer(100).sink(write_to_database)
```

And if we are pulling from an API with known limits then we might want to introduce artificial rate limits at 10ms.

```
source.rate_limit(0.010).map(json.loads).buffer(100).sink(write_to_database)
```

Operations like these (and more) allow us to shape the flow of data through our pipelines.

### 3.1.6 Modifying and Cleaning up Streams

When you call `Stream` you create a stream. When you call any method on a `Stream`, like `Stream.map`, you also create a stream. All operations can be chained together. Additionally, as discussed in the section on `Branching`, you can split multiple streams off of any point. Streams will pass their outputs on to all downstream streams so that anyone can hook in at any point, and get a full view of what that stream is producing.

If you delete a part of a stream then it will stop getting data. Streamz follows normal Python garbage collection semantics so once all references to a stream have been lost those operations will no longer occur. The one counter example to this is `sink`, which is intended to be used with side effects and will stick around even without a reference.

---

**Note:** Sink streams store themselves in `streamz.core._global_sinks`. You can remove them permanently by clearing that collection.

---

```

>>> source.map(print) # this doesn't do anything
>>> source.sink(print) # this stays active even without a reference
>>> s = source.map(print) # this works too because we have a handle to s

```

### 3.1.7 Recursion and Feedback

By connecting sources to sinks you can create feedback loops. As an example, here is a tiny web crawler:

```
from streamz import Stream
source = Stream()

pages = source.unique()
pages.sink(print)

content = pages.map(requests.get).map(lambda x: x.content)
links = content.map(get_list_of_links).flatten()
links.connect(source) # pipe new links back into pages

>>> source.emit('http://github.com')
http://github.com
http://github.com/features
http://github.com/business
http://github.com/explore
http://github.com/pricing
...
```

---

**Note:** Execution order is important here, as if the print was ordered after the map; get node then the print would never run.

---

### 3.1.8 Performance

Streamz adds microsecond overhead to normal Python operations.

```
from streamz import Stream

source = Stream()

def inc(x):
    return x + 1

source.sink(inc)

In [5]: %timeit source.emit(1)
100000 loops, best of 3: 3.19 µs per loop

In [6]: %timeit inc(1)
1000000 loops, best of 3: 91.5 ns per loop
```

You may want to avoid pushing millions of individual elements per second through a stream. However, you can avoid performance issues by collecting lots of data into single elements, for example by pushing through Pandas dataframes instead of individual integers and strings. This will be faster regardless, just because projects like NumPy and Pandas can be much faster than Python generally.

In the following example we pass filenames through a stream, convert them to Pandas dataframes, and then map pandas-level functions on those dataframes. For operations like this Streamz adds virtually no overhead.

```
source = Stream()
s = source.map(pd.read_csv).map(lambda df: df.value.sum()).accumulate(add)
```

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```
for fn in glob('data/2017-**-*.csv'):
    source.emit(fn)
```

Streams provides higher level APIs for situations just like this one. You may want to read further about *collections*

### 3.1.9 Metadata

Metadata can be emitted into the pipeline to accompany the data as a list of dictionaries. Most functions will pass the metadata to the downstream function without making any changes. However, functions that make the pipeline asynchronous require logic that dictates how and when the metadata will be passed downstream. Synchronous functions and asynchronous functions that have a 1:1 ratio of the number of values on the input to the number of values on the output will emit the metadata collection without any modification. However, functions that have multiple input streams or emit collections of data will emit the metadata associated with the emitted data as a collection.

### 3.1.10 Reference Counting and Checkpointing

Checkpointing is achieved in Streamz through the use of reference counting. With this method, a checkpoint can be saved when and only when data has progressed through all of the the pipeline without any issues. This prevents data loss and guarantees at-least-once semantics.

Any node that caches or holds data after it returns increments the reference counter associated with the given data by one. When a node is no longer holding the data, it will release it by decrementing the counter by one. When the counter changes to zero, a callback associated with the data is triggered.

References are passed in the metadata as a value of the *ref* keyword. Each metadata object contains only one reference counter object.

## 3.2 DataFrames

When handling large volumes of streaming tabular data it is often more efficient to pass around larger Pandas dataframes with many rows each rather than pass around individual Python tuples or dicts. Handling and computing on data with Pandas can be much faster than operating on Python objects.

So one could imagine building streaming dataframe pipelines using the `.map` and `.accumulate` streaming operators with functions that consume and produce Pandas dataframes as in the following example:

```
from streamz import Stream

def query(df):
    return df[df.name == 'Alice']

def aggregate(acc, df):
    return acc + df.amount.sum()

stream = Stream()
stream.map(query).accumulate(aggregate, start=0)
```

This is fine, and straightforward to do if you understand `streamz.core`, Pandas, and have some skill with developing algorithms.

### 3.2.1 Streaming Dataframes

The `streamz.dataframe` module provides a streaming dataframe object that implements many of these algorithms for you. It provides a Pandas-like interface on streaming data. Our example above is rewritten below using streaming dataframes:

```
import pandas as pd
from streamz.dataframe import DataFrame

example = pd.DataFrame({'name': [], 'amount': []})
sdf = DataFrame(stream, example=example)

sdf[sdf.name == 'Alice'].amount.sum()
```

The two examples are identical in terms of performance and execution. The resulting streaming dataframe contains a `.stream` attribute which is equivalent to the `stream` produced in the first example. Streaming dataframes are only syntactic sugar on core streams.

### 3.2.2 Supported Operations

Streaming dataframes support the following classes of operations

- Elementwise operations like `df.x + 1`
- Filtering like `df[df.name == 'Alice']`
- Column addition like `df['z'] = df.x + df.y`
- Reductions like `df.amount.mean()`
- Groupby-aggregations like `df.groupby(df.name).amount.mean()`
- Windowed aggregations (fixed length) like `df.window(n=100).amount.sum()`
- Windowed aggregations (index valued) like `df.window(value='2h').amount.sum()`
- Windowed groupby aggregations like `df.window(value='2h').groupby('name').amount.sum()`

### 3.2.3 DataFrame Aggregations

Dataframe aggregations are composed of an aggregation (like `sum`, `mean`, ...) and a windowing scheme (fixed sized windows, index-valued, all time, ...)

#### Aggregations

Streaming Dataframe aggregations are built from three methods

- `initial`: Creates initial state given an empty example dataframe
- `on_new`: Updates state and produces new result to emit given new data
- `on_old`: Updates state and produces new result to emit given decayed data

So a simple implementation of `sum` as an aggregation might look like the following:

```

from streamz.dataframe import Aggregation

class Mean(Aggregation):
    def initial(self, new):
        state = new.iloc[:0].sum(), new.iloc[:0].count()
        return state

    def on_new(self, state, new):
        total, count = state
        total = total + new.sum()
        count = count + new.count()
        new_state = (total, count)
        new_value = total / count
        return new_state, new_value

    def on_old(self, state, old):
        total, count = state
        total = total - old.sum() # switch + for - here
        count = count - old.count() # switch + for - here
        new_state = (total, count)
        new_value = total / count
        return new_state, new_value

```

These aggregations can then used in a variety of different windowing schemes with the `aggregate` method as follows:

```

df.aggregate(Mean())

df.window(n=100).aggregate(Mean())

df.window(value='60s').aggregate(Mean())

```

whose job it is to deliver new and old data to your aggregation for processing.

## Windowing Schemes

Different windowing schemes like fixed sized windows (last 100 elements) or value-indexed windows (last two hours of data) will track newly arrived and decaying data and call these methods accordingly. The mechanism to track data arriving and leaving is kept orthogonal from the aggregations themselves. These windowing schemes include the following:

1. All previous data. Only `initial` and `on_new` are called, `on_old` is never called.

```
>>> df.sum()
```

2. The previous `n` elements

```
>>> df.window(n=100).sum()
```

3. An index range, like a time range for a datetime index

```
>>> df.window(value='2h').sum()
```

Although this can be done for any range on any type of index, time is just a common case.

Windowing schemes generally maintain a deque of historical values within accumulated state. As new data comes in they inspect that state and eject data that no longer falls within the window.

## Grouping

Groupby aggregations also maintain historical data on the grouper and perform a parallel aggregation on the number of times any key has been seen, removing that key once it is no longer present.

### 3.2.4 Dask

In all cases, dataframe operations are only implemented with the `.map` and `.accumulate` operators, and so are equally compatible with core `Stream` and `DaskStream` objects.

### 3.2.5 Not Yet Supported

Streaming dataframes algorithms do not currently pay special attention to data arriving out-of-order.

## 3.3 Dask Integration

The `streamz.dask` module contains a `Dask`-powered implementation of the core `Stream` object. This is a drop-in implementation, but uses `Dask` for execution and so can scale to a multicore machine or a distributed cluster.

### 3.3.1 Quickstart

#### Installation

First install `dask` and `dask.distributed`:

```
conda install dask
or
pip install dask[complete] --upgrade
```

You may also want to install `Bokeh` for web diagnostics:

```
conda install -c bokeh bokeh
or
pip install bokeh --upgrade
```

#### Start Local Dask Client

Then start a local `Dask` cluster

```
from dask.distributed import Client
client = Client()
```

This operates on a local processes or threads. If you have `Bokeh` installed then this will also start a diagnostics web server at <http://localhost:8787/status> which you may want to open to get a real-time view of execution.

#### Sequential Execution

<code>Stream.emit(self, x[, asynchronous, metadata])</code>	Push data into the stream at this point
<code>map(upstream, func, *args, **kwargs)</code>	Apply a function to every element in the stream
<code>sink(upstream, func, *args, **kwargs)</code>	Apply a function on every element

Before we build a parallel stream, lets build a sequential stream that maps a simple function across data, and then prints those results. We use the core `Stream` object.

```
from time import sleep

def inc(x):
    sleep(1) # simulate actual work
    return x + 1

from streamz import Stream

source = Stream()
source.map(inc).sink(print)

for i in range(10):
    source.emit(i)
```

This should take ten seconds we call the `inc` function ten times sequentially.

## Parallel Execution

<code>scatter(*args, **kwargs)</code>	Convert local stream to Dask Stream
<code>buffer(upstream, n, **kwargs)</code>	Allow results to pile up at this point in the stream
<code>gather([upstream, upstreams, stream_name, ...])</code>	Wait on and gather results from DaskStream to local Stream

That example ran sequentially under normal execution, now we use `.scatter()` to convert our stream into a `DaskStream` and `.gather()` to convert back.

```
source = Stream()
source.scatter().map(inc).buffer(8).gather().sink(print)

for i in range(10):
    source.emit(i)
```

You may want to look at <http://localhost:8787/status> during execution to get a sense of the parallel execution.

This should have run much more quickly depending on how many cores you have on your machine. We added a few extra nodes to our stream, lets look at what they did.

- `scatter`: Converted our `Stream` into a `DaskStream`. The elements that we emitted into our source were sent to the Dask client, and the subsequent `map` call used that client's cores to perform the computations.
- `gather`: Converted our `DaskStream` back into a `Stream`, pulling data on our Dask client back to our local stream
- `buffer(5)`: Normally `gather` would exert back pressure so that the source would not accept new data until results finished and were pulled back to the local stream. This back-pressure would limit parallelism. To counter-act this we add a buffer of size eight to allow eight unfinished futures to build up in the pipeline before we start

to apply back-pressure to `source.emit()`.

## Gotchas

An important gotcha with `DaskStream` is that it is a subclass `Stream`, and so can be used as an input to any function expecting a `Stream`. If there is no intervening `.gather()`, then the downstream node will receive Dask futures instead of the data they represent:

```
source = Stream()
source2 = Stream()
a = source.scatter().map(inc)
b = source2.combine_latest(a)
```

In this case, the combine operation will get real values from `source2`, and Dask futures. Downstream nodes would be free to operate on the futures, but more likely, the line should be:

```
b = source2.combine_latest(a.gather())
```

## 3.4 Collections

Streamz high-level collection APIs are built on top of `streamz.core`, and bring special consideration to certain types of data:

1. `streamz.batch`: supports streams of lists of Python objects like tuples or dictionaries
2. `streamz.dataframe`: supports streams of Pandas/cudf dataframes or Pandas/cudf series. cudf support is in beta phase and has limited functionality as of cudf version 0.8

These high-level APIs help us handle common situations in data processing. They help us implement complex algorithms and also improve efficiency.

These APIs are built on the streamz core operations (`map`, `accumulate`, `buffer`, `timed_window`, ...) which provide the building blocks to build complex pipelines but offer no help with what those functions should be. The higher-level APIs help to fill in this gap for common situations.

### 3.4.1 Conversion

<code>Stream.to_batch(self, **kwargs)</code>	Convert a stream of lists to a Batch
<code>Stream.to_dataframe(self, example)</code>	Convert a stream of Pandas dataframes to a DataFrame

You can convert from core `Stream` objects to `Batch`, and `DataFrame` objects using the `.to_batch` and `.to_dataframe` methods. In each case we assume that the stream is a stream of batches (lists or tuples) or a list of Pandas dataframes.

```
>>> batch = stream.to_batch()
>>> sdf = stream.to_dataframe()
```

To convert back from a `Batch` or a `DataFrame` to a `core.Stream` you can access the `.stream` property.

```
>>> stream = sdf.stream
>>> stream = batch.stream
```

## 3.4.2 Example

We create a stream and connect it to a file object

```
file = ... # filename or file-like object
from streamz import Stream

source = Stream.from_textfile(file)
```

Our file produces line-delimited JSON serialized data on which we want to call `json.loads` to parse into dictionaries.

To reduce overhead we first batch our records up into 100-line batches and turn this into a Batch object. We provide our Batch object an example element that it will use to help it determine metadata.

```
example = [{'name': 'Alice', 'x': 1, 'y': 2}]
lines = source.partition(100).to_batch(example=example) # batches of 100 elements
records = lines.map(json.loads) # convert lines to text.
```

We could have done the `.map(json.loads)` command on the original stream, but this way reduce overhead by applying this function to lists of items, rather than one item at a time.

Now we convert these batches of records into pandas dataframes and do some basic filtering and groupby-aggregations.

```
sdf = records.to_dataframe()
sdf = sdf[sdf.name == "Alice"]
sdf = sdf.groupby(sdf.x).y.mean()
```

The DataFrames satisfy a subset of the Pandas API, but now rather than operate on the data directly, they set up a pipeline to compute the data in an online fashion.

Finally we convert this back to a stream and push the results into a fixed-size deque.

```
from collections import deque
d = deque(maxlen=10)

sdf.stream.sink(d.append)
```

See *Collections API* for more information.

## 3.5 API

### 3.5.1 Stream

<code>Stream([upstream, upstreams, stream_name, ...])</code>	A Stream is an infinite sequence of data
<code>Stream.connect(self, downstream)</code>	Connect this stream to a downstream element.
<code>Stream.destroy(self[, streams])</code>	Disconnect this stream from any upstream sources
<code>Stream.disconnect(self, downstream)</code>	Disconnect this stream to a downstream element.
<code>Stream.visualize(self[, filename])</code>	Render the computation of this object's task graph using graphviz.
<code>accumulate(upstream, func[, start, ...])</code>	Accumulate results with previous state

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<code>buffer(upstream, n, **kwargs)</code>	Allow results to pile up at this point in the stream
<code>collect(upstream[, cache, metadata_cache])</code>	Hold elements in a cache and emit them as a collection when flushed.
<code>combine_latest(*upstreams, **kwargs)</code>	Combine multiple streams together to a stream of tuples
<code>delay(upstream, interval, **kwargs)</code>	Add a time delay to results
<code>filter(upstream, predicate, *args, **kwargs)</code>	Only pass through elements that satisfy the predicate
<code>flatten([upstream, upstreams, stream_name, ...])</code>	Flatten streams of lists or iterables into a stream of elements
<code>map(upstream, func, *args, **kwargs)</code>	Apply a function to every element in the stream
<code>partition(upstream, n, **kwargs)</code>	Partition stream into tuples of equal size
<code>rate_limit(upstream, interval, **kwargs)</code>	Limit the flow of data
<code>scatter(*args, **kwargs)</code>	Convert local stream to Dask Stream
<code>sink(upstream, func, *args, **kwargs)</code>	Apply a function on every element
<code>slice(upstream[, start, end, step])</code>	Get only some events in a stream by position.
<code>sliding_window(upstream, n[, return_partial])</code>	Produce overlapping tuples of size n
<code>starmap(upstream, func, *args, **kwargs)</code>	Apply a function to every element in the stream, splayed out
<code>timed_window(upstream, interval, **kwargs)</code>	Emit a tuple of collected results every interval
<code>union(*upstreams, **kwargs)</code>	Combine multiple streams into one
<code>unique(upstream[, maxsize, key, hashable])</code>	Avoid sending through repeated elements
<code>pluck(upstream, pick, **kwargs)</code>	Select elements from elements in the stream.
<code>zip(*upstreams, **kwargs)</code>	Combine streams together into a stream of tuples
<code>zip_latest(lossless, *upstreams, **kwargs)</code>	Combine multiple streams together to a stream of tuples

`Stream.connect` (*self, downstream*)

Connect this stream to a downstream element.

#### Parameters

**downstream: Stream** The downstream stream to connect to

`Stream.disconnect` (*self, downstream*)

Disconnect this stream to a downstream element.

#### Parameters

**downstream: Stream** The downstream stream to disconnect from

`Stream.destroy` (*self, streams=None*)

Disconnect this stream from any upstream sources

`Stream.emit` (*self, x, asynchronous=False, metadata=None*)

Push data into the stream at this point

This is typically done only at source Streams but can theoretically be done at any point

#### Parameters

**x: any** an element of data

**asynchronous:** emit asynchronously

**metadata: list[dict], optional** Various types of metadata associated with the data element in *x*.

ref: RefCounter A reference counter used to check when data is done

`Stream.frequencies` (*self, \*\*kwargs*)

Count occurrences of elements



**classmethod** `Stream.register_api` (*modifier=<function identity at 0x7f5d72a31950>*)  
Add callable to Stream API

This allows you to register a new method onto this class. You can use it as a decorator:

```
>>> @Stream.register_api()
... class foo(Stream):
...     ...
>>> Stream().foo(...) # this works now
```

It attaches the callable as a normal attribute to the class object. In doing so it respects inheritance (all subclasses of Stream will also get the foo attribute).

By default callables are assumed to be instance methods. If you like you can include modifiers to apply before attaching to the class as in the following case where we construct a `staticmethod`.

```
>>> @Stream.register_api(staticmethod)
... class foo(Stream):
...     ...
```

```
>>> Stream.foo(...) # Foo operates as a static method
```

`Stream.sink_to_list` (*self*)

Append all elements of a stream to a list as they come in

### Examples

```
>>> source = Stream()
>>> L = source.map(lambda x: 10 * x).sink_to_list()
>>> for i in range(5):
...     source.emit(i)
>>> L
[0, 10, 20, 30, 40]
```

`Stream.update` (*self, x, who=None, metadata=None*)

`Stream.visualize` (*self, filename='mystream.png', \*\*kwargs*)

Render the computation of this object's task graph using graphviz.

Requires graphviz and networkx to be installed.

#### Parameters

**filename** [str, optional] The name of the file to write to disk.

**kwargs:** Graph attributes to pass to graphviz like `rankdir="LR"`

## 3.5.2 Sources

<code>filenames</code> (path[, poll_interval, start])	Stream over filenames in a directory
<code>from_kafka</code> (topics, consumer_params[, ...])	Accepts messages from Kafka
<code>from_kafka_batched</code> (topic, consumer_params[, ...])	Get messages and keys (optional) from Kafka in batches
<code>from_process</code> (cmd[, open_kwargs, ...])	Messages from a running external process

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Table 12 – continued from previous page

<code>from_textfile(f[, poll_interval, delimiter, ...])</code>	Stream data from a text file
<code>from_tcp(port[, delimiter, start, server_kwargs])</code>	Creates events by reading from a socket using tornado TCPServer
<code>from_http_server(port[, path, start, ...])</code>	Listen for HTTP POSTs on given port

### 3.5.3 DaskStream

<code>DaskStream(*args, **kwargs)</code>	A Parallel stream using Dask
<code>gather([upstream, upstreams, stream_name, ...])</code>	Wait on and gather results from DaskStream to local Stream

### 3.5.4 Definitions

`streamz.accumulate` (*upstream, func, start='no-default', returns\_state=False, \*\*kwargs*)

Accumulate results with previous state

This performs running or cumulative reductions, applying the function to the previous total and the new element. The function should take two arguments, the previous accumulated state and the next element and it should return a new accumulated state, - `state = func(previous_state, new_value)` (`returns_state=False`) - `state, result = func(previous_state, new_value)` (`returns_state=True`)

where the `new_state` is passed to the next invocation. The state or result is emitted downstream for the two cases.

#### Parameters

**func: callable**

**start: object** Initial value, passed as the value of `previous_state` on the first invocation. Defaults to the first submitted element

**returns\_state: boolean** If true then `func` should return both the state and the value to emit. If false then both values are the same, and `func` returns one value

**\*\*kwargs:** Keyword arguments to pass to `func`

#### Examples

A running total, producing triangular numbers

```
>>> source = Stream()
>>> source.accumulate(lambda acc, x: acc + x).sink(print)
>>> for i in range(5):
...     source.emit(i)
0
1
3
6
10
```

A count of number of events (including the current one)

```
>>> source = Stream()
>>> source.accumulate(lambda acc, x: acc + 1, start=0).sink(print)
>>> for _ in range(5):
...     source.emit(0)
```

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```
1
2
3
4
5
```

Like the builtin “enumerate”.

```
>>> source = Stream()
>>> source.accumulate(lambda acc, x: ((acc[0] + 1, x), (acc[0], x)),
...                   start=(0, 0), returns_state=True
...                   ).sink(print)
>>> for i in range(3):
...     source.emit(0)
(0, 0)
(1, 0)
(2, 0)
```

`streamz.buffer` (*upstream, n, \*\*kwargs*)

Allow results to pile up at this point in the stream

This allows results to buffer in place at various points in the stream. This can help to smooth flow through the system when backpressure is applied.

`streamz.collect` (*upstream, cache=None, metadata\_cache=None, \*\*kwargs*)

Hold elements in a cache and emit them as a collection when flushed.

## Examples

```
>>> source1 = Stream()
>>> source2 = Stream()
>>> collector = collect(source1)
>>> collector.sink(print)
>>> source2.sink(collector.flush)
>>> source1.emit(1)
>>> source1.emit(2)
>>> source2.emit('anything') # flushes collector
...
[1, 2]
```

`streamz.combine_latest` (*\*upstreams, \*\*kwargs*)

Combine multiple streams together to a stream of tuples

This will emit a new tuple of all of the most recent elements seen from any stream.

### Parameters

**emit\_on** [stream or list of streams or None] only emit upon update of the streams listed. If None, emit on update from any stream

See also:

[`zip`](#)

`streamz.delay` (*upstream, interval, \*\*kwargs*)

Add a time delay to results

`streamz.filter` (*upstream, predicate, \*args, \*\*kwargs*)

Only pass through elements that satisfy the predicate

#### Parameters

**predicate** [function] The predicate. Should return True or False, where True means that the predicate is satisfied.

**\*args**: The arguments to pass to the predicate.

**\*\*kwargs**: Keyword arguments to pass to predicate

#### Examples

```
>>> source = Stream()
>>> source.filter(lambda x: x % 2 == 0).sink(print)
>>> for i in range(5):
...     source.emit(i)
0
2
4
```

`streamz.flatten` (*upstream=None, upstreams=None, stream\_name=None, loop=None, asynchronous=None, ensure\_io\_loop=False*)

Flatten streams of lists or iterables into a stream of elements

**See also:**

[\*partition\*](#)

#### Examples

```
>>> source = Stream()
>>> source.flatten().sink(print)
>>> for x in [[1, 2, 3], [4, 5], [6, 7, 7]]:
...     source.emit(x)
1
2
3
4
5
6
7
```

`streamz.map` (*upstream, func, \*args, \*\*kwargs*)

Apply a function to every element in the stream

#### Parameters

**func: callable**

**\*args**: The arguments to pass to the function.

**\*\*kwargs**: Keyword arguments to pass to func

## Examples

```
>>> source = Stream()
>>> source.map(lambda x: 2*x).sink(print)
>>> for i in range(5):
...     source.emit(i)
0
2
4
6
8
```

`streamz.partition` (*upstream, n, \*\*kwargs*)  
Partition stream into tuples of equal size

## Examples

```
>>> source = Stream()
>>> source.partition(3).sink(print)
>>> for i in range(10):
...     source.emit(i)
(0, 1, 2)
(3, 4, 5)
(6, 7, 8)
```

`streamz.rate_limit` (*upstream, interval, \*\*kwargs*)  
Limit the flow of data

This stops two elements of streaming through in an interval shorter than the provided value.

### Parameters

**interval:** float Time in seconds

`streamz.sink` (*upstream, func, \*args, \*\*kwargs*)  
Apply a function on every element

**See also:**

[\*map\*](#)

[\*Stream.sink\\_to\\_list\*](#)

## Examples

```
>>> source = Stream()
>>> L = list()
>>> source.sink(L.append)
>>> source.sink(print)
>>> source.sink(print)
>>> source.emit(123)
123
123
>>> L
[123]
```

`streamz.sliding_window` (*upstream*, *n*, *return\_partial=True*, *\*\*kwargs*)  
Produce overlapping tuples of size *n*

#### Parameters

**return\_partial** [bool] If True, yield tuples as soon as any events come in, each tuple being smaller or equal to the window size. If False, only start yielding tuples once a full window has accrued.

#### Examples

```
>>> source = Stream()
>>> source.sliding_window(3, return_partial=False).sink(print)
>>> for i in range(8):
...     source.emit(i)
(0, 1, 2)
(1, 2, 3)
(2, 3, 4)
(3, 4, 5)
(4, 5, 6)
(5, 6, 7)
```

`streamz.Stream` (*upstream=None*, *upstreams=None*, *stream\_name=None*, *loop=None*, *asynchronous=None*, *ensure\_io\_loop=False*)  
A Stream is an infinite sequence of data

Streams subscribe to each other passing and transforming data between them. A Stream object listens for updates from upstream, reacts to these updates, and then emits more data to flow downstream to all Stream objects that subscribe to it. Downstream Stream objects may connect at any point of a Stream graph to get a full view of the data coming off of that point to do with as they will.

#### Parameters

**asynchronous: boolean or None** Whether or not this stream will be used in asynchronous functions or normal Python functions. Leave as None if you don't know. True will cause operations like emit to return awaitable Futures False will use an Event loop in another thread (starts it if necessary)

**ensure\_io\_loop: boolean** Ensure that some IOloop will be created. If asynchronous is None or False then this will be in a separate thread, otherwise it will be IOloop.current

#### Examples

```
>>> def inc(x):
...     return x + 1
```

```
>>> source = Stream() # Create a stream object
>>> s = source.map(inc).map(str) # Subscribe to make new streams
>>> s.sink(print) # take an action whenever an element reaches the end
```

```
>>> L = list()
>>> s.sink(L.append) # or take multiple actions (streams can branch)
```

```
>>> for i in range(5):
...     source.emit(i) # push data in at the source
```

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```
'1'
'2'
'3'
'4'
'5'
>>> L # and the actions happen at the sinks
['1', '2', '3', '4', '5']
```

`streamz.timed_window` (*upstream*, *interval*, *\*\*kwargs*)

Emit a tuple of collected results every interval

Every *interval* seconds this emits a tuple of all of the results seen so far. This can help to batch data coming off of a high-volume stream.

`streamz.union` (*\*upstreams*, *\*\*kwargs*)

Combine multiple streams into one

Every element from any of the upstreams streams will immediately flow into the output stream. They will not be combined with elements from other streams.

**See also:**

**`Stream.zip`**

**`Stream.combine_latest`**

`streamz.unique` (*upstream*, *maxsize=None*, *key=<function identity>*, *hashable=True*, *\*\*kwargs*)

Avoid sending through repeated elements

This deduplicates a stream so that only new elements pass through. You can control how much of a history is stored with the *maxsize=* parameter. For example setting *maxsize=1* avoids sending through elements when one is repeated right after the other.

#### Parameters

**maxsize:** *int* or *None*, *optional* number of stored unique values to check against

**key** [*function*, *optional*] Function which returns a representation of the incoming data. For example *key=lambda x: x['a']* could be used to allow only pieces of data with unique 'a' values to pass through.

**hashable** [*bool*, *optional*] If *True* then data is assumed to be hashable, else it is not. This is used for determining how to cache the history, if hashable then either dicts or LRU caches are used, otherwise a deque is used. Defaults to *True*.

#### Examples

```
>>> source = Stream()
>>> source.unique(maxsize=1).sink(print)
>>> for x in [1, 1, 2, 2, 2, 1, 3]:
...     source.emit(x)
1
2
1
3
```

`streamz.pluck` (*upstream*, *pick*, *\*\*kwargs*)

Select elements from elements in the stream.

### Parameters

**pluck** [object, list] The element(s) to pick from the incoming element in the stream. If an instance of list, will pick multiple elements.

### Examples

```
>>> source = Stream()
>>> source.pluck([0, 3]).sink(print)
>>> for x in [[1, 2, 3, 4], [4, 5, 6, 7], [8, 9, 10, 11]]:
...     source.emit(x)
(1, 4)
(4, 7)
(8, 11)
```

```
>>> source = Stream()
>>> source.pluck('name').sink(print)
>>> for x in [{'name': 'Alice', 'x': 123}, {'name': 'Bob', 'x': 456}]:
...     source.emit(x)
'Alice'
'Bob'
```

`streamz.zip(*upstreams, **kwargs)`

Combine streams together into a stream of tuples

We emit a new tuple once all streams have produce a new tuple.

**See also:**

[`combine\_latest`](#)

[`zip\_latest`](#)

`streamz.zip_latest(lossless, *upstreams, **kwargs)`

Combine multiple streams together to a stream of tuples

The stream which this is called from is lossless. All elements from the lossless stream are emitted regardless of when they came in. This will emit a new tuple consisting of an element from the lossless stream paired with the latest elements from the other streams. Elements are only emitted when an element on the lossless stream are received, similar to `combine_latest` with the `emit_on` flag.

**See also:**

`Stream.combine_latest`

`Stream.zip`

`streamz.filenames(path, poll_interval=0.1, start=False, **kwargs)`

Stream over filenames in a directory

### Parameters

**path:** string Directory path or globstring over which to search for files

**poll\_interval:** Number Seconds between checking path

**start:** bool (False) Whether to start running immediately; otherwise call `stream.start()` explicitly.



## Examples

```
>>> source = Stream.files('path/to/dir') # doctest: +SKIP
>>> source = Stream.files('path/to/*.csv', poll_interval=0.500) # doctest:
↳ +SKIP
```

`streamz.from_kafka` (*topics*, *consumer\_params*, *poll\_interval=0.1*, *start=False*, *\*\*kwargs*)  
Accepts messages from Kafka

Uses the confluent-kafka library, <https://docs.confluent.io/current/clients/confluent-kafka-python/>

### Parameters

**topics:** **list of str** Labels of Kafka topics to consume from

**consumer\_params:** **dict** Settings to set up the stream, see <https://docs.confluent.io/current/clients/confluent-kafka-python/#configuration> <https://github.com/edenhill/librdkafka/blob/master/CONFIGURATION.md> Examples: `bootstrap.servers`, Connection string(s) (host:port) by which to reach Kafka; `group.id`, Identity of the consumer. If multiple sources share the same group, each message will be passed to only one of them.

**poll\_interval:** **number** Seconds that elapse between polling Kafka for new messages

**start:** **bool (False)** Whether to start polling upon instantiation

## Examples

```
>>> source = Stream.from_kafka(['mytopic'],
...                             {'bootstrap.servers': 'localhost:9092',
...                             'group.id': 'streamz'}) # doctest: +SKIP
```

`streamz.from_kafka_batched` (*topic*, *consumer\_params*, *poll\_interval='1s'*, *npartitions=1*, *start=False*, *dask=False*, *max\_batch\_size=10000*, *keys=False*, *\*\*kwargs*)

Get messages and keys (optional) from Kafka in batches

Uses the confluent-kafka library, <https://docs.confluent.io/current/clients/confluent-kafka-python/>

This source will emit lists of messages for each partition of a single given topic per time interval, if there is new data. If using `dask`, one future will be produced per partition per time-step, if there is data.

Checkpointing is achieved through the use of reference counting. A reference counter is emitted downstream for each batch of data. A callback is triggered when the reference count reaches zero and the offsets are committed back to Kafka. Upon the start of this function, the previously committed offsets will be fetched from Kafka and begin reading from there. This will guarantee at-least-once semantics.

### Parameters

**topic:** **str** Kafka topic to consume from

**consumer\_params:** **dict** Settings to set up the stream, see <https://docs.confluent.io/current/clients/confluent-kafka-python/#configuration> <https://github.com/edenhill/librdkafka/blob/master/CONFIGURATION.md> Examples: `bootstrap.servers`: Connection string(s) (host:port) by which to reach Kafka `group.id`: Identity of the consumer. If multiple sources share the same

`group`, each message will be passed to only one of them.

**poll\_interval:** **number** Seconds that elapse between polling Kafka for new messages

**npartitions:** **int** Number of partitions in the topic

**start: bool (False)** Whether to start polling upon instantiation

**max\_batch\_size: int** The maximum number of messages per partition to be consumed per batch

**keys: bool (False)** Whether to extract keys along with the messages. If True, this will yield each message as a dict: {'key':msg.key(), 'value':msg.value()}

#### Important Kafka Configurations:

If 'auto.offset.reset': 'latest' is set in the consumer configs, the stream starts reading messages

from latest offset. Else, if it's set to 'earliest', it will read from the start offset.

### Examples

```
>>> source = Stream.from_kafka_batched('mytopic',
...     {'bootstrap.servers': 'localhost:9092',
...     'group.id': 'streamz'}, npartitions=4) # doctest: +SKIP
```

`streamz.from_textfile(f, poll_interval=0.1, delimiter='\n', start=False, from_end=False, **kwargs)`  
Stream data from a text file

#### Parameters

**f: file or string** Source of the data. If string, will be opened.

**poll\_interval: Number** Interval to poll file for new data in seconds

**delimiter: str** Character(s) to use to split the data into parts

**start: bool** Whether to start running immediately; otherwise call `stream.start()` explicitly.

**from\_end: bool** Whether to begin streaming from the end of the file (i.e., only emit lines appended after the stream starts).

#### Returns

Stream

### Examples

```
>>> source = Stream.from_textfile('myfile.json') # doctest: +SKIP
>>> source.map(json.loads).pluck('value').sum().sink(print) # doctest: +SKIP
>>> source.start() # doctest: +SKIP
```

`streamz.dask.DaskStream(*args, **kwargs)`  
A Parallel stream using Dask

This object is fully compliant with the `streamz.core.Stream` object but uses a Dask client for execution. Operations like `map` and `accumulate` submit functions to run on the Dask instance using `dask.distributed.Client.submit` and pass around Dask futures. Time-based operations like `timed_window`, `buffer`, and so on operate as normal.

Typically one transfers between normal `Stream` and `DaskStream` objects using the `Stream.scatter()` and `DaskStream.gather()` methods.

See also:

`dask.distributed.Client`

## Examples

```
>>> from dask.distributed import Client
>>> client = Client()
```

```
>>> from streamz import Stream
>>> source = Stream()
>>> source.scatter().map(func).accumulate(binop).gather().sink(...)
```

`streamz.dask.gather` (*upstream=None, upstreams=None, stream\_name=None, loop=None, asynchronous=None, ensure\_io\_loop=False*)

Wait on and gather results from DaskStream to local Stream

This waits on every result in the stream and then gathers that result back to the local stream. Warning, this can restrict parallelism. It is common to combine a `gather()` node with a `buffer()` to allow unfinished futures to pile up.

**See also:**

**buffer**

**scatter**

## Examples

```
>>> local_stream = dask_stream.buffer(20).gather()
```

## 3.6 Collections API

### 3.6.1 Collections

<code>Streaming</code> ([stream, example, stream_type])	Superclass for streaming collections
<code>Streaming.map_partitions</code> (func, <i>*args</i> , ...)	Map a function across all batch elements of this stream
<code>Streaming.accumulate_partitions</code> (self, func, ...)	Accumulate a function with state across batch elements
<code>Streaming.verify</code> (self, x)	Verify elements that pass through this stream

### 3.6.2 Batch

<code>Batch</code> ([stream, example])	A Stream of tuples or lists
<code>Batch.filter</code> (self, predicate)	Filter elements by a predicate
<code>Batch.map</code> (self, func, <i>*kwargs</i> )	Map a function across all elements
<code>Batch.pluck</code> (self, ind)	Pick a field out of all elements
<code>Batch.to_dataframe</code> (self)	Convert to a streaming dataframe
<code>Batch.to_stream</code> (self)	Concatenate batches and return base Stream

### 3.6.3 Dataframes

<code>DataFrame(*args, **kwargs)</code>	A Streaming dataframe
<code>DataFrame.groupby(self, other)</code>	Groupby aggregations
<code>DataFrame.rolling(self, window[, min_periods])</code>	Compute rolling aggregations
<code>DataFrame.assign(self, **kwargs)</code>	Assign new columns to this dataframe
<code>DataFrame.sum(self)</code>	Sum frame
<code>DataFrame.mean(self)</code>	Average
<code>DataFrame.cumsum(self)</code>	Cumulative sum
<code>DataFrame.cumprod(self)</code>	Cumulative product
<code>DataFrame.cummin(self)</code>	Cumulative minimum
<code>DataFrame.cummax(self)</code>	Cumulative maximum
<hr/>	
<code>GroupBy(root, grouper[, index])</code>	Groupby aggregations on streaming dataframes
<code>GroupBy.count(self)</code>	Groupby-count
<code>GroupBy.mean(self)</code>	Groupby-mean
<code>GroupBy.size(self)</code>	Groupby-size
<code>GroupBy.std(self[, ddof])</code>	Groupby-std
<code>GroupBy.sum(self)</code>	Groupby-sum
<code>GroupBy.var(self[, ddof])</code>	Groupby-variance
<hr/>	
<code>Rolling(sdf, window, min_periods)</code>	Rolling aggregations
<code>Rolling.aggregate(self, *args, **kwargs)</code>	Rolling aggregation
<code>Rolling.count(self, *args, **kwargs)</code>	Rolling count
<code>Rolling.max(self)</code>	Rolling maximum
<code>Rolling.mean(self)</code>	Rolling mean
<code>Rolling.median(self)</code>	Rolling median
<code>Rolling.min(self)</code>	Rolling minimum
<code>Rolling.quantile(self, *args, **kwargs)</code>	Rolling quantile
<code>Rolling.std(self, *args, **kwargs)</code>	Rolling standard deviation
<code>Rolling.sum(self)</code>	Rolling sum
<code>Rolling.var(self, *args, **kwargs)</code>	Rolling variance
<hr/>	
<code>DataFrame.window(self[, n, value])</code>	Sliding window operations
<code>Window.apply(self, func)</code>	Apply an arbitrary function over each window of data
<code>Window.count(self)</code>	Count elements within window
<code>Window.groupby(self, other)</code>	Groupby-aggregations within window
<code>Window.sum(self)</code>	Sum elements within window
<code>Window.size</code>	Number of elements within window
<code>Window.std(self[, ddof])</code>	Compute standard deviation of elements within window
<code>Window.var(self[, ddof])</code>	Compute variance of elements within window
<hr/>	
<code>Rolling.aggregate(self, *args, **kwargs)</code>	Rolling aggregation
<code>Rolling.count(self, *args, **kwargs)</code>	Rolling count
<code>Rolling.max(self)</code>	Rolling maximum
<code>Rolling.mean(self)</code>	Rolling mean
<code>Rolling.median(self)</code>	Rolling median
<code>Rolling.min(self)</code>	Rolling minimum
<code>Rolling.quantile(self, *args, **kwargs)</code>	Rolling quantile

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<code>Rolling.std(self, *args, **kwargs)</code>	Rolling standard deviation
<code>Rolling.sum(self)</code>	Rolling sum
<code>Rolling.var(self, *args, **kwargs)</code>	Rolling variance
<hr/>	
<code>Random([freq, interval, dask])</code>	A streaming dataframe of random data

### 3.6.4 Details

**class** `streamz.collection.Streaming` (*stream=None, example=None, stream\_type=None*)  
 Superclass for streaming collections

Do not create this class directly, use one of the subclasses instead.

#### Parameters

**stream:** `streamz.Stream`

**example:** `object` An object to represent an example element of this stream

See also:

`streamz.dataframe.StreamingDataFrame`

`streamz.dataframe.StreamingBatch`

#### Methods

<code>accumulate_partitions(self, func, *args, ...)</code>	Accumulate a function with state across batch elements
<code>map_partitions(func, *args, **kwargs)</code>	Map a function across all batch elements of this stream
<code>verify(self, x)</code>	Verify elements that pass through this stream

**emit**

**accumulate\_partitions** (*self, func, \*args, \*\*kwargs*)  
 Accumulate a function with state across batch elements

See also:

*[Streaming.map\\_partitions](#)*

**static map\_partitions** (*func, \*args, \*\*kwargs*)  
 Map a function across all batch elements of this stream

The output stream type will be determined by the action of that function on the example

See also:

*[Streaming.accumulate\\_partitions](#)*

**verify** (*self, x*)  
 Verify elements that pass through this stream

**class** `streamz.batch.Batch` (*stream=None, example=None*)

A Stream of tuples or lists

This streaming collection manages batches of Python objects such as lists of text or dictionaries. By batching many elements together we reduce overhead from Python.

This library is typically used at the early stages of data ingestion before handing off to streaming dataframes

### Examples

```
>>> text = Streaming.from_file(myfile) # doctest: +SKIP
>>> b = text.partition(100).map(json.loads) # doctest: +SKIP
```

### Methods

<code>accumulate_partitions(self, func, *args, ...)</code>	Accumulate a function with state across batch elements
<code>filter(self, predicate)</code>	Filter elements by a predicate
<code>map(self, func, **kwargs)</code>	Map a function across all elements
<code>map_partitions(func, *args, **kwargs)</code>	Map a function across all batch elements of this stream
<code>pluck(self, ind)</code>	Pick a field out of all elements
<code>sum(self)</code>	Sum elements
<code>to_dataframe(self)</code>	Convert to a streaming dataframe
<code>to_stream(self)</code>	Concatenate batches and return base Stream
<code>verify(self, x)</code>	Verify elements that pass through this stream

**emit**

**accumulate\_partitions** (*self, func, \*args, \*\*kwargs*)

Accumulate a function with state across batch elements

**See also:**

**Streaming.map\_partitions**

**filter** (*self, predicate*)

Filter elements by a predicate

**map** (*self, func, \*\*kwargs*)

Map a function across all elements

**static map\_partitions** (*func, \*args, \*\*kwargs*)

Map a function across all batch elements of this stream

The output stream type will be determined by the action of that function on the example

**See also:**

**Streaming.accumulate\_partitions**

**pluck** (*self, ind*)

Pick a field out of all elements

**sum** (*self*)

Sum elements

**to\_dataframe** (*self*)

Convert to a streaming dataframe

This calls `pd.DataFrame` on all list-elements of this stream**to\_stream** (*self*)

Concatenate batches and return base Stream

Returned stream will be composed of single elements

**verify** (*self*, *x*)

Verify elements that pass through this stream

**class** `streamz.dataframe.DataFrame` (\*args, \*\*kwargs)

A Streaming dataframe

This is a logical collection over a stream of Pandas dataframes. Operations on this object will translate to the appropriate operations on the underlying Pandas dataframes.

**See also:****Series****Attributes****columns****dtypes****index****size** size of frame**Methods**

<code>accumulate_partitions</code> (self, func, \*args, ...)	Accumulate a function with state across batch elements
<code>assign</code> (self, \*\*kwargs)	Assign new columns to this dataframe
<code>count</code> (self)	Count of frame
<code>cummax</code> (self)	Cumulative maximum
<code>cummin</code> (self)	Cumulative minimum
<code>cumprod</code> (self)	Cumulative product
<code>cumsum</code> (self)	Cumulative sum
<code>groupby</code> (self, other)	Groupby aggregations
<code>map_partitions</code> (func, \*args, \*\*kwargs)	Map a function across all batch elements of this stream
<code>mean</code> (self)	Average
<code>reset_index</code> (self)	Reset Index
<code>rolling</code> (self, window[, min_periods])	Compute rolling aggregations
<code>round</code> (self[, decimals])	Round elements in frame
<code>set_index</code> (self, index, \*\*kwargs)	Set Index
<code>sum</code> (self)	Sum frame
<code>tail</code> (self[, n])	Round elements in frame
<code>to_frame</code> (self)	Convert to a streaming dataframe

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<code>verify(self, x)</code>	Verify consistency of elements that pass through this stream
<code>window(self[, n, value])</code>	Sliding window operations

<b>aggregate</b>	
<b>astype</b>	
<b>emit</b>	
<b>map</b>	
<b>query</b>	

**accumulate\_partitions** (*self*, *func*, \**args*, \*\**kwargs*)  
Accumulate a function with state across batch elements

**See also:**

**Streaming.map\_partitions**

**assign** (*self*, \*\**kwargs*)  
Assign new columns to this dataframe  
Alternatively use setitem syntax

### Examples

```
>>> sdf = sdf.assign(z=sdf.x + sdf.y) # doctest: +SKIP
>>> sdf['z'] = sdf.x + sdf.y # doctest: +SKIP
```

**count** (*self*)  
Count of frame

**cummax** (*self*)  
Cumulative maximum

**cummin** (*self*)  
Cumulative minimum

**cumprod** (*self*)  
Cumulative product

**cumsum** (*self*)  
Cumulative sum

**groupby** (*self*, *other*)  
Groupby aggregations

**static map\_partitions** (*func*, \**args*, \*\**kwargs*)  
Map a function across all batch elements of this stream  
The output stream type will be determined by the action of that function on the example

**See also:**

**Streaming.accumulate\_partitions**

**mean** (*self*)  
Average



**reset\_index** (*self*)

Reset Index

**rolling** (*self*, *window*, *min\_periods=1*)

Compute rolling aggregations

When followed by an aggregation method like `sum`, `mean`, or `std` this produces a new Streaming dataframe whose values are aggregated over that window.

The window parameter can be either a number of rows or a `timedelta` like `"2 minutes"` in which case the index should be a datetime index.

This operates by keeping enough of a backlog of records to maintain an accurate stream. It performs a copy at every added dataframe. Because of this it may be slow if the rolling window is much larger than the average stream element.

**Parameters****window: int or timedelta** Window over which to roll**Returns****Rolling object****See also:**[\*DataFrame.window\*](#) more generic window operations**round** (*self*, *decimals=0*)

Round elements in frame

**set\_index** (*self*, *index*, *\*\*kwargs*)

Set Index

**size**

size of frame

**sum** (*self*)

Sum frame

**tail** (*self*, *n=5*)

Round elements in frame

**to\_frame** (*self*)

Convert to a streaming dataframe

**verify** (*self*, *x*)

Verify consistency of elements that pass through this stream

**window** (*self*, *n=None*, *value=None*)

Sliding window operations

Windowed operations are defined over a sliding window of data, either with a fixed number of elements:

```
>>> df.window(n=10).sum() # sum of the last ten elements
```

or over an index value range (index must be monotonic):

```
>>> df.window(value='2h').mean() # average over the last two hours
```

Windowed dataframes support all normal arithmetic, aggregations, and groupby-aggregations.

**See also:**

*DataFrame.rolling* mimic's Pandas rolling aggregations

### Examples

```
>>> df.window(n=10).std()
>>> df.window(value='2h').count()
```

```
>>> w = df.window(n=100)
>>> w.groupby(w.name).amount.sum()
>>> w.groupby(w.x % 10).y.var()
```

**class** `streamz.dataframe.Rolling` (*sdf, window, min\_periods*)

Rolling aggregations

This intermediate class enables rolling aggregations across either a fixed number of rows or a time window.

### Examples

```
>>> sdf.rolling(10).x.mean() # doctest: +SKIP
>>> sdf.rolling('100ms').x.mean() # doctest: +SKIP
```

### Methods

<i>aggregate</i> (self, <i>*args</i> , <i>**kwargs</i> )	Rolling aggregation
<i>count</i> (self, <i>*args</i> , <i>**kwargs</i> )	Rolling count
<i>max</i> (self)	Rolling maximum
<i>mean</i> (self)	Rolling mean
<i>median</i> (self)	Rolling median
<i>min</i> (self)	Rolling minimum
<i>quantile</i> (self, <i>*args</i> , <i>**kwargs</i> )	Rolling quantile
<i>std</i> (self, <i>*args</i> , <i>**kwargs</i> )	Rolling standard deviation
<i>sum</i> (self)	Rolling sum
<i>var</i> (self, <i>*args</i> , <i>**kwargs</i> )	Rolling variance

**aggregate** (*self, \*args, \*\*kwargs*)

Rolling aggregation

**count** (*self, \*args, \*\*kwargs*)

Rolling count

**max** (*self*)

Rolling maximum

**mean** (*self*)

Rolling mean

**median** (*self*)

Rolling median

**min** (*self*)

Rolling minimum

**quantile** (*self, \*args, \*\*kwargs*)

Rolling quantile

**std** (*self*, \*args, \*\*kwargs)  
Rolling standard deviation

**sum** (*self*)  
Rolling sum

**var** (*self*, \*args, \*\*kwargs)  
Rolling variance

**class** streamz.dataframe.**Window** (*sdf*, *n=None*, *value=None*)  
Windowed aggregations

This provides a set of aggregations that can be applied over a sliding window of data.

**See also:**

[DataFrame.window](#) contains full docstring

#### Attributes

**columns**

**dtypes**

**example**

**index**

**size** Number of elements within window

#### Methods

<i>apply</i> (self, func)	Apply an arbitrary function over each window of data
<i>count</i> (self)	Count elements within window
<i>groupby</i> (self, other)	Groupby-aggregations within window
<i>mean</i> (self)	Average elements within window
<i>std</i> (self[, ddof])	Compute standard deviation of elements within window
<i>sum</i> (self)	Sum elements within window
<i>value_counts</i> (self)	Count groups of elements within window
<i>var</i> (self[, ddof])	Compute variance of elements within window

<b>aggregate</b>	
<b>full</b>	
<b>map_partitions</b>	
<b>reset_index</b>	

**apply** (*self*, *func*)  
Apply an arbitrary function over each window of data

**count** (*self*)  
Count elements within window

**groupby** (*self*, *other*)

Groupby-aggregations within window

- mean** (*self*)  
Average elements within window
- size**  
Number of elements within window
- std** (*self*, *ddof=1*)  
Compute standard deviation of elements within window
- sum** (*self*)  
Sum elements within window
- value\_counts** (*self*)  
Count groups of elements within window
- var** (*self*, *ddof=1*)  
Compute variance of elements within window

**class** `streamz.dataframe.GroupBy` (*root*, *groupers*, *index=None*)  
Groupby aggregations on streaming dataframes

### Methods

<code>count(self)</code>	Groupby-count
<code>mean(self)</code>	Groupby-mean
<code>size(self)</code>	Groupby-size
<code>std(self[, ddof])</code>	Groupby-std
<code>sum(self)</code>	Groupby-sum
<code>var(self[, ddof])</code>	Groupby-variance

- count** (*self*)  
Groupby-count
- mean** (*self*)  
Groupby-mean
- size** (*self*)  
Groupby-size
- std** (*self*, *ddof=1*)  
Groupby-std
- sum** (*self*)  
Groupby-sum
- var** (*self*, *ddof=1*)  
Groupby-variance

**class** `streamz.dataframe.Random` (*freq='100ms'*, *interval='500ms'*, *dask=False*)  
A streaming dataframe of random data

The x column is uniformly distributed. The y column is poisson distributed. The z column is normally distributed.

This class is experimental and will likely be removed in the future

### Parameters

**freq: timedelta** The time interval between records

**interval: timedelta** The time interval between new dataframes, should be significantly larger than freq

#### Attributes

**columns**

**dtypes**

**index**

**size** size of frame

#### Methods

<code>accumulate_partitions(self, func, *args, ...)</code>	Accumulate a function with state across batch elements
<code>assign(self, **kwargs)</code>	Assign new columns to this dataframe
<code>count(self)</code>	Count of frame
<code>cummax(self)</code>	Cumulative maximum
<code>cummin(self)</code>	Cumulative minimum
<code>cumprod(self)</code>	Cumulative product
<code>cumsum(self)</code>	Cumulative sum
<code>groupby(self, other)</code>	Groupby aggregations
<code>map_partitions(func, *args, **kwargs)</code>	Map a function across all batch elements of this stream
<code>mean(self)</code>	Average
<code>reset_index(self)</code>	Reset Index
<code>rolling(self, window[, min_periods])</code>	Compute rolling aggregations
<code>round(self[, decimals])</code>	Round elements in frame
<code>set_index(self, index, **kwargs)</code>	Set Index
<code>sum(self)</code>	Sum frame
<code>tail(self[, n])</code>	Round elements in frame
<code>to_frame(self)</code>	Convert to a streaming dataframe
<code>verify(self, x)</code>	Verify consistency of elements that pass through this stream
<code>window(self[, n, value])</code>	Sliding window operations

<b>aggregate</b>	
<b>astype</b>	
<b>emit</b>	
<b>map</b>	
<b>query</b>	
<b>stop</b>	

## 3.7 Asynchronous Computation

*This section is only relevant if you want to use time-based functionality. If you are only using operations like map and accumulate then you can safely skip this section.*

When using time-based flow control like `rate_limit`, `delay`, or `timed_window` Streamz relies on the `Tornado` framework for concurrency. This allows us to handle many concurrent operations cheaply and consistently within a single thread. However, this also adds complexity and requires some understanding of asynchronous programming. There are a few different ways to use Streamz with a Tornado event loop.

We give a few examples below that all do the same thing, but with different styles. In each case we use the following toy functions:

```
from tornado import gen
import time

def increment(x):
    """ A blocking increment function

    Simulates a computational function that was not designed to work
    asynchronously
    """
    time.sleep(0.1)
    return x + 1

@gen.coroutine
def write(x):
    """ A non-blocking write function

    Simulates writing to a database asynchronously
    """
    yield gen.sleep(0.2)
    print(x)
```

### 3.7.1 Within the Event Loop

You may have an application that runs strictly within an event loop.

```
from streamz import Stream
from tornado.ioloop import IOLoop

@gen.coroutine
def f():
    source = Stream(asynchronous=True) # tell the stream we're working asynchronously
    source.map(increment).rate_limit(0.500).sink(write)

    for x in range(10):
        yield source.emit(x)

IOLoop().run_sync(f)
```

We call `Stream` with the `asynchronous=True` keyword, informing it that it should expect to operate within an event loop. This ensures that calls to `emit` return Tornado futures rather than block. We wait on results using `yield`.

```
yield source.emit(x) # waits until the pipeline is ready
```

This would also work with `async-await` syntax in Python 3

```
from streamz import Stream
from tornado.ioloop import IOLoop
```

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```

async def f():
    source = Stream(asynchronous=True) # tell the stream we're working asynchronously
    source.map(increment).rate_limit(0.500).sink(write)

    for x in range(10):
        await source.emit(x)

IOLoop().run_sync(f)

```

### 3.7.2 Event Loop on a Separate Thread

Sometimes the event loop runs on a separate thread. This is common when you want to support interactive workloads (the user needs their own thread for interaction) or when using Dask (next section).

```

from streamz import Stream

source = Stream(asynchronous=False) # starts IOloop in separate thread
source.map(increment).rate_limit('500ms').sink(write)

for x in range(10):
    source.emit(x)

```

In this case we pass `asynchronous=False` to inform the stream that it is expected to perform time-based computation (our write function is a coroutine) but that it should not expect to run in an event loop, and so needs to start its own in a separate thread. Now when we call `source.emit` normally without using `yield` or `await` the emit call blocks, waiting on a coroutine to finish within the `IOloop`.

All functions here happen on the `IOloop`. This is good for consistency, but can cause other concurrent applications to become unresponsive if your functions (like `increment`) block for long periods of time. You might address this by using Dask (see below) which will offload these computations onto separate threads or processes.

### 3.7.3 Using Dask

Dask is a parallel computing library that uses Tornado for concurrency and threads for computation. The `DaskStream` object is a drop-in replacement for `Stream` (mostly). Typically we create a Dask client, and then scatter a local `Stream` to become a `DaskStream`.

```

from dask.distributed import Client
client = Client(processes=False) # starts thread pool, IOloop in separate thread

from streamz import Stream
source = Stream()
(source.scatter() # scatter local elements to cluster, creating a DaskStream
 .map(increment) # map a function remotely
 .buffer(5) # allow five futures to stay on the cluster at any time
 .gather() # bring results back to local process
 .sink(write)) # call write locally

for x in range(10):
    source.emit(x)

```

This operates very much like the synchronous case in terms of coding style (no `@gen.coroutine` or `yield`) but does computations on separate threads. This also provides parallelism and access to a dashboard at <http://localhost:8787/status>.

### 3.7.4 Asynchronous Dask

Dask can also operate within an event loop if preferred. Here you can get the non-blocking operation within an event loop while also offloading computations to separate threads.

```
from dask.distributed import Client
from tornado.ioloop import IOLoop

async def f():
    client = await Client(processes=False, asynchronous=True)
    source = Stream(asynchronous=True)
    source.scatter().map(increment).rate_limit('500ms').gather().sink(write)

    for x in range(10):
        await source.emit(x)

IOLoop().run_sync(f)
```



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