
SCMData Documentation

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BRIEF SUMMARY

scmdata provides some useful data handling routines for dealing with data related to simple climate models (SCMs aka reduced complexity climate models, RCMs). In particular, it provides a high-performance way of handling and serialising (including to netCDF) timeseries data along with attached metadata. **scmdata** was inspired by [pyam](#) and was originally part of the [openscm](#) package.

1.1 License

scmdata is free software under a BSD 3-Clause License, see [LICENSE](#).

1.1.1 Installation

scmdata is tested to work with Python 3.6 and above

Installing with conda

The easiest way to install scmdata is using conda, either using the full [Anaconda](#) distribution which includes a collection of popular data science packages or the smaller [Miniconda](#) distribution. Using conda is the recommended method for installing scmdata for most users.

```
conda install -c conda-forge netcdf-scm
```

Installing with pip

scmdata can also be installed from [PyPi](#) using pip.

We recommend creating a virtual environment to manage this and any other libraries your project requires.

```
pip install scmdata
```

1.1.2 Data Model

Analysing the results from simple climate models involves a lot of timeseries handling, including:

- filtering
- plotting
- resampling
- serialization/deserialisation
- computation

As a result, **scmdata**'s approach to data handling focusses on efficient handling of timeseries.

The *ScmRun* class

The *scmdata.ScmRun* class represents a collection of timeseries data including metadata and provides methods for manipulating the data. Internally, *ScmRun* stores the timeseries data in a single *pandas.DataFrame* and the timeseries metadata *pandas.MultiIndex* of type *pandas.Categorical*, for efficient indexing.

This class is the primary way of handling timeseries data within the **scmdata** package. For example, the *ScmRun* can be filtered to only find the subset of data which have a "scenario" metadata label equal to "green" (see *ScmRun.filter* for full details). Other operations include grouping, setting and (basic) plotting.

The complete set of manipulation features can be found in the documentation pages of *ScmRun*.

ScmRun has three key properties and one key method, which allow the user to quickly access their data in more standard formats:

- *values* returns all of the timeseries as a single *numpy.ndarray* without any metadata or indication of the time axis.
- *meta* returns all of the timeseries' metadata as a single *pandas.DataFrame*. This allows users to quickly have an overview of the timeseries held by *scmdata.ScmRun* without having to also view the data itself.
- *metadata* <*scmdata.run.ScmRun.metadata* stores run-specific metadata, i.e. metadata which isn't tied to any timeseries specifically.
- *timeseries()* combines *values* and *meta* to form a *pandas.DataFrame* whose index is equal to *scmdata.ScmRun.meta* and whose values are equal to *scmdata.ScmRun.values*. The columns of the output of *timeseries()* are the time axis of the data.

Metadata handling

scmdata can store any kind of metadata about the timeseries, without restriction. This combination allows it to be a high performing, yet flexible library for timeseries data.

However, to do this it must make assumptions about the type of data it holds and these assumptions come with tradeoffs. In particular, **scmdata** cannot hold metadata at a level finer than a complete timeseries. For example, it couldn't handle a case where one point in a timeseries needed to be labelled with an 'erroneous' label. In such a case the entire timeseries would have to be labelled 'erroneous' (or a new timeseries made with just that data point, which may not be very performant). If behaviour of this type is required, we suggest trying another data handling approach.

The ScmDatabase class

When handling large datasets which may not fit into memory, it is important to be able to query subsets of the dataset without having to iterate over the entire dataset. `scmdata.database.ScmDatabase` helps with this issue by disaggregating a dataset into subsets according to unique combinations of metadata. The metadata of interest is specified by the user so that the database can be adapted to any use-case or access pattern.

One of the major benefits of `scmdata.database.ScmDatabase` is that the taxonomy of metadata does not need to be known at database creation making it easy to add new data to the database. Each unique subset of the database is stored as a single netCDF file. This ensures that if timeseries with new metadata are saved to the database, the existing files in the database do not need to be modified. Instead new files are written expanding the directory structure to accommodate the new metadata values.

Filtering using the metadata columns of interest is also very simple as the contents of a given file can be determined from the directory structure without having to load the file. Each file can then be loaded as the data is needed, minimising the need for reading data which will then immediately be filtered away of extra data that is needed to be unnecessarily read and then filtered away.

1.1.3 Development

If you're interested in contributing to SCMData, we'd love to have you on board! This section of the docs will (once we've written it) detail how to get setup to contribute and how best to communicate.

- *Contributing*
- *Getting setup*
 - *Getting help*
 - * *Development tools*
 - * *Other tools*
- *Formatting*
- *Buiding the docs*
 - *Gotchas*
 - *Docstring style*
- *Releasing*
 - *First step*
 - *PyPI*
 - *Conda*
 - *Push to repository*
- *Why is there a `Makefile` in a pure Python repository?*

Contributing

All contributions are welcome, some possible suggestions include:

- tutorials (or support questions which, once solved, result in a new tutorial :D)
- blog posts
- improving the documentation
- bug reports
- feature requests
- pull requests

Please report issues or discuss feature requests in the [SCMData issue tracker](#). If your issue is a feature request or a bug, please use the templates available, otherwise, simply open a normal issue :)

As a contributor, please follow a couple of conventions:

- Create issues in the [SCMData issue tracker](#) for changes and enhancements, this ensures that everyone in the community has a chance to comment
- Be welcoming to newcomers and encourage diverse new contributors from all backgrounds: see the [Python Community Code of Conduct](#)
- Only push to your own branches, this allows people to force push to their own branches as they need without fear or causing others headaches
- Start all pull requests as draft pull requests and only mark them as ready for review once they've been rebased onto master, this makes it much simpler for reviewers
- Try and make lots of small pull requests, this makes it easier for reviewers and faster for everyone as review time grows exponentially with the number of lines in a pull request

Getting setup

To get setup as a developer, we recommend the following steps (if any of these tools are unfamiliar, please see the resources we recommend in [Development tools](#)):

1. Install conda and make
2. Run `make virtual-environment`, if that fails you can try doing it manually
 1. Change your current directory to SCMData's root directory (i.e. the one which contains `README.rst`), `cd scmdata`
 2. Create a virtual environment to use with SCMData `python3 -m venv venv`
 3. Activate your virtual environment `source ./venv/bin/activate`
 4. Upgrade pip `pip install --upgrade pip`
 5. Install the development dependencies (very important, make sure your virtual environment is active before doing this) `pip install -e .[dev]`
3. Make sure the tests pass by running `make test-all`, if that fails the commands are
 1. Activate your virtual environment `source ./venv/bin/activate`
 2. Run the unit and integration tests `pytest --cov -r a --cov-report term-missing`

Getting help

Whilst developing, unexpected things can go wrong (that's why it's called 'developing', if we knew what we were doing, it would already be 'developed'). Normally, the fastest way to solve an issue is to contact us via the [issue tracker](#). The other option is to debug yourself. For this purpose, we provide a list of the tools we use during our development as starting points for your search to find what has gone wrong.

Development tools

This list of development tools is what we rely on to develop SCMData reliably and reproducibly. It gives you a few starting points in case things do go inexplicably wrong and you want to work out why. We include links with each of these tools to starting points that we think are useful, in case you want to learn more.

- [Git](#)
- [Make](#)
- [Conda virtual environments](#)
- [Pip and pip virtual environments](#)
- [Tests](#)
 - we use a blend of [pytest](#) and the inbuilt Python testing capabilities for our tests so checkout what we've already done in `tests` to get a feel for how it works
- [Continuous integration \(CI\)](#)
 - we use [Travis CI](#) for our CI but there are a number of good providers
- [Jupyter Notebooks](#)
 - Jupyter is automatically included in your virtual environment if you follow our [Getting setup](#) instructions
- [Sphinx](#)

Other tools

We also use some other tools which aren't necessarily the most familiar. Here we provide a list of these along with useful resources.

- [Regular expressions](#)
 - we use [regex101.com](#) to help us write and check our regular expressions, make sure the language is set to Python to make your life easy!

Formatting

To help us focus on what the code does, not how it looks, we use a couple of automatic formatting tools. These automatically format the code for us and tell us where the errors are. To use them, after setting yourself up (see [Getting setup](#)), simply run `make format`. Note that `make format` can only be run if you have committed all your work i.e. your working directory is 'clean'. This restriction is made to ensure that you don't format code without being able to undo it, just in case something goes wrong.

Buiding the docs

After setting yourself up (see [Getting setup](#)), building the docs is as simple as running `make docs` (note, run `make -B docs` to force the docs to rebuild and ignore make when it says ‘... index.html is up to date’). This will build the docs for you. You can preview them by opening `docs/build/html/index.html` in a browser.

For documentation we use [Sphinx](#). To get ourselves started with Sphinx, we started with [this example](#) then used [Sphinx’s getting started guide](#).

Gotchas

To get Sphinx to generate pdfs (rarely worth the hassle), you require [Latexmk](#). On a Mac this can be installed with `sudo tlmgr install latexmk`. You will most likely also need to install some other packages (if you don’t have the full distribution). You can check which package contains any missing files with `tlmgr search --global --file [filename]`. You can then install the packages with `sudo tlmgr install [package]`.

Docstring style

For our docstrings we use numpy style docstrings. For more information on these, [here is the full guide](#) and [the quick reference we also use](#).

Releasing

First step

1. Test installation with dependencies `make test-install`
2. Update `CHANGELOG.rst`:
 - add a header for the new version between `master` and the latest bullet point
 - this should leave the section underneath the master header empty
3. `git add .`
4. `git commit -m "release(vX.Y.Z)"`
5. `git tag vX.Y.Z`
6. Test version updated as intended with `make test-install`

PyPI

If uploading to PyPI, do the following (otherwise skip these steps)

1. `make publish-on-testpypi`
2. Go to [test PyPI](#) and check that the new release is as intended. If it isn’t, stop and debug.
3. Test the install with `make test-testpypi-install` (this doesn’t test all the imports as most required packages are not on test PyPI).

Assuming test PyPI worked, now upload to the main repository

1. `make publish-on-pypi`
2. Go to [SCMData’s PyPI](#) and check that the new release is as intended.

3. Test the install with `make test-pypi-install`

Conda

1. If you haven't already, fork the [SCMData conda feedstock](#). In your fork, add the feedstock upstream with `git remote add upstream https://github.com/conda-forge/scmdata-feedstock` (upstream should now appear in the output of `git remote -v`)
2. Update your fork's master to the upstream master with:
 1. `git checkout master`
 2. `git fetch upstream`
 3. `git reset --hard upstream/master`
3. Create a new branch in the feedstock for the version you want to bump to.
4. Edit `recipe/meta.yaml` and update:
 - version number in line 2 (don't include the 'v' in the version tag)
 - the build number to zero in line 13 (you should only be here if releasing a new version)
 - update sha256 in line 10 (you can get the sha from [SCMData's PyPI](#) by clicking on 'Download files' on the left and then clicking on 'SHA256' of the `.tar.gz` file to copy it to the clipboard)
5. `git add .`
6. `git commit -m "Update to vX.Y.Z"`
7. `git push`
8. Make a PR into the [SCMData conda feedstock](#)
9. If the PR passes (give it at least 10 minutes to run all the CI), merge
10. Check <https://anaconda.org/conda-forge/scmdata> to double check that the version has increased (this can take a few minutes to update)

Push to repository

Finally, push the tags and commit to the repository

1. `git push`
2. `git push --tags`

Why is there a Makefile in a pure Python repository?

Whilst it may not be standard practice, a `Makefile` is a simple way to automate general setup (environment setup in particular). Hence we have one here which basically acts as a notes file for how to do all those little jobs which we often forget e.g. setting up environments, running tests (and making sure we're in the right environment), building docs, setting up auxillary bits and pieces.

1.1.4 scmdata.database

Database for handling large datasets in a performant, but flexible way

Data is chunked using unique combinations of metadata. This allows for the database to expand as new data is added without having to change any of the existing data.

Subsets of data are also able to be read without having to load all the data and then filter. For example, one could save model results from a number of different climate models and then load just the Surface Temperature data for all models.

```
class scmdata.database.DatabaseBackend(**kwargs)
```

Bases: `abc.ABC`

Abstract backend for serialising/deserialising data

Data is stored as objects represented by keys. These keys can be used later to load data.

```
delete(key)
```

Delete a given key

Parameters `key` (`str`) –

```
abstract get(filters)
```

Get all matching keys for a given filter

Parameters `filters` (`dict of str`) – String filters If a level is missing then all values are fetched

Returns Each item is a key which may contain data which is of interest

Return type list of str

```
abstract load(key)
```

Load data at a given key

Parameters `key` (`str`) – Key to load

Returns

Return type `scmdata.ScmRun`

```
abstract save(sr)
```

Save data

Parameters `sr` (`scmdata.ScmRun`) –

Returns Key where the data is stored

Return type `str`

```
class scmdata.database.NetCDFBackend(**kwargs)
```

Bases: `scmdata.database.DatabaseBackend`

On-disk database handler for outputs from SCMs

Data is split into groups as specified by `levels`. This allows for fast reading and writing of new subsets of data when a single output file is no longer performant or data cannot all fit in memory.

```
delete(key)
```

Delete a key

Parameters `key` (`str`) –

```
get(filters)
```

Get all matching objects for a given filter

Parameters **filters** (*dict of str*) – String filters If a level is missing then all values are fetched

Returns

Return type list of str

get_key(*sr*)

Get key where the data will be stored

The key is the root directory joined with the other information provided. The filepath is also cleaned to remove spaces and special characters.

Parameters **sr** (`scmdata.ScmRun`) – Data to save

Raises

- **ValueError** – If non-unique metadata is found for each of `self.kwargs["levels"]`
- **KeyError** – If missing metadata is found for each of `self.kwargs["levels"]`

Returns Path in which to save the data without spaces or special characters

Return type str

load(*key*)

Parameters **key** (*str*) –

Returns

Return type `scmdata.ScmRun`

save(*sr*)

Save a `ScmRun` to the database

The dataset should not contain any duplicate metadata for the database levels

Parameters **sr** (`scmdata.ScmRun`) – Data to save

Raises

- **ValueError** – If duplicate metadata are present for the requested database levels
- **KeyError** – If metadata for the requested database levels are not found

Returns Key where the data is saved

Return type str

class `scmdata.database.ScmDatabase`(*root_dir*, *levels*=(*'climate_model'*, *'variable'*, *'region'*, *'scenario'*), *backend*=*'netcdf'*, *backend_config*=*None*)

Bases: `object`

On-disk database handler for outputs from SCMs

Data is split into groups as specified by `levels`. This allows for fast reading and writing of new subsets of data when a single output file is no longer performant or data cannot all fit in memory.

available_data()

Get all the data which is available to be loaded

If metadata includes non-alphanumeric characters then it might appear modified in the returned table. The original metadata values can still be used to filter data.

Returns

Return type `pd.DataFrame`

delete(***filters*)

Delete data from the database

Parameters **filters** (*dict of str*) – Filters for the data to load.

Defaults to deleting all data if nothing is specified.

Raises **ValueError** – If a filter for a level not in `levels` is specified

load(*disable_tqdm=False, **filters*)

Load data from the database

Parameters

- **disable_tqdm** (*bool*) – If True, do not show the progress bar
- **filters** (*dict of str : [str, list[str]]*) – Filters for the data to load.

Defaults to loading all values for a level if it isn't specified.

If a filter is a list then OR logic is applied within the level. For example, if we have `scenario=["ssp119", "ssp126"]` then both the ssp119 and ssp126 scenarios will be loaded.

Returns Loaded data

Return type `scmdata.ScmRun`

Raises **ValueError** – If a filter for a level not in `levels` is specified

If no data matching `filters` is found

property `root_dir`

Root directory of the database.

Returns

Return type `str`

save(*scmrun, disable_tqdm=False*)

Save data to the database

The results are saved with one file for each unique combination of `levels` in a directory structure underneath `root_dir`.

Use `available_data()` to see what data is available. Subsets of data can then be loaded as an `scmdata.ScmRun` using `load()`.

Parameters

- **scmrun** (`scmdata.ScmRun`) – Data to save.
The timeseries in this run should have valid metadata for each of the columns specified in `levels`.
- **disable_tqdm** (*bool*) – If True, do not show the progress bar

Raises **KeyError** – If a filter for a level not in `levels` is specified

`scmdata.database.ensure_dir_exists(fp)`

Ensure directory exists

Parameters **fp** (*str*) – Filepath of which to ensure the directory exists

1.1.5 scmdata.errors

Custom errors and exceptions used by scmdata

exception `scmdata.errors.MissingRequiredColumnError(columns)`

Bases: `ValueError`

Error raised when an operation produces missing metadata columns

exception `scmdata.errors.NonUniqueMetadataError(meta)`

Bases: `ValueError`

Error raised when metadata is not unique

1.1.6 scmdata.filters

Helpers for filtering data in `scmdata.run.ScmRun`.

Based upon `pyam.utils`.

`scmdata.filters.datetime_match(data: List, dts: Union[List[datetime.datetime], datetime.datetime]) → numpy.ndarray`

Match datetimes in time columns for data filtering.

Parameters

- **data** – Input data to perform filtering on
- **dts** – Datetimes to use for filtering

Returns Array where True indicates a match

Return type `numpy.ndarray` of `bool`

Raises `TypeError` – `dts` contains `int`

`scmdata.filters.day_match(data: List, days: Union[List[str], List[int], int, str]) → numpy.ndarray`

Match days in time columns for data filtering.

Parameters

- **data** – Input data to perform filtering on
- **days** – Days to match

Returns Array where True indicates a match

Return type `numpy.ndarray` of `bool`

`scmdata.filters.find_depth(meta_col: pandas.core.series.Series, s: str, level: Union[int, str], separator: str = '|') → numpy.ndarray`

Find all values which match given depth from a filter keyword.

Parameters

- **meta_col** – Column in which to find values which match the given depth
- **s** – Filter keyword, from which level should be applied
- **level** – Depth of value to match as defined by the number of separator in the value name. If an `int`, the depth is matched exactly. If a `str`, then the depth can be matched as either “X-“, for all levels up to level “X”, or “X+”, for all levels above level “X”.
- **separator** – The string used to separate levels in `s`. Defaults to a pipe (“|”).

Returns Array where True indicates a match

Return type `numpy.ndarray` of `bool`

Raises `ValueError` – If `level` cannot be understood

`scmdata.filters.hour_match(data: List, hours: Union[List[int], int]) → numpy.ndarray`

Match hours in time columns for data filtering.

Parameters

- **data** – Input data to perform filtering on
- **hours** – Hours to match

Returns Array where True indicates a match

Return type `numpy.ndarray` of `bool`

`scmdata.filters.is_in(vals: List, items: List) → numpy.ndarray`

Find elements of `vals` which are in `items`.

Parameters

- **vals** – The list of values to check
- **items** – The options used to determine whether each element of `vals` is in the desired subset or not

Returns Array of the same length as `vals` where the element is True if the corresponding element of `vals` is in `items` and False otherwise

Return type `numpy.ndarray` of `bool`

`scmdata.filters.month_match(data: List, months: Union[List[str], List[int], int, str]) → numpy.ndarray`

Match months in time columns for data filtering.

Parameters

- **data** – Input data to perform filtering on
- **months** – Months to match

Returns Array where True indicates a match

Return type `numpy.ndarray` of `bool`

`scmdata.filters.pattern_match(meta_col: pandas.core.series.Series, values: Union[Iterable[str], str], level: Optional[Union[str, int]] = None, regexp: bool = False, separator: str = '|') → numpy.ndarray`

Filter data by matching metadata columns to given patterns.

Parameters

- **meta_col** – Column to perform filtering on
- **values** – Values to match
- **level** – Passed to `find_depth()`. For usage, see docstring of `find_depth()`.
- **regexp** – If True, match using regexp rather than our pseudo regexp syntax.
- **has_nan** – If True, convert all nan values in `meta_col` to empty string before applying filters. This means that “” and “*” will match rows with `numpy.nan`. If False, the conversion is not applied and so a search in a string column which contains `numpy.nan` will result in a `TypeError`.
- **separator** – String used to separate the hierarchy levels in values. Defaults to ‘|’

Returns Array where True indicates a match

Return type `numpy.ndarray` of `bool`

Raises `TypeError` – Filtering is performed on a string metadata column which contains `numpy.nan` and `has_nan` is `False`

`scmdata.filters.time_match(data: List, times: Union[List[str], List[int], int, str], conv_codes: List[str], strptime_attr: str, name: str) → numpy.ndarray`

Match times by applying conversion codes to filtering list.

Parameters

- **data** – Input data to perform filtering on
- **times** – Times to match
- **conv_codes** – If `times` contains strings, conversion codes to try passing to `time.strptime()` to convert `times` to `datetime.datetime`
- **strptime_attr** – If `times` contains strings, the `datetime.datetime` attribute to finalize the conversion of strings to integers
- **name** – Name of the part of a datetime to extract, used to produce useful error messages.

Returns Array where True indicates a match

Return type `numpy.ndarray` of `bool`

Raises `ValueError` – If input times cannot be converted understood or if input strings do not lead to increasing integers (i.e. “Nov-Feb” will not work, one must use [“Nov-Dec”, “Jan-Feb”] instead)

`scmdata.filters.years_match(data: List, years: Union[List[int], numpy.ndarray, int]) → numpy.ndarray`

Match years in time columns for data filtering.

Parameters

- **data** – Input data to perform filtering on
- **years** – Years to match

Returns Array where True indicates a match

Return type `numpy.ndarray` of `bool`

Raises `TypeError` – If `years` is not `int` or list of `int`

1.1.7 scmdata.groupby

Functionality for grouping and filtering `ScmRun` objects

class `scmdata.groupby.RunGroupBy(run, groups)`

Bases: `scmdata.groupby._GroupBy`

GroupBy object specialized to grouping `ScmRun` objects

all(*dim=None, axis=None, **kwargs*)

Reduce this `RunGroupBy`’s data by applying *all* along some dimension(s).

Parameters

- **dim**(*str* or *sequence of str, optional*) – Dimension(s) over which to apply *all*.
- **axis**(*int* or *sequence of int, optional*) – Axis(es) over which to apply *all*. Only one of the ‘dim’ and ‘axis’ arguments can be supplied. If neither are supplied, then *all* is calculated over axes.

- **keep_attrs** (*bool*, *optional*) – If True, the attributes (*attrs*) will be copied from the original object to the new one. If False (default), the new object will be returned without attributes.
- ****kwargs** (*dict*) – Additional keyword arguments passed on to the appropriate array function for calculating *all* on this object's data.

Returns **reduced** – New RunGroupBy object with *all* applied to its data and the indicated dimension(s) removed.

Return type *RunGroupBy*

any(*dim=None, axis=None, **kwargs*)

Reduce this RunGroupBy's data by applying *any* along some dimension(s).

Parameters

- **dim** (*str* or *sequence of str*, *optional*) – Dimension(s) over which to apply *any*.
- **axis** (*int* or *sequence of int*, *optional*) – Axis(es) over which to apply *any*. Only one of the 'dim' and 'axis' arguments can be supplied. If neither are supplied, then *any* is calculated over axes.
- **keep_attrs** (*bool*, *optional*) – If True, the attributes (*attrs*) will be copied from the original object to the new one. If False (default), the new object will be returned without attributes.
- ****kwargs** (*dict*) – Additional keyword arguments passed on to the appropriate array function for calculating *any* on this object's data.

Returns **reduced** – New RunGroupBy object with *any* applied to its data and the indicated dimension(s) removed.

Return type *RunGroupBy*

count(*dim=None, axis=None, **kwargs*)

Reduce this RunGroupBy's data by applying *count* along some dimension(s).

Parameters

- **dim** (*str* or *sequence of str*, *optional*) – Dimension(s) over which to apply *count*.
- **axis** (*int* or *sequence of int*, *optional*) – Axis(es) over which to apply *count*. Only one of the 'dim' and 'axis' arguments can be supplied. If neither are supplied, then *count* is calculated over axes.
- **keep_attrs** (*bool*, *optional*) – If True, the attributes (*attrs*) will be copied from the original object to the new one. If False (default), the new object will be returned without attributes.
- ****kwargs** (*dict*) – Additional keyword arguments passed on to the appropriate array function for calculating *count* on this object's data.

Returns **reduced** – New RunGroupBy object with *count* applied to its data and the indicated dimension(s) removed.

Return type *RunGroupBy*

map(*func, *args, **kwargs*)

Apply a function to each group and append the results

func is called like *func(ar, *args, **kwargs)* for each *ScmRun* *ar* in this group. If the result of this function call is None, then it is excluded from the results.

The results are appended together using `run_append()`. The function can change the size of the input `ScmRun` as long as `run_append()` can be applied to all results.

Examples

```
>>> def write_csv(arr):
...     variable = arr.get_unique_meta("variable")
...     arr.to_csv("out-{}.csv".format(variable))
>>> df.groupby("variable").map(write_csv)
```

Parameters

- **func** (*function*) – Callable to apply to each timeseries.
- ***args** – Positional arguments passed to *func*.
- ****kwargs** – Used to call *func(ar, **kwargs)* for each array *ar*.

Returns **applied** – The result of splitting, applying and combining this array.

Return type `ScmRun`

max(*dim=None, axis=None, skipna=None, **kwargs*)

Reduce this RunGroupBy's data by applying *max* along some dimension(s).

Parameters

- **dim** (*str* or *sequence of str, optional*) – Dimension(s) over which to apply *max*.
- **axis** (*int* or *sequence of int, optional*) – Axis(es) over which to apply *max*. Only one of the 'dim' and 'axis' arguments can be supplied. If neither are supplied, then *max* is calculated over axes.
- **skipna** (*bool, optional*) – If True, skip missing values (as marked by NaN). By default, only skips missing values for float dtypes; other dtypes either do not have a sentinel missing value (int) or skipna=True has not been implemented (object, datetime64 or timedelta64).
- **keep_attrs** (*bool, optional*) – If True, the attributes (*attrs*) will be copied from the original object to the new one. If False (default), the new object will be returned without attributes.
- ****kwargs** (*dict*) – Additional keyword arguments passed on to the appropriate array function for calculating *max* on this object's data.

Returns **reduced** – New RunGroupBy object with *max* applied to its data and the indicated dimension(s) removed.

Return type `RunGroupBy`

mean(*dim=None, axis=None, skipna=None, **kwargs*)

Reduce this RunGroupBy's data by applying *mean* along some dimension(s).

Parameters

- **dim** (*str* or *sequence of str, optional*) – Dimension(s) over which to apply *mean*.
- **axis** (*int* or *sequence of int, optional*) – Axis(es) over which to apply *mean*. Only one of the 'dim' and 'axis' arguments can be supplied. If neither are supplied, then *mean* is calculated over axes.

- **skipna**(*bool*, *optional*) – If True, skip missing values (as marked by NaN). By default, only skips missing values for float dtypes; other dtypes either do not have a sentinel missing value (int) or skipna=True has not been implemented (object, datetime64 or timedelta64).
- **keep_attrs**(*bool*, *optional*) – If True, the attributes (*attrs*) will be copied from the original object to the new one. If False (default), the new object will be returned without attributes.
- ****kwargs**(*dict*) – Additional keyword arguments passed on to the appropriate array function for calculating *mean* on this object's data.

Returns **reduced** – New RunGroupBy object with *mean* applied to its data and the indicated dimension(s) removed.

Return type *RunGroupBy*

median(*dim=None*, *axis=None*, *skipna=None*, ***kwargs*)

Reduce this RunGroupBy's data by applying *median* along some dimension(s).

Parameters

- **dim**(*str* or *sequence of str*, *optional*) – Dimension(s) over which to apply *median*.
- **axis**(*int* or *sequence of int*, *optional*) – Axis(es) over which to apply *median*. Only one of the 'dim' and 'axis' arguments can be supplied. If neither are supplied, then *median* is calculated over axes.
- **skipna**(*bool*, *optional*) – If True, skip missing values (as marked by NaN). By default, only skips missing values for float dtypes; other dtypes either do not have a sentinel missing value (int) or skipna=True has not been implemented (object, datetime64 or timedelta64).
- **keep_attrs**(*bool*, *optional*) – If True, the attributes (*attrs*) will be copied from the original object to the new one. If False (default), the new object will be returned without attributes.
- ****kwargs**(*dict*) – Additional keyword arguments passed on to the appropriate array function for calculating *median* on this object's data.

Returns **reduced** – New RunGroupBy object with *median* applied to its data and the indicated dimension(s) removed.

Return type *RunGroupBy*

min(*dim=None*, *axis=None*, *skipna=None*, ***kwargs*)

Reduce this RunGroupBy's data by applying *min* along some dimension(s).

Parameters

- **dim**(*str* or *sequence of str*, *optional*) – Dimension(s) over which to apply *min*.
- **axis**(*int* or *sequence of int*, *optional*) – Axis(es) over which to apply *min*. Only one of the 'dim' and 'axis' arguments can be supplied. If neither are supplied, then *min* is calculated over axes.
- **skipna**(*bool*, *optional*) – If True, skip missing values (as marked by NaN). By default, only skips missing values for float dtypes; other dtypes either do not have a sentinel missing value (int) or skipna=True has not been implemented (object, datetime64 or timedelta64).
- **keep_attrs**(*bool*, *optional*) – If True, the attributes (*attrs*) will be copied from the original object to the new one. If False (default), the new object will be returned without attributes.

- ****kwargs** (*dict*) – Additional keyword arguments passed on to the appropriate array function for calculating *min* on this object’s data.

Returns **reduced** – New RunGroupBy object with *min* applied to its data and the indicated dimension(s) removed.

Return type *RunGroupBy*

prod(*dim=None, axis=None, skipna=None, **kwargs*)

Reduce this RunGroupBy’s data by applying *prod* along some dimension(s).

Parameters

- **dim** (*str* or *sequence of str, optional*) – Dimension(s) over which to apply *prod*.
- **axis** (*int* or *sequence of int, optional*) – Axis(es) over which to apply *prod*. Only one of the ‘dim’ and ‘axis’ arguments can be supplied. If neither are supplied, then *prod* is calculated over axes.
- **skipna** (*bool, optional*) – If True, skip missing values (as marked by NaN). By default, only skips missing values for float dtypes; other dtypes either do not have a sentinel missing value (int) or skipna=True has not been implemented (object, datetime64 or timedelta64).
- **min_count** (*int, default: None*) – The required number of valid values to perform the operation. If fewer than min_count non-NA values are present the result will be NA. Only used if skipna is set to True or defaults to True for the array’s dtype. New in version 0.10.8: Added with the default being None. Changed in version 0.17.0: if specified on an integer array and skipna=True, the result will be a float array.
- **keep_attrs** (*bool, optional*) – If True, the attributes (*attrs*) will be copied from the original object to the new one. If False (default), the new object will be returned without attributes.
- ****kwargs** (*dict*) – Additional keyword arguments passed on to the appropriate array function for calculating *prod* on this object’s data.

Returns **reduced** – New RunGroupBy object with *prod* applied to its data and the indicated dimension(s) removed.

Return type *RunGroupBy*

reduce(*func, dim=None, axis=None, **kwargs*)

Reduce the items in this group by applying *func* along some dimension(s).

Parameters

- **func** (*function*) – Function which can be called in the form *func(x, axis=axis, **kwargs)* to return the result of collapsing an np.ndarray over an integer valued axis.
- **dim** (*..., str* or *sequence of str, optional*) – Not used in this implementation
- **axis** (*int* or *sequence of int, optional*) – Axis(es) over which to apply *func*. Only one of the ‘dimension’ and ‘axis’ arguments can be supplied. If neither are supplied, then *func* is calculated over all dimension for each group item.
- ****kwargs** (*dict*) – Additional keyword arguments passed on to *func*.

Returns **reduced** – Array with summarized data and the indicated dimension(s) removed.

Return type *ScmRun*

std(*dim=None, axis=None, skipna=None, **kwargs*)

Reduce this RunGroupBy’s data by applying *std* along some dimension(s).

Parameters

- **dim**(*str* or *sequence of str*, *optional*) – Dimension(s) over which to apply *std*.
- **axis**(*int* or *sequence of int*, *optional*) – Axis(es) over which to apply *std*. Only one of the ‘dim’ and ‘axis’ arguments can be supplied. If neither are supplied, then *std* is calculated over axes.
- **skipna**(*bool*, *optional*) – If True, skip missing values (as marked by NaN). By default, only skips missing values for float dtypes; other dtypes either do not have a sentinel missing value (int) or skipna=True has not been implemented (object, datetime64 or timedelta64).
- **keep_attrs**(*bool*, *optional*) – If True, the attributes (*attrs*) will be copied from the original object to the new one. If False (default), the new object will be returned without attributes.
- ****kwargs**(*dict*) – Additional keyword arguments passed on to the appropriate array function for calculating *std* on this object’s data.

Returns **reduced** – New RunGroupBy object with *std* applied to its data and the indicated dimension(s) removed.

Return type *RunGroupBy*

sum(*dim=None*, *axis=None*, *skipna=None*, ***kwargs*)

Reduce this RunGroupBy’s data by applying *sum* along some dimension(s).

Parameters

- **dim**(*str* or *sequence of str*, *optional*) – Dimension(s) over which to apply *sum*.
- **axis**(*int* or *sequence of int*, *optional*) – Axis(es) over which to apply *sum*. Only one of the ‘dim’ and ‘axis’ arguments can be supplied. If neither are supplied, then *sum* is calculated over axes.
- **skipna**(*bool*, *optional*) – If True, skip missing values (as marked by NaN). By default, only skips missing values for float dtypes; other dtypes either do not have a sentinel missing value (int) or skipna=True has not been implemented (object, datetime64 or timedelta64).
- **min_count**(*int*, *default: None*) – The required number of valid values to perform the operation. If fewer than min_count non-NA values are present the result will be NA. Only used if skipna is set to True or defaults to True for the array’s dtype. New in version 0.10.8: Added with the default being None. Changed in version 0.17.0: if specified on an integer array and skipna=True, the result will be a float array.
- **keep_attrs**(*bool*, *optional*) – If True, the attributes (*attrs*) will be copied from the original object to the new one. If False (default), the new object will be returned without attributes.
- ****kwargs**(*dict*) – Additional keyword arguments passed on to the appropriate array function for calculating *sum* on this object’s data.

Returns **reduced** – New RunGroupBy object with *sum* applied to its data and the indicated dimension(s) removed.

Return type *RunGroupBy*

var(*dim=None*, *axis=None*, *skipna=None*, ***kwargs*)

Reduce this RunGroupBy’s data by applying *var* along some dimension(s).

Parameters

- **dim**(*str* or *sequence of str*, *optional*) – Dimension(s) over which to apply *var*.

- **axis** (*int* or *sequence of int*, *optional*) – Axis(es) over which to apply *var*. Only one of the ‘dim’ and ‘axis’ arguments can be supplied. If neither are supplied, then *var* is calculated over axes.
- **skipna** (*bool*, *optional*) – If True, skip missing values (as marked by NaN). By default, only skips missing values for float dtypes; other dtypes either do not have a sentinel missing value (int) or skipna=True has not been implemented (object, datetime64 or timedelta64).
- **keep_attrs** (*bool*, *optional*) – If True, the attributes (*attrs*) will be copied from the original object to the new one. If False (default), the new object will be returned without attributes.
- ****kwargs** (*dict*) – Additional keyword arguments passed on to the appropriate array function for calculating *var* on this object’s data.

Returns **reduced** – New RunGroupBy object with *var* applied to its data and the indicated dimension(s) removed.

Return type *RunGroupBy*

1.1.8 scmdata.netcdf

NetCDF4 file operations

Reading and writing *ScmRun* to disk as binary

`scmdata.netcdf.inject_nc_methods(cls)`

Add the to/from nc methods to a class

Parameters **cls** – Class to add methods to

`scmdata.netcdf.nc_to_run(cls, fname)`

Read a netCDF4 file from disk

Parameters **fname** (*str*) – Filename to read

See also:

`scmdata.run.ScmRun.from_nc()`

`scmdata.netcdf.run_to_nc(run, fname, dimensions=('region'), extras=(), **kwargs)`

Write timeseries to disk as a netCDF4 file

Each unique variable will be written as a variable within the netCDF file. Choosing the dimensions and extras such that there are as few empty (or nan) values as possible will lead to the best compression on disk.

Parameters

- **fname** (*str*) – Path to write the file into
- **dimensions** (*iterable of str*) – Dimensions to include in the netCDF file. The time dimension is always included (if not provided it will be the last dimension). An additional dimension (specifically a co-ordinate in xarray terms), “_id”, will be included if **extras** is provided and any of the metadata in **extras** is not uniquely defined by **dimensions**. “_id” maps the timeseries in each variable to their relevant metadata.
- **extras** (*iterable of str*) – Metadata columns to write as variables in the netCDF file (specifically as “non-dimension co-ordinates” in xarray terms, see [xarray terminology](#) for more details). Where possible, these non-dimension co-ordinates will use dimension co-ordinates as their own co-ordinates. However, if the metadata in **extras** is not defined by a single dimension in **dimensions**, then the **extras** co-ordinates will have dimensions of “_id”. This “_id” co-ordinate maps the values in the **extras** co-ordinates to each timeseries

in the serialised dataset. Where “_id” is required, an extra “_id” dimension will also be added to dimensions.

- **kwargs** – Passed through to `xarray.Dataset.to_netcdf()`

See also:

`scmdata.run.ScmRun.to_nc()`

1.1.9 scmdata.offsets

Allow stepping through time using `xarray`’s offset functionality

Provides similar functionality to https://pandas.pydata.org/pandas-docs/stable/user_guide/timeseries.html#dateoffset-objects

```
scmdata.offsets.generate_range(start: cftime._cftime.datetime, end: cftime._cftime.datetime, offset:
                               xarray.coding.cftime_offsets.BaseCFTimeOffset, date_cls:
                               cftime._cftime.datetime = <class 'cftime._cftime.DatetimeGregorian'>) →
                               Iterable[cftime._cftime.datetime]
```

Generate a range of datetime objects between start and end, using offset to determine the steps.

The range will extend both ends of the span to the next valid timestep, see examples.

Parameters

- **start** (`cftime.datetime`) – Starting datetime from which to generate the range (noting roll backward mentioned above and illustrated in the examples).
- **end** (`cftime.datetime`) – Last datetime from which to generate the range (noting roll forward mentioned above and illustrated in the examples).
- **offset** – Offset object for determining the timesteps.
- **date_cls** (`cftime.datetime`) – The time points will be returned as instances of `date_cls`

Yields `cftime.datetime` – Next datetime in the range (the exact class is specified by `date_cls`)

Raises `ValueError` – Offset does not result in increasing `cftime.datetime`’s

Examples

The range is extended at either end to the nearest timestep. In the example below, the first timestep is rolled back to 1st Jan 2001 whilst the last is extended to 1st Jan 2006.

```
>>> import datetime as dt
>>> from pprint import pprint
>>> from scmdata.offsets import to_offset, generate_range
>>> g = generate_range(
...     dt.datetime(2001, 4, 1),
...     dt.datetime(2005, 6, 3),
...     to_offset("AS"),
... )
```

```
>>> pprint([d for d in g])
[cftime.DatetimeGregorian(2001, 1, 1, 0, 0, 0, 0),
 cftime.DatetimeGregorian(2002, 1, 1, 0, 0, 0, 0),
 cftime.DatetimeGregorian(2003, 1, 1, 0, 0, 0, 0),
```

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```
cftime.DatetimeGregorian(2004, 1, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2005, 1, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2006, 1, 1, 0, 0, 0, 0)]
```

In this example the first timestep is rolled back to 31st Dec 2000 whilst the last is extended to 31st Dec 2005.

```
>>> g = generate_range(
...     dt.datetime(2001, 4, 1),
...     dt.datetime(2005, 6, 3),
...     to_offset("A"),
... )
>>> pprint([d for d in g])
[cftime.DatetimeGregorian(2000, 12, 31, 0, 0, 0, 0),
cftime.DatetimeGregorian(2001, 12, 31, 0, 0, 0, 0),
cftime.DatetimeGregorian(2002, 12, 31, 0, 0, 0, 0),
cftime.DatetimeGregorian(2003, 12, 31, 0, 0, 0, 0),
cftime.DatetimeGregorian(2004, 12, 31, 0, 0, 0, 0),
cftime.DatetimeGregorian(2005, 12, 31, 0, 0, 0, 0)]
```

In this example the first timestep is already on the offset so stays there, the last timestep is to 1st Sep 2005.

```
>>> g = generate_range(
...     dt.datetime(2001, 4, 1),
...     dt.datetime(2005, 6, 3),
...     to_offset("QS"),
... )
>>> pprint([d for d in g])
[cftime.DatetimeGregorian(2001, 4, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2001, 7, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2001, 10, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2002, 1, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2002, 4, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2002, 7, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2002, 10, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2003, 1, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2003, 4, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2003, 7, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2003, 10, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2004, 1, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2004, 4, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2004, 7, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2004, 10, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2005, 1, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2005, 4, 1, 0, 0, 0, 0),
cftime.DatetimeGregorian(2005, 7, 1, 0, 0, 0, 0)]
```

1.1.10 scmdata.ops

Operations for *ScmRun* objects

These largely rely on *Pint's Pandas interface* to handle unit conversions automatically

`scmdata.ops.add(self, other, op_cols, **kwargs)`

Add values

Parameters

- **other** (*ScmRun*) – *ScmRun* containing data to add
- **op_cols** (*dict of str: str*) – Dictionary containing the columns to drop before adding as the keys and the value those columns should hold in the output as the values. For example, if we have `op_cols={"variable": "Emissions|CO2 - Emissions|CO2|Fossil"}` then the addition will be performed with an index that uses all columns except the “variable” column and the output will have a “variable” column with the value “Emissions|CO2 - Emissions|CO2|Fossil”.
- ****kwargs** (*any*) – Passed to `prep_for_op()`

Returns Sum of `self` and `other`, using `op_cols` to define the columns which should be dropped before the data is aligned and to define the value of these columns in the output.

Return type *ScmRun*

Examples

```
>>> import numpy as np
>>> from scmdata import ScmRun
>>>
>>> IDX = [2010, 2020, 2030]
>>>
>>> start = ScmRun(
...     data=np.arange(18).reshape(3, 6),
...     index=IDX,
...     columns={
...         "variable": [
...             "Emissions|CO2|Fossil",
...             "Emissions|CO2|AFOLU",
...             "Emissions|CO2|Fossil",
...             "Emissions|CO2|AFOLU",
...             "Cumulative Emissions|CO2",
...             "Surface Air Temperature Change",
...         ],
...         "unit": ["GtC / yr", "GtC / yr", "GtC / yr", "GtC / yr", "GtC", "K"],
...         "region": ["World|NH", "World|NH", "World|SH", "World|SH", "World",
... ↪ "World"],
...         "model": "idealised",
...         "scenario": "idealised",
...     },
... )
>>>
>>> start.head()
```

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```

time                                     2010-01-01 00:00:00
→ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable          unit    region  model    scenario
Emissions|CO2|Fossil  GtC / yr World|NH idealised idealised      0.0
→                6.0                12.0
Emissions|CO2|AFOLU   GtC / yr World|NH idealised idealised      1.0
→                7.0                13.0
Emissions|CO2|Fossil  GtC / yr World|SH idealised idealised      2.0
→                8.0                14.0
Emissions|CO2|AFOLU   GtC / yr World|SH idealised idealised      3.0
→                9.0                15.0
Cumulative Emissions|CO2 GtC      World  idealised idealised      4.0
→                10.0               16.0
>>> fos = start.filter(variable="*Fossil")
>>> fos.head()
time                                     2010-01-01 00:00:00
→ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable          unit    region  model    scenario
Emissions|CO2|Fossil GtC / yr World|NH idealised idealised      0.0
→                6.0                12.0
→                World|SH idealised idealised      2.0
→                8.0                14.0
>>>
>>> afolu = start.filter(variable="*AFOLU")
>>> afolu.head()
time                                     2010-01-01 00:00:00
→ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable          unit    region  model    scenario
Emissions|CO2|AFOLU GtC / yr World|NH idealised idealised      1.0
→                7.0                13.0
→                World|SH idealised idealised      3.0
→                9.0                15.0
>>>
>>> total = fos.add(afolu, op_cols={"variable": "Emissions|CO2"})
>>> total.head()
time                                     2010-01-01 00:00:00  2020-01-
→ 01 00:00:00  2030-01-01 00:00:00
model    scenario region  variable    unit
idealised idealised World|NH Emissions|CO2 gigatC / a      1.0
→        13.0                25.0
→        World|SH Emissions|CO2 gigatC / a      5.0
→        17.0                29.0
>>>
>>> nh = start.filter(region="*NH")
>>> nh.head()
time                                     2010-01-01 00:00:00
→ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable          unit    region  model    scenario
Emissions|CO2|Fossil GtC / yr World|NH idealised idealised      0.0
→                6.0                12.0
Emissions|CO2|AFOLU   GtC / yr World|NH idealised idealised      1.0
→                7.0                13.0

```

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```

>>>
>>> sh = start.filter(region="*SH")
>>> sh.head()
time                                     2010-01-01 00:00:00
→ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model      scenario
Emissions|CO2|Fossil GtC / yr World|SH idealised idealised      2.0
→              8.0              14.0
Emissions|CO2|AFOLU  GtC / yr World|SH idealised idealised      3.0
→              9.0              15.0
>>>
>>> world = nh.add(sh, op_cols={"region": "World"})
>>> world.head()
time                                     2010-01-01 00:00:00
→ 2020-01-01 00:00:00  2030-01-01 00:00:00
model      scenario region variable      unit
idealised idealised World  Emissions|CO2|Fossil gigatC / a      2.0
→              14.0              26.0
              Emissions|CO2|AFOLU  gigatC / a      4.0
→              16.0              28.0

```

`scmdata.ops.delta_per_delta_time(self, out_var=None)`

Calculate change in timeseries values for each timestep, divided by the size of the timestep

The output is placed on the middle of each timestep and is one timestep shorter than the input.

Parameters `out_var` (*str*) – If provided, the variable column of the output is set equal to `out_var`. Otherwise, the output variables are equal to the input variables, prefixed with “Delta”.

Returns `scmdata.ScmRun` containing the changes in values of `self`, normalised by the change in time

Return type `scmdata.ScmRun`

Warns `UserWarning` – The data contains nans. If this happens, the output data will also contain nans.

`scmdata.ops.divide(self, other, op_cols, **kwargs)`

Divide values (self / other)

Parameters

- **other** (`ScmRun`) – `ScmRun` containing data to divide
- **op_cols** (*dict of str: str*) – Dictionary containing the columns to drop before dividing as the keys and the value those columns should hold in the output as the values. For example, if we have `op_cols={"variable": "Emissions|CO2 - Emissions|CO2|Fossil"}` then the division will be performed with an index that uses all columns except the “variable” column and the output will have a “variable” column with the value “Emissions|CO2 - Emissions|CO2|Fossil”.
- ****kwargs** (*any*) – Passed to `prep_for_op()`

Returns Quotient of `self` and `other`, using `op_cols` to define the columns which should be dropped before the data is aligned and to define the value of these columns in the output.

Return type `ScmRun`

Examples

```

>>> import numpy as np
>>> from scmdata import ScmRun
>>>
>>> IDX = [2010, 2020, 2030]
>>>
>>> start = ScmRun(
...     data=np.arange(18).reshape(3, 6),
...     index=IDX,
...     columns={
...         "variable": [
...             "Emissions|CO2|Fossil",
...             "Emissions|CO2|AFOLU",
...             "Emissions|CO2|Fossil",
...             "Emissions|CO2|AFOLU",
...             "Cumulative Emissions|CO2",
...             "Surface Air Temperature Change",
...         ],
...         "unit": ["GtC / yr", "GtC / yr", "GtC / yr", "GtC / yr", "GtC", "K"],
...         "region": ["World|NH", "World|NH", "World|SH", "World|SH", "World",
...             ↪ "World"],
...         "model": "idealised",
...         "scenario": "idealised",
...     },
... )
>>>
>>> start.head()
time                                     2010-01-01 00:00:00 ↪
↪ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model      scenario
Emissions|CO2|Fossil  GtC / yr World|NH idealised idealised      0.0 ↪
↪          6.0          12.0
Emissions|CO2|AFOLU   GtC / yr World|NH idealised idealised      1.0 ↪
↪          7.0          13.0
Emissions|CO2|Fossil  GtC / yr World|SH idealised idealised      2.0 ↪
↪          8.0          14.0
Emissions|CO2|AFOLU   GtC / yr World|SH idealised idealised      3.0 ↪
↪          9.0          15.0
Cumulative Emissions|CO2 GtC      World      idealised idealised      4.0 ↪
↪          10.0          16.0
>>> fos = start.filter(variable="*Fossil")
>>> fos.head()
time                                     2010-01-01 00:00:00 ↪
↪ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model      scenario
Emissions|CO2|Fossil GtC / yr World|NH idealised idealised      0.0 ↪
↪          6.0          12.0
↪          World|SH idealised idealised      2.0 ↪
↪          8.0          14.0
>>>
>>> afolu = start.filter(variable="*AFOLU")

```

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```

>>> afolu.head()
time                                2010-01-01 00:00:00
→ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model  scenario
Emissions|CO2|AFOLU GtC / yr World|NH idealised idealised      1.0
→              7.0              13.0
→              9.0              15.0
World|SH idealised idealised      3.0
→
>>>
>>> fos_afolu_ratio = fos.divide(
...     afolu, op_cols={"variable": "Emissions|CO2|Fossil : AFOLU"}
... )
>>> fos_afolu_ratio.head()
time                                2010-01-01
→ 00:00:00  2020-01-01 00:00:00  2030-01-01 00:00:00
model      scenario region  variable      unit
idealised idealised World|NH Emissions|CO2|Fossil : AFOLU dimensionless
→ 0.0000000      0.857143      0.923077
World|SH Emissions|CO2|Fossil : AFOLU dimensionless
→ 0.666667      0.888889      0.933333

```

`scmdata.ops.inject_ops_methods(cls)`

Inject the operation methods

Parameters `cls` – Target class

`scmdata.ops.integrate(self, out_var=None)`

Integrate with respect to time

Parameters `out_var` (`str`) – If provided, the variable column of the output is set equal to `out_var`. Otherwise, the output variables are equal to the input variables, prefixed with “Cumulative”.

Returns `scmdata.ScmRun` containing the integral of `self` with respect to time

Return type `scmdata.ScmRun`

Warns `UserWarning` – The data being integrated contains nans. If this happens, the output data will also contain nans.

`scmdata.ops.linear_regression(self)`

Calculate linear regression of each timeseries

Note: Times in seconds since 1970-01-01 are used as the x-axis for the regressions. Such values can be accessed with `self.time_points.values.astype("datetime64[s]").astype("int")`. This decision does not matter for the gradients, but is important for the intercept values.

Returns `list of dict[str]` – List of dictionaries. Each dictionary contains the metadata for the time-series plus the gradient (with key “gradient”) and intercept (with key “intercept”). The gradient and intercept are stored as `pint.Quantity`.

Return type `Any`

`scmdata.ops.linear_regression_gradient(self, unit=None)`

Calculate gradients of a linear regression of each timeseries

Parameters **unit** (*str*) – Output unit for gradients. If not supplied, the gradients' units will not be converted to a common unit.

Returns `self.meta` plus a column with the value of the gradient for each timeseries. The "unit" column is updated to show the unit of the gradient.

Return type `pandas.DataFrame`

`scmdata.ops.linear_regression_intercept(self, unit=None)`

Calculate intercepts of a linear regression of each timeseries

Note: Times in seconds since 1970-01-01 are used as the x-axis for the regressions. Such values can be accessed with `self.time_points.values.astype("datetime64[s]").astype("int")`. This decision does not matter for the gradients, but is important for the intercept values.

Parameters **unit** (*str*) – Output unit for gradients. If not supplied, the gradients' units will not be converted to a common unit.

Returns `self.meta` plus a column with the value of the gradient for each timeseries. The "unit" column is updated to show the unit of the gradient.

Return type `pandas.DataFrame`

`scmdata.ops.linear_regression_scmrun(self)`

Re-calculate the timeseries based on a linear regression

Returns The timeseries, re-calculated based on a linear regression

Return type `scmdata.ScmRun`

`scmdata.ops.multiply(self, other, op_cols, **kwargs)`

Multiply values

Parameters

- **other** (*ScmRun*) – *ScmRun* containing data to multiply
- **op_cols** (*dict of str: str*) – Dictionary containing the columns to drop before multiplying as the keys and the value those columns should hold in the output as the values. For example, if we have `op_cols={"variable": "Emissions|CO2 - Emissions|CO2|Fossil"}` then the multiplication will be performed with an index that uses all columns except the "variable" column and the output will have a "variable" column with the value "Emissions|CO2 - Emissions|CO2|Fossil".
- ****kwargs** (*any*) – Passed to `prep_for_op()`

Returns Product of `self` and `other`, using `op_cols` to define the columns which should be dropped before the data is aligned and to define the value of these columns in the output.

Return type `ScmRun`

Examples

```

>>> import numpy as np
>>> from scmdata import ScmRun
>>>
>>> IDX = [2010, 2020, 2030]
>>>
>>> start = ScmRun(
...     data=np.arange(18).reshape(3, 6),
...     index=IDX,
...     columns={
...         "variable": [
...             "Emissions|CO2|Fossil",
...             "Emissions|CO2|AFOLU",
...             "Emissions|CO2|Fossil",
...             "Emissions|CO2|AFOLU",
...             "Cumulative Emissions|CO2",
...             "Surface Air Temperature Change",
...         ],
...         "unit": ["GtC / yr", "GtC / yr", "GtC / yr", "GtC / yr", "GtC", "K"],
...         "region": ["World|NH", "World|NH", "World|SH", "World|SH", "World",
...             ↪ "World"],
...         "model": "idealised",
...         "scenario": "idealised",
...     },
... )
>>>
>>> start.head()
time                                     2010-01-01 00:00:00 ↪
↪ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model      scenario
Emissions|CO2|Fossil  GtC / yr World|NH idealised idealised      0.0 ↪
↪          6.0          12.0
Emissions|CO2|AFOLU   GtC / yr World|NH idealised idealised      1.0 ↪
↪          7.0          13.0
Emissions|CO2|Fossil  GtC / yr World|SH idealised idealised      2.0 ↪
↪          8.0          14.0
Emissions|CO2|AFOLU   GtC / yr World|SH idealised idealised      3.0 ↪
↪          9.0          15.0
Cumulative Emissions|CO2 GtC      World      idealised idealised      4.0 ↪
↪          10.0          16.0
>>> fos = start.filter(variable="*Fossil")
>>> fos.head()
time                                     2010-01-01 00:00:00 ↪
↪ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model      scenario
Emissions|CO2|Fossil GtC / yr World|NH idealised idealised      0.0 ↪
↪          6.0          12.0
↪          World|SH idealised idealised      2.0 ↪
↪          8.0          14.0
>>>
>>> afolu = start.filter(variable="*AFOLU")

```

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```

>>> afolu.head()
time                                2010-01-01 00:00:00
→ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model  scenario
Emissions|CO2|AFOLU GtC / yr World|NH idealised idealised      1.0
→              7.0              13.0
→              9.0              15.0
World|SH idealised idealised      3.0
→              15.0
>>>
>>> fos_times_afolu = fos.multiply(
...     afolu, op_cols={"variable": "Emissions|CO2|Fossil : AFOLU"}
... )
>>> fos_times_afolu.head()
time                                2010-01-01 00:00:00
→ 2010-01-01 00:00:00  2020-01-01 00:00:00  2030-01-01 00:00:00
model      scenario region  variable      unit
idealised idealised World|NH Emissions|CO2|Fossil : AFOLU gigatC ** 2 / a ** 2
→              0.0              42.0              156.0
→              6.0              72.0              210.0
World|SH Emissions|CO2|Fossil : AFOLU gigatC ** 2 / a ** 2
→              6.0              72.0              210.0

```

`scmdata.ops.prep_for_op(inp, op_cols, meta, ur=<openscm_units._unit_registry.ScmUnitRegistry object>)`
 Prepare dataframe for operation

Parameters

- **inp** (*ScmRun*) – *ScmRun* containing data to prepare
- **op_cols** (*dict of str: str*) – Dictionary containing the columns to drop in order to prepare for the operation as the keys (the values are not used). For example, if we have `op_cols={"variable": "Emissions|CO2 - Emissions|CO2|Fossil"}` then we will drop the “variable” column from the index.
- **ur** (*pint.UnitRegistry*) – Pint unit registry to use for the operation

Returns

Timeseries to use for the operation. They are the transpose of the normal *ScmRun.timeseries()* output with the columns being Pint arrays (unless “unit” is in `op_cols` in which case no units are available to be used so the columns are standard numpy arrays). We do this so that we can use *Pint’s Pandas interface* to handle unit conversions automatically.

Return type *pandas.DataFrame*

`scmdata.ops.set_op_values(output, op_cols)`
 Set operation values in output

Parameters

- **output** (*pandas.DataFrame*) – Dataframe of which to update the values
- **op_cols** (*dict of str: str*) – Dictionary containing the columns to update as the keys and the value those columns should hold in the output as the values. For example, if we have `op_cols={"variable": "Emissions|CO2 - Emissions|CO2|Fossil"}` then the output will have a “variable” column with the value “Emissions|CO2 - Emissions|CO2|Fossil”.

Returns output with the relevant columns being set according to `op_cols`.

Return type pandas.DataFrame

scmdata.ops.**subtract**(self, other, op_cols, **kwargs)
Subtract values

Parameters

- **other** (*ScmRun*) – *ScmRun* containing data to subtract
- **op_cols** (*dict of str: str*) – Dictionary containing the columns to drop before subtracting as the keys and the value those columns should hold in the output as the values. For example, if we have op_cols={"variable": "Emissions|CO2 - Emissions|CO2|Fossil"} then the subtraction will be performed with an index that uses all columns except the “variable” column and the output will have a “variable” column with the value “Emissions|CO2 - Emissions|CO2|Fossil”.
- ****kwargs** (*any*) – Passed to *prep_for_op()*

Returns Difference between self and other, using op_cols to define the columns which should be dropped before the data is aligned and to define the value of these columns in the output.

Return type *ScmRun*

Examples

```
>>> import numpy as np
>>> from scmdata import ScmRun
>>>
>>> IDX = [2010, 2020, 2030]
>>>
>>> start = ScmRun(
...     data=np.arange(18).reshape(3, 6),
...     index=IDX,
...     columns={
...         "variable": [
...             "Emissions|CO2|Fossil",
...             "Emissions|CO2|AFOLU",
...             "Emissions|CO2|Fossil",
...             "Emissions|CO2|AFOLU",
...             "Cumulative Emissions|CO2",
...             "Surface Air Temperature Change",
...         ],
...         "unit": ["GtC / yr", "GtC / yr", "GtC / yr", "GtC / yr", "GtC", "K"],
...         "region": ["World|NH", "World|NH", "World|SH", "World|SH", "World",
... ↪ "World"],
...         "model": "idealised",
...         "scenario": "idealised",
...     },
... )
>>>
>>> start.head()
time                                     2010-01-01 00:00:00 ↪
↪ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable          unit    region  model    scenario
Emissions|CO2|Fossil  GtC / yr World|NH idealised idealised          0.0 ↪
↪                               6.0                12.0                (continues on next page)
```

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```

Emissions|CO2|AFOLU      GtC / yr World|NH idealised idealised      1.0
↪      7.0                13.0
Emissions|CO2|Fossil      GtC / yr World|SH idealised idealised      2.0
↪      8.0                14.0
Emissions|CO2|AFOLU      GtC / yr World|SH idealised idealised      3.0
↪      9.0                15.0
Cumulative Emissions|CO2 GtC      World      idealised idealised      4.0
↪      10.0               16.0
>>> fos = start.filter(variable="*Fossil")
>>> fos.head()
time                                2010-01-01 00:00:00
↪2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model      scenario
Emissions|CO2|Fossil GtC / yr World|NH idealised idealised      0.0
↪      6.0                12.0
                        World|SH idealised idealised      2.0
↪      8.0                14.0
>>>
>>> afolu = start.filter(variable="*AFOLU")
>>> afolu.head()
time                                2010-01-01 00:00:00
↪2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model      scenario
Emissions|CO2|AFOLU GtC / yr World|NH idealised idealised      1.0
↪      7.0                13.0
                        World|SH idealised idealised      3.0
↪      9.0                15.0
>>>
>>> fos_minus_afolu = fos.subtract(
...     afolu, op_cols={"variable": "Emissions|CO2|Fossil - AFOLU"}
... )
>>> fos_minus_afolu.head()
time                                2010-01-01
↪00:00:00  2020-01-01 00:00:00  2030-01-01 00:00:00
model      scenario region  variable      unit
idealised idealised World|NH Emissions|CO2|Fossil - AFOLU gigatC / a
↪ -1.0                -1.0                -1.0
                        World|SH Emissions|CO2|Fossil - AFOLU gigatC / a
↪ -1.0                -1.0                -1.0
>>>
>>> nh_minus_sh = nh.subtract(sh, op_cols={"region": "World|NH - SH"})
>>> nh_minus_sh.head()
time                                2010-01-01
↪00:00:00  2020-01-01 00:00:00  2030-01-01 00:00:00
model      scenario region  variable      unit
idealised idealised World|NH - SH Emissions|CO2|Fossil gigatC / a      -
↪2.0                -2.0                -2.0
                        Emissions|CO2|AFOLU gigatC / a      -
↪2.0                -2.0                -2.0

```

1.1.11 scmdata.plotting

Plotting helpers for *ScmRun*

See the example notebook ‘plotting-with-seaborn.ipynb’ for usage examples

`scmdata.plotting.inject_plotting_methods(cls)`

Inject the plotting methods

Parameters `cls` – Target class

`scmdata.plotting.lineplot(self, time_axis=None, **kwargs)`

Make a line plot via *seaborn*’s `lineplot`

If only a single unit is present, it will be used as the y-axis label. The axis object is returned so this can be changed by the user if desired.

Parameters

- **time_axis** (`{None, "year", "year-month", "days since 1970-01-01", "seconds since 1970-01-01"}` # *noqa: E501*) – Time axis to use for the plot.

If `None`, `datetime.datetime` objects will be used.

If `"year"`, the year of each time point will be used.

If `"year-month"`, the year plus (month - 0.5) / 12 will be used.

If `"days since 1970-01-01"`, the number of days since 1st Jan 1970 will be used (calculated using the `datetime` module).

If `"seconds since 1970-01-01"`, the number of seconds since 1st Jan 1970 will be used (calculated using the `datetime` module).

- ****kwargs** – Keyword arguments to be passed to `seaborn.lineplot`. If none are passed, sensible defaults will be used.

Returns Output of call to `seaborn.lineplot`

Return type `matplotlib.axes._subplots.AxesSubplot`

`scmdata.plotting.plumeplot(self, ax=None, quantiles_plumes=[((0.05, 0.95), 0.5), ((0.5, 1.0)], hue_var='scenario', hue_label='Scenario', palette=None, style_var='variable', style_label='Variable', dashes=None, linewidth=2, time_axis=None, pre_calculated=False, quantile_over=('ensemble_member',))`

Make a plume plot, showing plumes for custom quantiles

Parameters

- **ax** (`matplotlib.axes._subplots.AxesSubplot`) – Axes on which to make the plot
- **quantiles_plumes** (`list[tuple[tuple, float]]`) – Configuration to use when plotting quantiles. Each element is a tuple, the first element of which is itself a tuple and the second element of which is the alpha to use for the quantile. If the first element has length two, these two elements are the quantiles to plot and a plume will be made between these two quantiles. If the first element has length one, then a line will be plotted to represent this quantile.
- **hue_var** (`str`) – The column of `self.meta` which should be used to distinguish different hues.
- **hue_label** (`str`) – Label to use in the legend for `hue_var`.
- **palette** (`dict`) – Dictionary defining the colour to use for different values of `hue_var`.

- **style_var** (*str*) – The column of `self.meta` which should be used to distinguish different styles.
- **style_label** (*str*) – Label to use in the legend for `style_var`.
- **dashes** (*dict*) – Dictionary defining the style to use for different values of `style_var`.
- **linewidth** (*float*) – Width of lines to use (for quantiles which are not to be shown as plumes)
- **time_axis** (*str*) – Time axis to use for the plot (see `timeseries()`)
- **pre_calculated** (*bool*) – Are the quantiles pre-calculated? If no, the quantiles will be calculated within this function. Pre-calculating the quantiles using `ScmRun.quantiles_over()` can lead to faster plotting if multiple plots are to be made with the same quantiles.
- **quantile_over** (*str*, *tuple[str]*) – Columns of `self.meta` over which the quantiles should be calculated. Only used if `pre_calculated` is `False`.

Returns Axes on which the plot was made and the legend items we have made (in case the user wants to move the legend to a different position for example)

Return type `matplotlib.axes._subplots.AxesSubplot`, list

Examples

```
>>> scmrun = ScmRun(
...     data=np.random.random((10, 3)).T,
...     columns={
...         "model": ["a_iam"],
...         "climate_model": ["a_model"] * 5 + ["a_model_2"] * 5,
...         "scenario": ["a_scenario"] * 5 + ["a_scenario_2"] * 5,
...         "ensemble_member": list(range(5)) + list(range(5)),
...         "region": ["World"],
...         "variable": ["Surface Air Temperature Change"],
...         "unit": ["K"],
...     },
...     index=[2005, 2010, 2015],
... )
```

Plot the plumes, calculated over the different ensemble members.

```
>>> scmrun.plumeplot(quantile_over="ensemble_member")
```

Pre-calculate the quantiles, then plot

```
>>> summary_stats = ScmRun(
...     scmrun.quantiles_over("ensemble_member", quantiles=quantiles)
... )
>>> summary_stats.plumeplot(pre_calculated=True)
```

Note: `scmdata` is not a plotting library so this function is provided as is, with little testing. In some ways, it is more intended as inspiration for other users than as a robust plotting tool.

1.1.12 scmdata.run

```
class scmdata.run.ScRun(data: Any, index: Optional[Any] = None, columns: Optional[Union[Dict[str, list],
Dict[str, str]]] = None, metadata: Optional[Dict[str, Union[str, int, float]]] =
None, copy_data: bool = False, **kwargs: Any)
```

Bases: scmdata.run.BaseScRun

Data container for holding one or many time-series of SCM data.

```
__init__(data: Any, index: Optional[Any] = None, columns: Optional[Union[Dict[str, list], Dict[str, str]]]
= None, metadata: Optional[Dict[str, Union[str, int, float]]] = None, copy_data: bool = False,
**kwargs: Any)
```

Initialize the container with timeseries data.

Parameters

- **data** (`Union[ScRun, IamDataFrame, pd.DataFrame, np.ndarray, str]`) – If a `ScRun` object is provided, then a new `ScRun` is created with a copy of the values and metadata from :obj: `data`.

A `pandas.DataFrame` with IAMC-format data columns (the result from `ScRun.timeseries()`) can be provided without any additional columns and index information.

If a numpy array of timeseries data is provided, columns and index must also be specified. The shape of the numpy array should be (`n_times`, `n_series`) where `n_times` is the number of timesteps and `n_series` is the number of time series.

If a string is passed, data will be attempted to be read from file. Currently, reading from CSV, gzipped CSV and Excel formatted files is supported.

- **index** (`np.ndarray`) – If index is not `None`, then the index is used as the timesteps for run. All timeseries in the run use the same set of timesteps.

The values will be attempted to be converted to `numpy.datetime[s]` values. Possible input formats include :

- `datetime.datetime`
- `int` Start of year
- `float` Decimal year
- `str` Uses `dateutil.parser()`. Slow and should be avoided if possible

If index is `None`, then the time index will be obtained from the data if possible.

- **columns** – If `None`, `ScRun` will attempt to infer the values from the source. Otherwise, use this dict to write the metadata for each timeseries in data. For each metadata key (e.g. “model”, “scenario”), an array of values (one per time series) is expected. Alternatively, providing a list of length 1 applies the same value to all timeseries in data. For example, if you had three timeseries from ‘rcp26’ for 3 different models ‘model’, ‘model2’ and ‘model3’, the column dict would look like either ‘col_1’ or ‘col_2’:

```
>>> col_1 = {
    "scenario": ["rcp26"],
    "model": ["model1", "model2", "model3"],
    "region": ["unspecified"],
    "variable": ["unspecified"],
    "unit": ["unspecified"]
}
>>> col_2 = {
```

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```

    "scenario": ["rcp26", "rcp26", "rcp26"],
    "model": ["model1", "model2", "model3"],
    "region": ["unspecified"],
    "variable": ["unspecified"],
    "unit": ["unspecified"]
}
>>> assert pd.testing.assert_frame_equal(
    ScmRun(d, columns=col_1).meta,
    ScmRun(d, columns=col_2).meta
)

```

- **metadata** – Optional dictionary of metadata for instance as a whole.

This can be used to store information such as the longer-form information about a particular dataset, for example, dataset description or DOIs.

Defaults to an empty `dict` if no default metadata are provided.

- **copy_data** (*bool*) – If True, an explicit copy of data is performed.

Note: The copy can be very expensive on large timeseries and should only be needed in cases where the original data is manipulated.

- ****kwargs** – Additional parameters passed to `_read_file()` to read files

Raises

- **ValueError** –
 - If you try to load from multiple files at once. If you wish to do this, please use `scmdata.run.run_append()` instead. * Not specifying index and columns if data is a `numpy.ndarray`
- **scmdata.errors.MissingRequiredColumn** – If metadata for `required_cols` is not found
- **TypeError** – Timeseries cannot be read from data

add(*other*, *op_cols*, ***kwargs*)

Add values

Parameters

- **other** (*ScmRun*) – *ScmRun* containing data to add
- **op_cols** (*dict of str: str*) – Dictionary containing the columns to drop before adding as the keys and the value those columns should hold in the output as the values. For example, if we have `op_cols={"variable": "Emissions|CO2 - Emissions|CO2|Fossil"}` then the addition will be performed with an index that uses all columns except the “variable” column and the output will have a “variable” column with the value “Emissions|CO2 - Emissions|CO2|Fossil”.
- ****kwargs** (*any*) – Passed to `prep_for_op()`

Returns Sum of self and other, using `op_cols` to define the columns which should be dropped before the data is aligned and to define the value of these columns in the output.

Return type *ScmRun*

Examples

```

>>> import numpy as np
>>> from scmdata import ScmRun
>>>
>>> IDX = [2010, 2020, 2030]
>>>
>>> start = ScmRun(
...     data=np.arange(18).reshape(3, 6),
...     index=IDX,
...     columns={
...         "variable": [
...             "Emissions|CO2|Fossil",
...             "Emissions|CO2|AFOLU",
...             "Emissions|CO2|Fossil",
...             "Emissions|CO2|AFOLU",
...             "Cumulative Emissions|CO2",
...             "Surface Air Temperature Change",
...         ],
...         "unit": ["GtC / yr", "GtC / yr", "GtC / yr", "GtC / yr", "GtC", "K"],
...         "region": ["World|NH", "World|NH", "World|SH", "World|SH", "World", "World"],
...         "model": "idealised",
...         "scenario": "idealised",
...     },
... )
>>>
>>> start.head()
time                                2010-01-01
00:00:00  2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model  scenario
Emissions|CO2|Fossil  GtC / yr World|NH idealised idealised
0.0                6.0                12.0
Emissions|CO2|AFOLU   GtC / yr World|NH idealised idealised
1.0                7.0                13.0
Emissions|CO2|Fossil  GtC / yr World|SH idealised idealised
2.0                8.0                14.0
Emissions|CO2|AFOLU   GtC / yr World|SH idealised idealised
3.0                9.0                15.0
Cumulative Emissions|CO2  GtC      World  idealised idealised
4.0                10.0             16.0
>>> fos = start.filter(variable="*Fossil")
>>> fos.head()
time                                2010-01-01 00:00:00
2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model  scenario
Emissions|CO2|Fossil  GtC / yr World|NH idealised idealised  0.0
6.0                12.0
World|SH idealised idealised  2.0
8.0                14.0

```

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```

>>> afolu = start.filter(variable="*AFOLU")
>>> afolu.head()
time                                2010-01-01 00:00:00
↳ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model      scenario
Emissions|CO2|AFOLU GtC / yr World|NH idealised idealised      1.0
↳                      7.0                      13.0
↳                      World|SH idealised idealised      3.0
↳                      9.0                      15.0
>>>
>>> total = fos.add(afolu, op_cols={"variable": "Emissions|CO2"})
>>> total.head()
time                                2010-01-01 00:00:00
↳ 2020-01-01 00:00:00  2030-01-01 00:00:00
model      scenario region  variable      unit
idealised idealised World|NH Emissions|CO2 gigatC / a      1.0
↳                      13.0                      25.0
↳                      World|SH Emissions|CO2 gigatC / a      5.0
↳                      17.0                      29.0
>>>
>>> nh = start.filter(region="*NH")
>>> nh.head()
time                                2010-01-01 00:00:00
↳ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model      scenario
Emissions|CO2|Fossil GtC / yr World|NH idealised idealised      0.0
↳                      6.0                      12.0
Emissions|CO2|AFOLU  GtC / yr World|NH idealised idealised      1.0
↳                      7.0                      13.0
>>>
>>> sh = start.filter(region="*SH")
>>> sh.head()
time                                2010-01-01 00:00:00
↳ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model      scenario
Emissions|CO2|Fossil GtC / yr World|SH idealised idealised      2.0
↳                      8.0                      14.0
Emissions|CO2|AFOLU  GtC / yr World|SH idealised idealised      3.0
↳                      9.0                      15.0
>>>
>>> world = nh.add(sh, op_cols={"region": "World"})
>>> world.head()
time                                2010-01-01 00:00:00
↳ 2020-01-01 00:00:00  2030-01-01 00:00:00
model      scenario region variable      unit
idealised idealised World  Emissions|CO2|Fossil gigatC / a      2.0
↳                      14.0                      26.0
↳                      Emissions|CO2|AFOLU  gigatC / a      4.0
↳                      16.0                      28.0

```

append(other, inplace: *bool* = False, duplicate_msg: Union[str, *bool*] = True, metadata: Optional[Dict[str, Union[str, int, float]]] = None, **kwargs: Any)

Append additional data to the current dataframe.

For details, see [run_append\(\)](#).

Parameters

- **other** – Data (in format which can be cast to [ScmRun](#)) to append
- **inplace** – If True, append data in place and return None. Otherwise, return a new [ScmRun](#) instance with the appended data.
- **duplicate_msg** – If True, raise a [scmdata.errors.NonUniqueMetadataError](#) error so the user can see the duplicate timeseries. If False, take the average and do not raise a warning or error. If "warn", raise a warning if duplicate data is detected.
- **metadata** – If not None, override the metadata of the resulting [ScmRun](#) with metadata. Otherwise, the metadata for the runs are merged. In the case where there are duplicate metadata keys, the values from the first run are used.
- ****kwargs** – Keywords to pass to [ScmRun.__init__\(\)](#) when reading other

Returns If not inplace, return a new [ScmRun](#) instance containing the result of the append.

Return type [ScmRun](#)

Raises [NonUniqueMetadataError](#) – If the appending results in timeseries with duplicate metadata and duplicate_msg is True

convert_unit(unit: [str](#), context: *Optional[str]* = None, inplace: *bool* = False, **kwargs: Any)

Convert the units of a selection of timeseries.

Uses [scmdata.units.UnitConverter](#) to perform the conversion.

Parameters

- **unit** – Unit to convert to. This must be recognised by UnitConverter.
- **context** – Context to use for the conversion i.e. which metric to apply when performing CO2-equivalent calculations. If None, no metric will be applied and CO2-equivalent calculations will raise DimensionalityError.
- **inplace** – If True, apply the conversion inplace and return None
- ****kwargs** – Extra arguments which are passed to [filter\(\)](#) to limit the timeseries which are attempted to be converted. Defaults to selecting the entire ScmRun, which will likely fail.

Returns If inplace is not False, a new [ScmRun](#) instance with the converted units.

Return type [ScmRun](#)

Notes

If context is not None, then the context used for the conversion will be checked against any existing metadata and, if the conversion is valid, stored in the output's metadata.

Raises [ValueError](#) – "unit_context" is already included in self's [meta_attributes\(\)](#) and it does not match context for the variables to be converted.

copy()

Return a [copy.deepcopy\(\)](#) of self.

Also creates copies the underlying Timeseries data

Returns [copy.deepcopy\(\)](#) of self

Return type [ScmRun](#)

data_hierarchy_separator = '|'

String used to define different levels in our data hierarchies.

By default we follow pyam and use "|". In such a case, emissions of CO₂ for energy from coal would be "Emissions|CO2|Energy|Coal".

Type `str`

delta_per_delta_time(*out_var=None*)

Calculate change in timeseries values for each timestep, divided by the size of the timestep

The output is placed on the middle of each timestep and is one timestep shorter than the input.

Parameters **out_var** (`str`) – If provided, the variable column of the output is set equal to `out_var`. Otherwise, the output variables are equal to the input variables, prefixed with "Delta".

Returns `scmdata.ScmRun` containing the changes in values of `self`, normalised by the change in time

Return type `scmdata.ScmRun`

Warns **UserWarning** – The data contains nans. If this happens, the output data will also contain nans.

divide(*other, op_cols, **kwargs*)

Divide values (self / other)

Parameters

- **other** (`ScmRun`) – `ScmRun` containing data to divide
- **op_cols** (*dict of str: str*) – Dictionary containing the columns to drop before dividing as the keys and the value those columns should hold in the output as the values. For example, if we have `op_cols={"variable": "Emissions|CO2 - Emissions|CO2|Fossil"}` then the division will be performed with an index that uses all columns except the "variable" column and the output will have a "variable" column with the value "Emissions|CO2 - Emissions|CO2|Fossil".
- ****kwargs** (*any*) – Passed to `prep_for_op()`

Returns Quotient of `self` and `other`, using `op_cols` to define the columns which should be dropped before the data is aligned and to define the value of these columns in the output.

Return type `ScmRun`

Examples

```
>>> import numpy as np
>>> from scmdata import ScmRun
>>>
>>> IDX = [2010, 2020, 2030]
>>>
>>> start = ScmRun(
...     data=np.arange(18).reshape(3, 6),
...     index=IDX,
...     columns={
...         "variable": [
...             "Emissions|CO2|Fossil",
```

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```

...         "Emissions|CO2|AFOLU",
...         "Emissions|CO2|Fossil",
...         "Emissions|CO2|AFOLU",
...         "Cumulative Emissions|CO2",
...         "Surface Air Temperature Change",
...     ],
...     "unit": ["GtC / yr", "GtC / yr", "GtC / yr", "GtC / yr", "GtC", "K
↪"],
...     "region": ["World|NH", "World|NH", "World|SH", "World|SH", "World",
↪"World"],
...     "model": "idealised",
...     "scenario": "idealised",
... },
... )
>>>
>>> start.head()
time                                     2010-01-01↪
↪00:00:00  2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model      scenario
Emissions|CO2|Fossil  GtC / yr World|NH idealised idealised ↪
↪0.0          6.0          12.0
Emissions|CO2|AFOLU   GtC / yr World|NH idealised idealised ↪
↪1.0          7.0          13.0
Emissions|CO2|Fossil  GtC / yr World|SH idealised idealised ↪
↪2.0          8.0          14.0
Emissions|CO2|AFOLU   GtC / yr World|SH idealised idealised ↪
↪3.0          9.0          15.0
Cumulative Emissions|CO2 GtC      World  idealised idealised ↪
↪4.0          10.0         16.0
>>> fos = start.filter(variable="*Fossil")
>>> fos.head()
time                                     2010-01-01 00:00:00↪
↪ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model      scenario
Emissions|CO2|Fossil GtC / yr World|NH idealised idealised 0.0↪
↪          6.0          12.0
↪          World|SH idealised idealised 2.0↪
↪          8.0          14.0
>>>
>>> afolu = start.filter(variable="*AFOLU")
>>> afolu.head()
time                                     2010-01-01 00:00:00 ↪
↪2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model      scenario
Emissions|CO2|AFOLU GtC / yr World|NH idealised idealised 1.0 ↪
↪          7.0          13.0
↪          World|SH idealised idealised 3.0 ↪
↪          9.0          15.0
>>>
>>> fos_afolu_ratio = fos.divide(
...     afolu, op_cols={"variable": "Emissions|CO2|Fossil : AFOLU"}
... )

```

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```
>>> fos_afolu_ratio.head()
time                                     2010-
01-01 00:00:00  2020-01-01 00:00:00  2030-01-01 00:00:00
model    scenario region  variable          unit
idealised idealised World|NH Emissions|CO2|Fossil : AFOLU dimensionless
0.000000          0.857143          0.923077
World|SH Emissions|CO2|Fossil : AFOLU dimensionless
0.666667          0.888889          0.933333
```

drop_meta(columns: Union[list, str], inplace: Optional[bool] = False)

Drop meta columns out of the Run

Parameters

- **columns** – The column or columns to drop
- **inplace** – If True, do operation inplace and return None.

Raises **KeyError** – If any of the columns do not exist in the meta DataFrame

property empty: bool

Indicate whether *ScmRun* is empty i.e. contains no data

Returns If *ScmRun* is empty, return True, if not return False

Return type bool

filter(keep: bool = True, inplace: bool = False, log_if_empty: bool = True, **kwargs: Any)

Return a filtered ScmRun (i.e., a subset of the data).

```
>>> df
<scmdata.ScmRun (timeseries: 3, timepoints: 3)>
Time:
  Start: 2005-01-01T00:00:00
  End: 2015-01-01T00:00:00
Meta:
   model    scenario region          variable  unit climate_model
0  a_iam  a_scenario  World  Primary Energy  EJ/yr      a_model
1  a_iam  a_scenario  World Primary Energy|Coal  EJ/yr      a_model
2  a_iam  a_scenario2  World  Primary Energy  EJ/yr      a_model
[3 rows x 7 columns]

>>> df.filter(scenario="a_scenario")
<scmdata.ScmRun (timeseries: 2, timepoints: 3)>
Time:
  Start: 2005-01-01T00:00:00
  End: 2015-01-01T00:00:00
Meta:
   model    scenario region          variable  unit climate_model
0  a_iam  a_scenario  World  Primary Energy  EJ/yr      a_model
1  a_iam  a_scenario  World Primary Energy|Coal  EJ/yr      a_model
[2 rows x 7 columns]

>>> df.filter(scenario="a_scenario", keep=False)
<scmdata.ScmRun (timeseries: 1, timepoints: 3)>
Time:
```

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```

Start: 2005-01-01T00:00:00
End: 2015-01-01T00:00:00
Meta:
      model      scenario region      variable  unit climate_model
2  a_iam  a_scenario2  World      Primary Energy  EJ/yr      a_model
[1 rows x 7 columns]

>>> df.filter(level=1)
<scmdata.ScmRun (timeseries: 2, timepoints: 3)>
Time:
Start: 2005-01-01T00:00:00
End: 2015-01-01T00:00:00
Meta:
      model      scenario region      variable  unit climate_model
0  a_iam  a_scenario  World      Primary Energy  EJ/yr      a_model
2  a_iam  a_scenario2  World      Primary Energy  EJ/yr      a_model
[2 rows x 7 columns]

>>> df.filter(year=range(2000, 2011))
<scmdata.ScmRun (timeseries: 3, timepoints: 2)>
Time:
Start: 2005-01-01T00:00:00
End: 2010-01-01T00:00:00
Meta:
      model      scenario region      variable  unit climate_model
0  a_iam  a_scenario  World      Primary Energy  EJ/yr      a_model
1  a_iam  a_scenario  World  Primary Energy|Coal  EJ/yr      a_model
2  a_iam  a_scenario2  World      Primary Energy  EJ/yr      a_model
[2 rows x 7 columns]

```

Parameters

- **keep** – If True, keep all timeseries satisfying the filters, otherwise drop all the timeseries satisfying the filters
- **inplace** – If True, do operation inplace and return None
- **log_if_empty** – If True, log a warning level message if the result is empty.
- ****kwargs** – Argument names are keys with which to filter, values are used to do the filtering. Filtering can be done on:
 - all metadata columns with strings, “*” can be used as a wildcard in search strings
 - ‘level’: the maximum “depth” of IAM variables (number of hierarchy levels, excluding the strings given in the ‘variable’ argument)
 - ‘time’: takes a `datetime.datetime` or list of `datetime.datetime`’s TODO: default to `np.datetime64`
 - ‘year’, ‘month’, ‘day’, ‘hour’: takes an `int` or list of `int`’s (‘month’ and ‘day’ also accept `str` or list of `str`)

If `regex=True` is included in `kwargs` then the pseudo-regex syntax in `pattern_match()` is disabled.

Returns If not `inplace`, return a new instance with the filtered data.

Return type `ScmRun`

classmethod `from_nc(fname)`

Read a netCDF4 file from disk

Parameters `fname` (*str*) – Filename to read

See also:

`scmdata.run.ScmRun.from_nc()`

get_unique_meta(*meta*: *str*, *no_duplicates*: *Optional[bool]* = *False*) → Union[List[Any], Any]

Get unique values in a metadata column.

Parameters

- **meta** – Column to retrieve metadata for
- **no_duplicates** – Should I raise an error if there is more than one unique value in the metadata column?

Raises

- **ValueError** – There is more than one unique value in the metadata column and `no_duplicates` is `True`.
- **KeyError** – If a meta column does not exist in the run's metadata

Returns List of unique metadata values. If `no_duplicates` is `True` the metadata value will be returned (rather than a list).

Return type [List[Any], Any]

groupby(**group*)

Group the object by unique metadata

Enables iteration over groups of data. For example, to iterate over each scenario in the object

```
>>> for group in df.groupby("scenario"):
>>>     print(group)
<scmdata.ScmRun (timeseries: 2, timepoints: 3)>
Time:
  Start: 2005-01-01T00:00:00
  End: 2015-01-01T00:00:00
Meta:
   model  scenario region      variable  unit climate_model
0  a_iam  a_scenario World  Primary Energy  EJ/yr      a_model
1  a_iam  a_scenario World  Primary Energy|Coal  EJ/yr      a_model
<scmdata.ScmRun (timeseries: 1, timepoints: 3)>
Time:
  Start: 2005-01-01T00:00:00
  End: 2015-01-01T00:00:00
Meta:
   model  scenario region      variable  unit climate_model
2  a_iam  a_scenario2 World  Primary Energy  EJ/yr      a_model
```

Parameters `group` (*str* or *list of str*) – Columns to group by

Returns See the documentation for `RunGroupBy` for more information

Return type `RunGroupBy`

head(*args, **kwargs)

Return head of `self.timeseries()`.

Parameters

- ***args** – Passed to `self.timeseries().head()`
- ****kwargs** – Passed to `self.timeseries().head()`

Returns Tail of `self.timeseries()`

Return type `pandas.DataFrame`

integrate(*out_var=None*)

Integrate with respect to time

Parameters **out_var** (*str*) – If provided, the variable column of the output is set equal to `out_var`. Otherwise, the output variables are equal to the input variables, prefixed with “Cumulative”.

Returns `scmdata.ScmRun` containing the integral of `self` with respect to time

Return type `scmdata.ScmRun`

Warns **UserWarning** – The data being integrated contains nans. If this happens, the output data will also contain nans.

interpolate(*target_times: Union[numpy.ndarray, List[Union[datetime.datetime, int]]], interpolation_type: str = 'linear', extrapolation_type: str = 'linear'*)

Interpolate the dataframe onto a new time frame.

Parameters

- **target_times** – Time grid onto which to interpolate
- **interpolation_type** (*str*) – Interpolation type. Options are ‘linear’
- **extrapolation_type** (*str* or *None*) – Extrapolation type. Options are *None*, ‘linear’ or ‘constant’

Returns A new `ScmRun` containing the data interpolated onto the `target_times` grid

Return type `ScmRun`

line_plot(**kwargs)

Make a line plot via `seaborn’s lineplot`

Deprecated: use `lineplot()` instead

Parameters ****kwargs** – Keyword arguments to be passed to `seaborn.lineplot`. If none are passed, sensible defaults will be used.

Returns Output of call to `seaborn.lineplot`

Return type `matplotlib.axes._subplots.AxesSubplot`

linear_regression()

Calculate linear regression of each timeseries

Note: Times in seconds since 1970-01-01 are used as the x-axis for the regressions. Such values can be accessed with `self.time_points.values.astype("datetime64[s]").astype("int")`. This decision does not matter for the gradients, but is important for the intercept values.

Returns `list of dict[str]` – List of dictionaries. Each dictionary contains the metadata for the timeseries plus the gradient (with key "gradient") and intercept (with key "intercept"). The gradient and intercept are stored as `pint.Quantity`.

Return type Any]

linear_regression_gradient(*unit=None*)

Calculate gradients of a linear regression of each timeseries

Parameters `unit (str)` – Output unit for gradients. If not supplied, the gradients' units will not be converted to a common unit.

Returns `self.meta` plus a column with the value of the gradient for each timeseries. The "unit" column is updated to show the unit of the gradient.

Return type `pandas.DataFrame`

linear_regression_intercept(*unit=None*)

Calculate intercepts of a linear regression of each timeseries

Note: Times in seconds since 1970-01-01 are used as the x-axis for the regressions. Such values can be accessed with `self.time_points.values.astype("datetime64[s]").astype("int")`. This decision does not matter for the gradients, but is important for the intercept values.

Parameters `unit (str)` – Output unit for gradients. If not supplied, the gradients' units will not be converted to a common unit.

Returns `self.meta` plus a column with the value of the gradient for each timeseries. The "unit" column is updated to show the unit of the gradient.

Return type `pandas.DataFrame`

linear_regression_scmrun()

Re-calculate the timeseries based on a linear regression

Returns The timeseries, re-calculated based on a linear regression

Return type `scmdata.ScmRun`

lineplot(*time_axis=None, **kwargs*)

Make a line plot via `seaborn's lineplot`

If only a single unit is present, it will be used as the y-axis label. The axis object is returned so this can be changed by the user if desired.

Parameters

- **time_axis** (`{None, "year", "year-month", "days since 1970-01-01", "seconds since 1970-01-01"}` # *noqa: E501*) – Time axis to use for the plot.

If `None`, `datetime.datetime` objects will be used.

If "year", the year of each time point will be used.

If "year-month", the year plus (month - 0.5) / 12 will be used.

If "days since 1970-01-01", the number of days since 1st Jan 1970 will be used (calculated using the `datetime` module).

If "seconds since 1970-01-01", the number of seconds since 1st Jan 1970 will be used (calculated using the `datetime` module).

- ****kwargs** – Keyword arguments to be passed to `seaborn.lineplot`. If none are passed, sensible defaults will be used.

Returns Output of call to `seaborn.lineplot`

Return type `matplotlib.axes._subplots.AxesSubplot`

long_data(*time_axis=None*)

Return data in long form, particularly useful for plotting with seaborn

Parameters **time_axis** (*{None, "year", "year-month", "days since 1970-01-01", "seconds since 1970-01-01"}*) – Time axis to use for the output's columns.

If `None`, `datetime.datetime` objects will be used.

If `"year"`, the year of each time point will be used.

If `"year-month"`, the year plus (month - 0.5) / 12 will be used.

If `"days since 1970-01-01"`, the number of days since 1st Jan 1970 will be used (calculated using the `datetime` module).

If `"seconds since 1970-01-01"`, the number of seconds since 1st Jan 1970 will be used (calculated using the `datetime` module).

Returns `pandas.DataFrame` containing the data in 'long form' (i.e. one observation per row).

Return type `pandas.DataFrame`

property meta: `pandas.core.frame.DataFrame`

Metadata

property meta_attributes

Get a list of all meta keys

Returns Sorted list of meta keys

Return type `list`

multiply(*other, op_cols, **kwargs*)

Multiply values

Parameters

- **other** (*ScmRun*) – *ScmRun* containing data to multiply
- **op_cols** (*dict of str: str*) – Dictionary containing the columns to drop before multiplying as the keys and the value those columns should hold in the output as the values. For example, if we have `op_cols={"variable": "Emissions|CO2 - Emissions|CO2|Fossil"}` then the multiplication will be performed with an index that uses all columns except the "variable" column and the output will have a "variable" column with the value "Emissions|CO2 - Emissions|CO2|Fossil".
- ****kwargs** (*any*) – Passed to `prep_for_op()`

Returns Product of `self` and `other`, using `op_cols` to define the columns which should be dropped before the data is aligned and to define the value of these columns in the output.

Return type *ScmRun*

Examples

```

>>> import numpy as np
>>> from scmdata import ScmRun
>>>
>>> IDX = [2010, 2020, 2030]
>>>
>>> start = ScmRun(
...     data=np.arange(18).reshape(3, 6),
...     index=IDX,
...     columns={
...         "variable": [
...             "Emissions|CO2|Fossil",
...             "Emissions|CO2|AFOLU",
...             "Emissions|CO2|Fossil",
...             "Emissions|CO2|AFOLU",
...             "Cumulative Emissions|CO2",
...             "Surface Air Temperature Change",
...         ],
...         "unit": ["GtC / yr", "GtC / yr", "GtC / yr", "GtC / yr", "GtC", "K"],
...         "region": ["World|NH", "World|NH", "World|SH", "World|SH", "World", "World"],
...         "model": "idealised",
...         "scenario": "idealised",
...     },
... )
>>>
>>> start.head()
time                                     2010-01-01
00:00:00  2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model  scenario
Emissions|CO2|Fossil  GtC / yr World|NH idealised idealised
0.0                6.0                12.0
Emissions|CO2|AFOLU   GtC / yr World|NH idealised idealised
1.0                7.0                13.0
Emissions|CO2|Fossil  GtC / yr World|SH idealised idealised
2.0                8.0                14.0
Emissions|CO2|AFOLU   GtC / yr World|SH idealised idealised
3.0                9.0                15.0
Cumulative Emissions|CO2  GtC      World  idealised idealised
4.0                10.0             16.0
>>> fos = start.filter(variable="*Fossil")
>>> fos.head()
time                                     2010-01-01 00:00:00
2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model  scenario
Emissions|CO2|Fossil  GtC / yr World|NH idealised idealised  0.0
6.0                12.0
World|SH idealised idealised  2.0
8.0                14.0

```

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```

>>> afolu = start.filter(variable="*AFOLU")
>>> afolu.head()
time                                2010-01-01 00:00:00
↪ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model      scenario
Emissions|CO2|AFOLU GtC / yr World|NH idealised idealised      1.0
↪                      7.0                      13.0
↪                      World|SH idealised idealised      3.0
↪                      9.0                      15.0
>>>
>>> fos_times_afolu = fos.multiply(
...     afolu, op_cols={"variable": "Emissions|CO2|Fossil : AFOLU"}
... )
>>> fos_times_afolu.head()
time                                2010-01-01 00:00:00  2020-01-01 00:00:00  2030-01-01 00:00:00
model      scenario region  variable      unit
idealised idealised World|NH Emissions|CO2|Fossil : AFOLU gigatC ** 2 / a ** 2
↪                      0.0                      42.0                      156.0
↪                      World|SH Emissions|CO2|Fossil : AFOLU gigatC ** 2 / a ** 2
↪                      6.0                      72.0                      210.0

```

plumeplot(*ax=None*, *quantiles_plumes=[((0.05, 0.95), 0.5), ((0.5,), 1.0)]*, *hue_var='scenario'*,
hue_label='Scenario', *palette=None*, *style_var='variable'*, *style_label='Variable'*, *dashes=None*,
linewidth=2, *time_axis=None*, *pre_calculated=False*, *quantile_over=('ensemble_member',)*)

Make a plume plot, showing plumes for custom quantiles

Parameters

- **ax** (*matplotlib.axes._subplots.AxesSubplot*) – Axes on which to make the plot
- **quantiles_plumes** (*list[tuple[tuple, float]]*) – Configuration to use when plotting quantiles. Each element is a tuple, the first element of which is itself a tuple and the second element of which is the alpha to use for the quantile. If the first element has length two, these two elements are the quantiles to plot and a plume will be made between these two quantiles. If the first element has length one, then a line will be plotted to represent this quantile.
- **hue_var** (*str*) – The column of `self.meta` which should be used to distinguish different hues.
- **hue_label** (*str*) – Label to use in the legend for `hue_var`.
- **palette** (*dict*) – Dictionary defining the colour to use for different values of `hue_var`.
- **style_var** (*str*) – The column of `self.meta` which should be used to distinguish different styles.
- **style_label** (*str*) – Label to use in the legend for `style_var`.
- **dashes** (*dict*) – Dictionary defining the style to use for different values of `style_var`.
- **linewidth** (*float*) – Width of lines to use (for quantiles which are not to be shown as plumes)
- **time_axis** (*str*) – Time axis to use for the plot (see `timeseries()`)
- **pre_calculated** (*bool*) – Are the quantiles pre-calculated? If no, the quantiles will be calculated within this function. Pre-calculating the quantiles using `ScmRun`.

`quantiles_over()` can lead to faster plotting if multiple plots are to be made with the same quantiles.

- **quantile_over**(*str*, *tuple*[*str*]) – Columns of `self.meta` over which the quantiles should be calculated. Only used if `pre_calculated` is `False`.

Returns Axes on which the plot was made and the legend items we have made (in case the user wants to move the legend to a different position for example)

Return type `matplotlib.axes._subplots.AxesSubplot`, list

Examples

```
>>> scmrun = ScmRun(
...     data=np.random.random((10, 3)).T,
...     columns={
...         "model": ["a_iam"],
...         "climate_model": ["a_model"] * 5 + ["a_model_2"] * 5,
...         "scenario": ["a_scenario"] * 5 + ["a_scenario_2"] * 5,
...         "ensemble_member": list(range(5)) + list(range(5)),
...         "region": ["World"],
...         "variable": ["Surface Air Temperature Change"],
...         "unit": ["K"],
...     },
...     index=[2005, 2010, 2015],
... )
```

Plot the plumes, calculated over the different ensemble members.

```
>>> scmrun.plumeplot(quantile_over="ensemble_member")
```

Pre-calculate the quantiles, then plot

```
>>> summary_stats = ScmRun(
...     scmrun.quantiles_over("ensemble_member", quantiles=quantiles)
... )
>>> summary_stats.plumeplot(pre_calculated=True)
```

Note: `scmdata` is not a plotting library so this function is provided as is, with little testing. In some ways, it is more intended as inspiration for other users than as a robust plotting tool.

process_over(*cols*: Union[*str*, List[*str*]], *operation*: Union[*str*, Callable[[`pandas.core.frame.DataFrame`], Union[`pandas.core.frame.DataFrame`, `pandas.core.series.Series`, `float`]]], *na_override*=1000000.0, ***kwargs*: Any) → `pandas.core.frame.DataFrame`

Process the data over the input columns.

Parameters

- **cols** – Columns to perform the operation on. The timeseries will be grouped by all other columns in *meta*.
- **operation** (*str* or *func*) – The operation to perform.

If a string is provided, the equivalent pandas groupby function is used. Note that not all groupby functions are available as some do not make sense for this particular application.

Additional information about the arguments for the pandas groupby functions can be found at <https://pandas.pydata.org/pandas-docs/stable/reference/groupby.html>.

If a function is provided, it will be applied to each group. The function must take a dataframe as its first argument and return a DataFrame, Series or scalar.

Note that quantile means the value of the data at a given point in the cumulative distribution of values at each point in the timeseries, for each timeseries once the groupby is applied. As a result, using `q=0.5` is the same as taking the median and not the same as taking the mean/average.

- **na_override** (`[int, float]`) – Convert any nan value in the timeseries meta to this value during processing. The meta values converted back to nan's before the dataframe is returned. This should not need to be changed unless the existing metadata clashes with the default `na_override` value.

This functionality is disabled if `na_override` is None, but may result incorrect results if the timeseries meta includes any nan's.

- ****kwargs** – Keyword arguments to pass to the pandas operation

Returns The quantiles of the timeseries, grouped by all columns in *meta* other than `cols`

Return type `pandas.DataFrame`

Raises `ValueError` – If the operation is not an allowed operation

If the value of `na_override` clashes with any existing metadata

quantiles_over(*cols*: Union[str, List[str]], *quantiles*: Union[str, List[float]], ***kwargs*: Any) →
`pandas.core.frame.DataFrame`

Calculate quantiles of the data over the input columns.

Parameters

- **cols** – Columns to perform the operation on. The timeseries will be grouped by all other columns in *meta*.
- **quantiles** – The quantiles to calculate. This should be a list of quantiles to calculate (quantile values between 0 and 1). `quantiles` can also include the strings “median” or “mean” if these values are to be calculated.
- ****kwargs** – Passed to `process_over()`.

Returns The quantiles of the timeseries, grouped by all columns in *meta* other than `cols`. Each calculated quantile is given a label which is stored in the `quantile` column within the output index.

Return type `pandas.DataFrame`

Raises `TypeError` – operation is included in `kwargs`. The operation is inferred from `quantiles`.

reduce(*func*, *dim=None*, *axis=None*, ***kwargs*)

Apply a function along a given axis

This is to provide the GroupBy functionality in `ScmRun.groupby()` and is not generally called directly.

This implementation is very bare-bones - no reduction along the time dimension is allowed and only the *dim* parameter is used.

Parameters

- **func** (*function*) –

- **dim** (*str*) – Ignored
- **axis** (*int*) – The dimension along which the function is applied. The only valid value is 0 which corresponds to the along the time-series dimension.
- **kwargs** – Other parameters passed to *func*

Returns**Return type** *ScmRun***Raises**

- **ValueError** – If a dimension other than None is provided
- **NotImplementedError** – If *axis* is anything other than 0

relative_to_ref_period_mean(*append_str=None, **kwargs*)

Return the timeseries relative to a given reference period mean.

The reference period mean is subtracted from all values in the input timeseries.

Parameters

- **append_str** – Deprecated
- ****kwargs** – Arguments to pass to *filter()* to determine the data to be included in the reference time period. See the docs of *filter()* for valid options.

Returns New object containing the timeseries, adjusted to the reference period mean. The reference period year bounds are stored in the meta columns "reference_period_start_year" and "reference_period_end_year".**Return type** *ScmRun***Raises** **NotImplementedError** – *append_str* is not None**required_cols** = ('model', 'scenario', 'region', 'variable', 'unit')Minimum metadata columns required by an *ScmRun*.If an application requires a different set of required metadata, this can be specified by overriding *required_cols* on a custom class inheriting *scmdata.run.BaseScmRun*. Note that at a minimum, ("variable", "unit") columns are required.**resample**(*rule: str = 'AS', **kwargs: Any*)

Resample the time index of the timeseries data onto a custom grid.

This helper function allows for values to be easily interpolated onto annual or monthly timesteps using the rules='AS' or 'MS' respectively. Internally, the interpolate function performs the regridding.

Parameters

- **rule** – See the pandas [user guide](#) for a list of options. Note that Business-related offsets such as "BusinessDay" are not supported.
- ****kwargs** – Other arguments to pass through to *interpolate()*

Returns New *ScmRun* instance on a new time index**Return type** *ScmRun*

Examples

Resample a dataframe to annual values

```
>>> scm_df = ScmRun(
...     pd.Series([1, 2, 10], index=(2000, 2001, 2009)),
...     columns={
...         "model": ["a_iam"],
...         "scenario": ["a_scenario"],
...         "region": ["World"],
...         "variable": ["Primary Energy"],
...         "unit": ["EJ/y"],
...     }
... )
>>> scm_df.timeseries().T
model          a_iam
scenario      a_scenario
region        World
variable Primary Energy
unit          EJ/y
year
2000          1
2010         10
```

An annual timeseries can be created by interpolating to the start of years using the rule 'AS'.

```
>>> res = scm_df.resample('AS')
>>> res.timeseries().T
model          a_iam
scenario      a_scenario
region        World
variable      Primary Energy
unit          EJ/y
time
2000-01-01 00:00:00    1.000000
2001-01-01 00:00:00    2.001825
2002-01-01 00:00:00    3.000912
2003-01-01 00:00:00    4.000000
2004-01-01 00:00:00    4.999088
2005-01-01 00:00:00    6.000912
2006-01-01 00:00:00    7.000000
2007-01-01 00:00:00    7.999088
2008-01-01 00:00:00    8.998175
2009-01-01 00:00:00   10.000000
```

```
>>> m_df = scm_df.resample('MS')
>>> m_df.timeseries().T
model          a_iam
scenario      a_scenario
region        World
variable      Primary Energy
unit          EJ/y
time
```

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2000-01-01 00:00:00	1.000000
2000-02-01 00:00:00	1.084854
2000-03-01 00:00:00	1.164234
2000-04-01 00:00:00	1.249088
2000-05-01 00:00:00	1.331204
2000-06-01 00:00:00	1.416058
2000-07-01 00:00:00	1.498175
2000-08-01 00:00:00	1.583029
2000-09-01 00:00:00	1.667883
...	
2008-05-01 00:00:00	9.329380
2008-06-01 00:00:00	9.414234
2008-07-01 00:00:00	9.496350
2008-08-01 00:00:00	9.581204
2008-09-01 00:00:00	9.666058
2008-10-01 00:00:00	9.748175
2008-11-01 00:00:00	9.833029
2008-12-01 00:00:00	9.915146
2009-01-01 00:00:00	10.000000
[109 rows x 1 columns]	

Note that the values do not fall exactly on integer values as not all years are exactly the same length.

References

See the pandas documentation for *resample* <<http://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.Series.resample.html>> for more information about possible arguments.

property shape: tuple

Get the shape of the underlying data as (num_timeseries, num_timesteps)

Returns

Return type tuple of int

subtract(*other*, *op_cols*, ***kwargs*)

Subtract values

Parameters

- **other** (*ScmRun*) – *ScmRun* containing data to subtract
- **op_cols** (*dict of str: str*) – Dictionary containing the columns to drop before subtracting as the keys and the value those columns should hold in the output as the values. For example, if we have `op_cols={"variable": "Emissions|CO2 - Emissions|CO2|Fossil"}` then the subtraction will be performed with an index that uses all columns except the “variable” column and the output will have a “variable” column with the value “Emissions|CO2 - Emissions|CO2|Fossil”.
- ****kwargs** (*any*) – Passed to `prep_for_op()`

Returns Difference between `self` and `other`, using `op_cols` to define the columns which should be dropped before the data is aligned and to define the value of these columns in the output.

Return type *ScmRun*

Examples

```

>>> import numpy as np
>>> from scmdata import ScmRun
>>>
>>> IDX = [2010, 2020, 2030]
>>>
>>> start = ScmRun(
...     data=np.arange(18).reshape(3, 6),
...     index=IDX,
...     columns={
...         "variable": [
...             "Emissions|CO2|Fossil",
...             "Emissions|CO2|AFOLU",
...             "Emissions|CO2|Fossil",
...             "Emissions|CO2|AFOLU",
...             "Cumulative Emissions|CO2",
...             "Surface Air Temperature Change",
...         ],
...         "unit": ["GtC / yr", "GtC / yr", "GtC / yr", "GtC / yr", "GtC", "K"],
...         "region": ["World|NH", "World|NH", "World|SH", "World|SH", "World",
...             ↪ "World"],
...         "model": "idealised",
...         "scenario": "idealised",
...     },
... )
>>>
>>> start.head()
time                                     2010-01-01 ↪
↪ 00:00:00  2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model  scenario
Emissions|CO2|Fossil  GtC / yr World|NH idealised idealised ↪
↪ 0.0          6.0          12.0
Emissions|CO2|AFOLU   GtC / yr World|NH idealised idealised ↪
↪ 1.0          7.0          13.0
Emissions|CO2|Fossil  GtC / yr World|SH idealised idealised ↪
↪ 2.0          8.0          14.0
Emissions|CO2|AFOLU   GtC / yr World|SH idealised idealised ↪
↪ 3.0          9.0          15.0
Cumulative Emissions|CO2 GtC      World  idealised idealised ↪
↪ 4.0          10.0         16.0
>>> fos = start.filter(variable="*Fossil")
>>> fos.head()
time                                     2010-01-01 00:00:00 ↪
↪ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model  scenario
Emissions|CO2|Fossil GtC / yr World|NH idealised idealised 0.0 ↪
↪          6.0          12.0
          World|SH idealised idealised 2.0 ↪
↪          8.0          14.0
>>>

```

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```

>>> afolu = start.filter(variable="*AFOLU")
>>> afolu.head()
time                                2010-01-01 00:00:00
↪ 2020-01-01 00:00:00  2030-01-01 00:00:00
variable      unit      region  model      scenario
Emissions|CO2|AFOLU GtC / yr World|NH idealised idealised      1.0
↪              7.0              13.0
↪              World|SH idealised idealised      3.0
↪              9.0              15.0
>>>
>>> fos_minus_afolu = fos.subtract(
...     afolu, op_cols={"variable": "Emissions|CO2|Fossil - AFOLU"}
... )
>>> fos_minus_afolu.head()
time                                2010-01-
↪ 01 00:00:00  2020-01-01 00:00:00  2030-01-01 00:00:00
model      scenario region  variable      unit
idealised idealised World|NH Emissions|CO2|Fossil - AFOLU gigatC / a
↪      -1.0              -1.0              -1.0
↪              World|SH Emissions|CO2|Fossil - AFOLU gigatC / a
↪      -1.0              -1.0              -1.0
>>>
>>> nh_minus_sh = nh.subtract(sh, op_cols={"region": "World|NH - SH"})
>>> nh_minus_sh.head()
time                                2010-01-01
↪ 00:00:00  2020-01-01 00:00:00  2030-01-01 00:00:00
model      scenario region  variable      unit
idealised idealised World|NH - SH Emissions|CO2|Fossil gigatC / a
↪      -2.0              -2.0              -2.0
↪              Emissions|CO2|AFOLU gigatC / a
↪      -2.0              -2.0              -2.0

```

tail(*args: Any, **kwargs: Any) → pandas.core.frame.DataFrame
Return tail of self.timeseries().

Parameters

- ***args** – Passed to self.timeseries().tail()
- ****kwargs** – Passed to self.timeseries().tail()

Returns Tail of self.timeseries()

Return type pandas.DataFrame

time_mean(rule: str)

Take time mean of self

Note that this method will not copy the metadata attribute to the returned value.

Parameters **rule** (["AC", "AS", "A"]) – How to take the time mean. The names reflect the pandas [user guide](#) where they can, but only the options given above are supported. For clarity, if rule is 'AC', then the mean is an annual mean i.e. each time point in the result is the mean of all values for that particular year. If rule is 'AS', then the mean is an annual mean centred on the beginning of the year i.e. each time point in the result is the mean of all values from July 1st in the previous year to June 30 in the given year. If rule is 'A', then the mean is an

annual mean centred on the end of the year i.e. each time point in the result is the mean of all values from July 1st of the given year to June 30 in the next year.

Returns The time mean of `self`.

Return type `ScmRun`

property `time_points`

Time points of the data

Returns

Return type `scmdata.time.TimePoints`

timeseries(*meta=None, check_duplicated=True, time_axis=None, drop_all_nan_times=False*)

Return the data with metadata as a `pandas.DataFrame`.

Parameters

- **meta** (*list[str]*) – The list of meta columns that will be included in the output’s Multi-Index. If `None` (default), then all metadata will be used.
- **check_duplicated** (*bool*) – If `True`, an exception is raised if any of the timeseries have duplicated metadata
- **time_axis** (*{None, "year", "year-month", "days since 1970-01-01", "seconds since 1970-01-01"}*) – See `long_data()` for a description of the options.
- **drop_all_nan_times** (*bool*) – Should time points which contain only nan values be dropped? This operation is applied after any transforms introduced by the value of `time_axis`.

Returns `DataFrame` with datetimes as columns and timeseries as rows. Metadata is in the index.

Return type `pandas.DataFrame`

Raises

- **NonUniqueMetadataError** – If the metadata are not unique between timeseries and `check_duplicated` is `True`
- **NotImplementedError** – The value of `time_axis` is not recognised
- **ValueError** – The value of `time_axis` would result in columns which aren’t unique

to_csv(*fname: str, **kwargs: Any*) → `None`

Write timeseries data to a csv file

Parameters **fname** – Path to write the file into

to_iamdataframe() → `None`

Convert to a `LongDatetimeIamDataFrame` instance.

`LongDatetimeIamDataFrame` is a subclass of `pyam.IamDataFrame`. We use `LongDatetimeIamDataFrame` to ensure all times can be handled, see docstring of `LongDatetimeIamDataFrame` for details.

Returns `LongDatetimeIamDataFrame` instance containing the same data.

Return type `LongDatetimeIamDataFrame`

Raises **ImportError** – If `pyam` is not installed

to_nc(*fname, dimensions=('region',), extras=(), **kwargs*)

Write timeseries to disk as a netCDF4 file

Each unique variable will be written as a variable within the netCDF file. Choosing the dimensions and extras such that there are as few empty (or nan) values as possible will lead to the best compression on disk.

Parameters

- **fname** (*str*) – Path to write the file into
- **dimensions** (*iterable of str*) – Dimensions to include in the netCDF file. The time dimension is always included (if not provided it will be the last dimension). An additional dimension (specifically a co-ordinate in xarray terms), “_id”, will be included if **extras** is provided and any of the metadata in **extras** is not uniquely defined by **dimensions**. “_id” maps the timeseries in each variable to their relevant metadata.
- **extras** (*iterable of str*) – Metadata columns to write as variables in the netCDF file (specifically as “non-dimension co-ordinates” in xarray terms, see [xarray terminology](#) for more details). Where possible, these non-dimension co-ordinates will use dimension co-ordinates as their own co-ordinates. However, if the metadata in **extras** is not defined by a single dimension in **dimensions**, then the **extras** co-ordinates will have dimensions of “_id”. This “_id” co-ordinate maps the values in the **extras** co-ordinates to each time-series in the serialised dataset. Where “_id” is required, an extra “_id” dimension will also be added to **dimensions**.
- **kwargs** – Passed through to `xarray.Dataset.to_netcdf()`

See also:

`scmdata.run.ScmRun.to_nc()`

`to_xarray(dimensions=('region',), extras=(), unify_units=True)`

Convert to a `xarray.Dataset`

Parameters

- **dimensions** (*iterable of str*) –
Dimensions for each variable in the returned dataset. If an “_id” co-ordinate is required (see **extras** documentation for when “_id” is required) and is not included in **dimensions** then it will be the last dimension (or second last dimension if “time” is also not included in **dimensions**). If “time” is not included in **dimensions** it will be the last dimension.
- **extras** (*iterable of str*) – Columns in `self.meta` from which to create “non-dimension co-ordinates” (see [xarray terminology](#) for more details). These non-dimension co-ordinates store extra information and can be mapped to each timeseries found in the data variables of the output `xarray.Dataset`. Where possible, these non-dimension co-ordinates will use dimension co-ordinates as their own co-ordinates. However, if the metadata in **extras** is not defined by a single dimension in **dimensions**, then the **extras** co-ordinates will have dimensions of “_id”. This “_id” co-ordinate maps the values in the **extras** co-ordinates to each timeseries in the serialised dataset. Where “_id” is required, an extra “_id” dimension will also be added to **dimensions**.
- **unify_units** (*bool*) – If a given variable has multiple units, should we attempt to unify them?

Returns Data in self, re-formatted as an `xarray.Dataset`

Return type `xarray.Dataset`

Raises

- **ValueError** – If a variable has multiple units and `unify_units` is False.

- **ValueError** – If a variable has multiple units which are not able to be converted to a common unit because they have different base units.

property values: `numpy.ndarray`

Timeseries values without metadata

The values are returned such that each row is a different timeseries being a row and each column is a different time (although no time information is included as a plain `numpy.ndarray` is returned).

Returns The array in the same shape as `ScmRun.shape()`, that is (num_timeseries, num_timesteps).

Return type `np.ndarray`

`scmdata.run.run_append(runs, inplace: bool = False, duplicate_msg: Union[str, bool] = True, metadata: Optional[Dict[str, Union[str, int, float]]] = None)`

Append together many objects.

When appending many objects, it may be more efficient to call this routine once with a list of `ScmRun`'s, than using `ScmRun.append()` multiple times.

If timeseries with duplicate metadata are found, the timeseries are appended and values falling on the same timestep are averaged if `duplicate_msg` is not "return". If `duplicate_msg` is "return", then the result will contain the duplicated timeseries for further inspection.

```
>>> res = base.append(other, duplicate_msg="return")
<scmdata.ScmRun (timeseries: 5, timepoints: 3)>
Time:
  Start: 2005-01-01T00:00:00
  End: 2015-06-12T00:00:00
Meta:
      scenario          variable  model climate_model region  unit
0  a_scenario    Primary Energy  a_iam      a_model  World  EJ/yr
1  a_scenario    Primary Energy|Coal  a_iam      a_model  World  EJ/yr
2  a_scenario2    Primary Energy  a_iam      a_model  World  EJ/yr
3  a_scenario3    Primary Energy  a_iam      a_model  World  EJ/yr
4  a_scenario    Primary Energy  a_iam      a_model  World  EJ/yr
>>> ts = res.timeseries(check_duplicated=False)
>>> ts[ts.index.duplicated(keep=False)]
time                                     2005-01-01  ...  2015-
→ 06-12
scenario  variable          model climate_model region unit      ...
a_scenario Primary Energy  a_iam a_model      World  EJ/yr      1.0  ...
→ 7.0
                                     EJ/yr      -1.0  ...
→ 1.0
```

Parameters

- **runs** (list of `ScmRun`) – The runs to append. Values will be attempted to be cast to `ScmRun`.
- **inplace** – If True, then the operation updates the first item in `runs` and returns None.
- **duplicate_msg** – If True, raise a `NonUniqueMetadataError` error so the user can see the duplicate timeseries. If False, take the average and do not raise a warning or error. If "warn", raise a warning if duplicate data is detected.
- **metadata** – If not None, override the metadata of the resulting `ScmRun` with metadata.

Otherwise, the metadata for the runs are merged. In the case where there are duplicate meta-data keys, the values from the first run are used.

Returns If not `inplace`, the return value is the object containing the merged data. The resultant class will be determined by the type of the first object.

Return type `ScmRun`

Raises

- **TypeError** – If `inplace` is `True` but the first element in `dfs` is not an instance of `ScmRun` runs argument is not a list
- **ValueError** – `duplicate_msg` option is not recognised.
No runs are provided to be appended

1.1.13 scmdata.testing

Testing utilities

`scmdata.testing.assert_scm_df_almost_equal(left, right, allow_unordered=False, check_ts_names=True, rtol=1e-05, atol=1e-08)`

Check that left and right `ScmRun` are equal.

Parameters

- **left** (`ScmRun`) –
- **right** (`ScmRun`) –
- **allow_unordered** (`bool`) – If true, the order of the timeseries is not checked
- **check_ts_names** (`bool`) – If true, check that the meta names are the same
- **rtol** (`float`) – Relative tolerance on numeric comparisons
- **atol** (`float`) – Absolute tolerance on numeric comparisons

Raises **AssertionError** – left and right are not equal

1.1.14 scmdata.time

Time period handling and interpolation

A large portion of this module was originally from `openscm`. Thanks to the original author, Sven Willner

exception `scmdata.time.InsufficientDataError`

Bases: `Exception`

Insufficient data is available to interpolate/extrapolate

args

with_traceback()

`Exception.with_traceback(tb)` – set `self.__traceback__` to `tb` and return `self`.

class `scmdata.time.TimePoints(values)`

Bases: `object`

Handles time points by wrapping `numpy.ndarray` of `numpy.datetime64`.

as_cftime(date_cls=<class 'cftime._cftime.DatetimeGregorian'>) → list

Format time points as cftime.datetime

Parameters **date_cls** (cftime.datetime) – The time points will be returned as instances of date_cls

Returns Time points as a list of date_cls objects

Return type list of cftime.datetime

days() → numpy.ndarray

Get day of each time point.

Returns Day of each time point

Return type numpy.ndarray of int

hours() → numpy.ndarray

Get hour of each time point.

Returns Hour of each time point

Return type numpy.ndarray of int

months() → numpy.ndarray

Get month of each time point.

Returns Month of each time point

Return type numpy.ndarray of int

to_index() → pandas.core.indexes.base.Index

Get time points as pandas.Index.

Returns pandas.Index of numpy.dtype object with name "time" made from the time points represented as datetime.datetime.

Return type pandas.Index

property values: numpy.ndarray

Time points

weekdays() → numpy.ndarray

Get weekday of each time point.

Returns Day of the week of each time point

Return type numpy.ndarray of int

years() → numpy.ndarray

Get year of each time point.

Returns Year of each time point

Return type numpy.ndarray of int

class scmdata.time.**TimeseriesConverter**(source_time_points: numpy.ndarray, target_time_points: numpy.ndarray, interpolation_type='linear', extrapolation_type='linear')

Bases: object

Interpolator used to convert data between different time bases

This is a modified version originally in openscm.time.TimeseriesConverter. The integral preserving interpolation was removed as it is outside the scope of this package.

Parameters

- **source_time_points** (*np.ndarray*) – Source timeseries time points
- **target_time_points** (*np.ndarray*) – Target timeseries time points
- **interpolation_type** (*{"linear"}*) – Interpolation type. Options are 'linear'
- **extrapolation_type** (*{"linear", "constant", None}*) – Extrapolation type. Options are None, 'linear' or 'constant'

Raises *InsufficientDataError* – Timeseries too short to extrapolate

convert_from(*values: numpy.ndarray*) → *numpy.ndarray*

Convert value **from** source timeseries time points to target timeseries time points.

Parameters *values* (*np.ndarray*) – Value

Returns Converted data for timeseries values into the target timebase

Return type *np.ndarray*

convert_to(*values: numpy.ndarray*) → *numpy.ndarray*

Convert value from target timeseries time points **to** source timeseries time points.

Parameters *values* (*np.ndarray*) – Value

Returns Converted data for timeseries values into the source timebase

Return type *np.ndarray*

points_are_compatible(*source: numpy.ndarray, target: numpy.ndarray*) → *bool*

Are the two sets of time points compatible i.e. can I convert between the two?

Parameters

- **source** – Source timeseries time points
- **target** – Target timeseries time points

Returns Can I convert between the time points?

Return type *bool*

1.1.15 scmdata.timeseries

TimeSeries handling

Functionality for handling and storing individual time-series

class *scmdata.timeseries.TimeSeries*(*data, time=None, **kwargs*)

Bases: *scmdata._base.OpsMixin*

A 1D time-series with metadata

Proxies an *xarray.DataArray* with a single time dimension

copy()

Create a deep copy of the timeseries.

Any further modifications to the *Timeseries* returned copy will not be reflected in the current *Timeseries*

Returns

Return type *Timeseries*

interpolate(*target_times: Union[numpy.ndarray, List[Union[datetime.datetime, int]]], interpolation_type: str = 'linear', extrapolation_type: str = 'linear'*)

Interpolate the timeseries onto a new time axis

Parameters

- **target_times** – Time grid onto which to interpolate
- **interpolation_type** (*str*) – Interpolation type. Options are ‘linear’
- **extrapolation_type** (*str* or *None*) – Extrapolation type. Options are None, ‘linear’ or ‘constant’

Returns A new TimeSeries with the new time dimension

Return type *TimeSeries*

property meta

Metadata associated with the timeseries

Returns

Return type *dict*

property name

Timeseries name

If no name was provided this will be an automatically incrementing number

reindex(*time*, ***kwargs*)

Update the time dimension, filling in the missing values with NaN’s

This is different to interpolating to fill in the missing values. Uses *xarray.DataArray.reindex* to perform the reindexing

Parameters

- **time** (*obj*:*np.ndarray*) – Time values to reindex the data to. Should be *np.datetime64* values
- ****kwargs** – Additional arguments passed to *xarray*’s *DataArray.reindex* function

Returns A new TimeSeries with the new time dimension

Return type *TimeSeries*

References

http://xarray.pydata.org/en/stable/generated/xarray.DataArray.reindex_like.html#xarray.DataArray.reindex_like

property time_points

Time points of the data

Returns

Return type *numpy.ndarray*

property values

Get the data as a numpy array

Returns

Return type *numpy.ndarray*

1.1.16 scmdata.units

Unit handling

class scmdata.units.**UnitConverter**(source: *str*, target: *str*, context: *Optional[str]* = None)

Bases: `object`

Converts numbers between two units.

property contexts: `Sequence[str]`

Available contexts for unit conversions

convert_from(v: *Union[float, numpy.ndarray]*) → *Union[float, numpy.ndarray]*

Convert value **from** source unit to target unit.

Parameters *value* – Value in source unit

Returns Value in target unit

Return type *Union[float, np.ndarray]*

convert_to(v: *Union[float, numpy.ndarray]*) → *Union[float, numpy.ndarray]*

Convert value from target unit **to** source unit.

Parameters *value* – Value in target unit

Returns Value in source unit

Return type *Union[float, np.ndarray]*

property source: `str`

Source unit

property target: `str`

Target unit

property unit_registry: `openscm_units._unit_registry.ScmUnitRegistry`

Underlying unit registry

1.1.17 Changelog

v0.12.0

- (#161) Loosen requirements and drop Python3.6 support

v0.11.0

- (#159) Allow access to more functions in `scmdata.run.BaseScmRun.process_over`, including arbitrary functions
- (#158) Return `cftime.DatetimeGregorian` rather than `cftime.datetime` from `scmdata.time.TimePoints.as_cftime()` and `scmdata.offsets.generate_range()` to ensure better interoperability with other libraries (e.g. `xarray`'s plotting functionality). Add `date_cls` argument to `scmdata.time.TimePoints.as_cftime()` and `scmdata.offsets.generate_range()` so that the output date type can be user specified.
- (#148) Refactor `scmdata.database.ScmDatabase` to be able to use custom backends
- (#157) Add `disable_tqdm` parameter to `scmdata.database.ScmDatabase.load()` and `scmdata.database.ScmDatabase.save()` to disable displaying progress bars

- (#156) Fix `pandas` and `xarray` documentation links
- (#155) Simplify flake8 configuration

v0.10.1

- (#154) Refactor common binary operators for `scmdata.run.BaseScmRun` and `scmdata.timeseries.Timeseries` into a mixin following the removal of `xarray.core.ops.inject_binary_ops()` in *xarray==1.18.0*

v0.10.0

- (#151) Add `ScmRun.to_xarray()` (improves conversion to `xarray` and ability of user to control dimensions etc. when writing netCDF files)
- (#149) Fix bug in testcase for `xarray<=0.16.1`
- (#147) Re-do netCDF reading and writing to make use of `xarray` and provide better handling of extras (results in speedups of 10-100x)
- (#146) Update CI-CD workflow to include more sensible dependencies and also test Python3.9
- (#145) Allow `ScmDatabase.load()` to handle lists as filter values

v0.9.1

- (#144) Fix `ScmRun.plumeplot()` style handling (previously, if dashes was not supplied each line would be a different style even if all the lines had the same value for `style_var`)

v0.9.0

- (#143) Alter time axis when serialising to netCDF so that time axis is easily read by other tools (e.g. `xarray`)

v0.8.0

- (#139) Update filter to handle metadata columns which contain a mix of data types
- (#139) Add `ScmRun.plumeplot()`
- (#140) Add workaround for installing `scmdata` with Python 3.6 on windows to handle lack of `cftime 1.3.1` wheel
- (#138) Add `ScmRun.quantiles_over()`
- (#137) Fix `scmdata.ScmRun.to_csv()` so that writing and reading is circular (i.e. you end up where you started if you write a file and then read it straight back into a new *scmdata.ScmRun* instance)

v0.7.6

- (#136) Make filtering by year able to handle a `np.ndarray` of integers (previously this would raise a `TypeError`)
- (#135) Make `scipy` lazy loading in `scmdata.time` follow lazy loading seen in other modules
- (#134) Add CI run in which `seaborn` is not installed to check `scipy` importing

v0.7.5

- (#133) Pin `pandas`<1.2 to avoid `pint-pandas` installation failure (see [pint-pandas #51](#))

v0.7.4

- (#132) Update to new `openscm-units` 0.2
- (#130) Add stack info to warning message when filtering results in an empty `scmdata.run.ScRun`

v0.7.3

- (#124) Add `scmdata.run.BaseScRun` and `scmdata.run.BaseScRun.required_cols` so new sub-classes can be defined which use a different set of required columns from `scmdata.run.ScRun`. Also added `scmdata.errors.MissingRequiredColumn` and tidied up the docs.
- (#75) Add test to ensure that `scmdata.ScRun.groupby()` cannot pick up the same timeseries twice even if metadata is changed by the function being applied
- (#125) Fix edge-case when filtering an empty `scmdata.ScRun`
- (#123) Add `scmdata.database.ScDatabase` to read/write data using multiple files. (closes #103)

v0.7.2

- (#121) Faster implementation of `scmdata.run.run_append()`. The original timeseries indexes and order are no longer maintained after an append.
- (#120) Check the type and length of the `runs` argument in `scmdata.run.run_append()` (closes #101)

v0.7.1

- (#119) Make `groupby` support grouping by metadata with integer values
- (#119) Ensure using `scmdata.run.run_append()` does not mangle the index to `pd.DatetimeIndex`

v0.7.0

- (#118) Make `scipy` an optional dependency
- (#117) Sort timeseries index ordering (closes #97)
- (#116) Update `scmdata.ScRun.drop_meta()` inplace behaviour
- (#115) Add `na_override` argument to `scmdata.ScRun.process_over()` for handling nan metadata (closes #113)

- (#114) Add operations: `scmdata.ScmRun.linear_regression()`, `scmdata.ScmRun.linear_regression_gradient()`, `scmdata.ScmRun.linear_regression_intercept()` and `scmdata.ScmRun.linear_regression_scmrun()`
- (#111) Add operation: `scmdata.ScmRun.delta_per_delta_time()`
- (#112) Ensure unit conversion doesn't fall over when the target unit is in the input
- (#110) Revert to using `pd.DataFrame` with `pd.Categorical` series as meta indexes.
- (#108) Remove deprecated `ScmDataFrame` (closes #60)
- (#105) Add performance benchmarks for `ScmRun`
- (#106) Add `ScmRun.integrate()` so we can integrate timeseries with respect to time
- (#104) Fix bug when reading csv/excel files which use integer years and `lowercase_cols=True` (closes #102)

v0.6.4

- (#96) Fix non-unique timeseries metadata checks for `ScmRun.timeseries()`
- (#100) When initialising `ScmRun` from file, make the default be to read with `pd.read_csv()`. This means we now initialise reading from gzipped CSV files.
- (#99) Hotfix failing notebook test
- (#94) Fix edge-case issue with `drop_meta` (closes #92)
- (#95) Add `drop_all_nan_times` keyword argument to `ScmRun.timeseries()` so time points with no data of interest can easily be removed

v0.6.3

- (#91) Provide support for `pandas==1.1`

v0.6.2

- (#87) Upgrade workflow to use `isort>=5`
- (#82) Add support for adding Pint scalars and vectors to `scmdata.Timeseries` and `scmdata.ScmRun` instances
- (#85) Allow required columns to be read as `extras` from netCDF files (closes #83)
- (#84) Raise a `DeprecationWarning` if no default `inplace` argument is provided for `ScmRun.drop_meta()`. `inplace` default behaviour scheduled to be changed to `False` in v0.7.0
- (#81) Add `scmdata.run.ScmRun.metadata` to track `ScmRun` instance-specific metadata (closes #77)
- (#80) No longer use `pandas.tseries.offsets.BusinessMixin` to determine Business-related offsets in `scmdata.offsets.to_offset()`. (closes #78)
- (#79) Introduce `scmdata.errors.NonUniqueMetadataError`. Update handling of duplicate metadata so default behaviour of `run_append` is to raise a `NonUniqueMetadataError`. (closes #76)

v0.6.1

- (#74) Update handling of unit conversion context during unit conversions
- (#73) Only reindex timeseries when dealing with different time points

v0.5.2

- (#65) Use pint for ops, making them automatically unit aware
- (#71) Start adding arithmetic support via *scmdata.ops*. So far only add and subtract are supported.
- (#70) Automatically set y-axis label to units if it makes sense in `ScmRun`'s `lineplot()` method

v0.5.1

- (#68) Rename `scmdata.run.df_append()` to `:func`scmdata.run.run_append``. `:func`scmdata.run.df_append`` deprecated and will be removed in v0.6.0
- (#67) Update the documentation for `ScmRun.append()`
- (#66) Raise `ValueError` if index/columns arguments are not provided when instantiating a `:class`ScmRun`` object with a numpy array. Add `lowercase_cols` argument to coerce the column names in CSV files to lowercase

v0.5.0

- (#64) Remove spurious warning from `ScmRun`'s `filter()` method
- (#63) Remove `set_meta()` from `ScmRun` in preference for using the `__setitem__()` method
- (#62) Fix interpolation when the data contains nan values
- (#61) Hotfix filters to also include caret ("^") in pseudo-regexp syntax. Also adds `empty()` property to `ScmRun`
- (#59) Deprecate `ScmDataFrame`. To be removed in v0.6.0
- (#58) Use `cftime` datetimes when appending `ScmRun` objects to avoid `OutOfBounds` errors when datetimes span many centuries
- (#55) Add `time_axis` keyword argument to `ScmRun.timeseries`, `ScmRun.long_data` and `ScmRun.lineplot` to give greater control of the time axis when retrieving data
- (#54) Add `drop_meta()` to `ScmRun` for dropping metadata columns
- (#53) Don't convert case of variable names written to file. No longer convert case of serialized dataframes
- (#51) Refactor `relative_to_ref_period_mean()` so that it returns an instance of the input data type (rather than a `pd.DataFrame`) and puts the reference period in separate meta columns rather than mangling the variable name.
- (#47) Update README and `setup.py` to make it easier for new users

v0.4.3

- (#46) Add test of conda installation

v0.4.2

- (#45) Make installing seaborn optional

v0.4.1

- (#44) Add multi-dimensional handling to `scmdata.netcdf`
- (#43) Fix minor bugs in netCDF handling and address minor code coverage issues
- (#41) Update documentation of the data model. Additionally:
 - makes `.time_points` attributes consistently return `scmdata.time.TimePoints` instances
 - ensures `.meta` is used consistently throughout the code base (removing `.metadata`)
- (#33) Remove dependency on `pyam`. Plotting is done with `seaborn` instead.
- (#34) Allow the serialization/deserialization of `scmdata.run.ScRun` and `scmdata.ScDataFrame` as netCDF4 files.
- (#30) Swap to using `openscm-units` for unit handling (hence remove much of the `scmdata.units` module)
- (#21) Added `scmdata.run.ScRun` as a proposed replacement for `scmdata.dataframe.ScDataFrame`. This new class provides an identical interface as a `ScDataFrame`, but uses a different underlying data structure to the `ScDataFrame`. The purpose of `ScRun` is to provide performance improvements when handling large sets of time-series data. Removed support for Python 3.5 until `pyam` dependency is optional
- (#31) Tidy up repository after changing location

v0.4.0

- (#28) Expose `scmdata.units.unit_registry`

v0.3.1

- (#25) Make `scipy` an optional dependency
- (#24) Fix missing “N2O” unit (see #14). Also updates test of year to day conversion, it is 365.25 to within 0.01% (but depends on the Pint release).

v0.3.0

- (#20) Add support for python=3.5
- (#19) Add support for python=3.6

v0.2.2

- (#16) Only rename columns when initialising data if needed

v0.2.1

- (#13) Ensure LICENSE is included in package
- (#11) Add SO2F2 unit and update to Pyam v0.3.0
- (#12) Add `get_unique_meta` convenience method
- (#10) Fix extrapolation bug which prevented any extrapolation from occurring

v0.2.0

- (#9) Add `time_mean` method
- (#8) Add `make docs` target

v0.1.2

- (#7) Add notebook tests
- (#4) Unit conversions for CH4 and N2O contexts now work for compound units (e.g. 'Mt CH4 / yr' to 'Gt C / day')
- (#6) Add auto-formatting

v0.1.1

- (#5) Add `scmdata.dataframe.df_append` to `__init__.py`

v0.1.0

- (#3) Added documentation for the api and Makefile targets for releasing
- (#2) Refactored `scmdataframe` from [openclimatedata/openscm@077f9b5](https://github.com/openclimatedata/openscm) into a standalone package
- (#1) Add docs folder

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