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cubble: An R Package for Structuring Spatio-temporal Data

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Abstract

The abstract of the article.

Keywords: spatio-temporal data, R.

1. Introduction

Motivation

Many data structures have been proposed for spatial (`sf` by Pebesma (2018)) and temporal (`tsibble` by Wang, Cook, and Hyndman (2020)) data in the R community, while less has been done for spatio-temporal data. The lack of such tools could potentially because analysts usually treat the spatial and temporal dimension of the data separately, without realising the need to create a new data structure. While this approach follows the third tidy data principal (Wickham 2014) (*Each type of observational unit forms a table*), analysts always need to manually join results from different observational units or combining multiple tables into one for downstream analysis. This additional step doesn't add new operations into the data but can be error prone.

Existing packages

Currently, available spatio-temporal data structure in R includes: `spacetime` (Pebesma 2012), which proposes four space-time layouts: Full grid (STF), sparse grid (STS), irregular (STI), and trajectory (STT). The data structure it uses is based on `sp` (Pebesma and Bivand 2005) and `xts` (Ryan and Ulrich 2020), both of which has been replaced by more recent implementations. `spatstat` (Baddeley and Turner 2005) implements a `ppp` class for point pattern data; and more recent, `stars` (Pebesma 2021) implements a spatio-temporal array with the `dplyr`'s data cube structure `cubelyr` (Wickham 2020) as its backend. While these implementations either store spatial and temporal variables all in a single table, hence duplicate the spatial variables for each temporal unit; or split them into two separate tables that has the problem of manually joining, mentioned in the previously. None of these packages enjoy both the benefits of being able to separate manipulation in the two dimensions while also keep the data object as a whole. This create a gap in the software development. The requirement for such a tool is important given the ubiquity of spatio-temporal vector data in the wild: the Ireland wind data from `gstat` is an classic example data that splits variables into spatial (`wind.loc`) and temporal (`wind`) dimension; Bureau of Meteorology (BoM) provides climate observations that are widely applied in agriculture and ecology study; air pollution data.

Our new data structure for spatio-temporal data

This paper describes the implementation of a new spatio-temporal data structure: `cubble`. `cubble` implements a relational data structure that uses two forms to manage the switch between spatial and temporal dimension. With this structure, users can manipulate the spatial or temporal dimension separately, while leaves the linking of two dimensions to `cubble`. The software is available from the Comprehensive R Archive Network (CRAN) at [CRAN link].

Section division

The rest of the paper will be divided as follows: [complete when the paper structure is more solid]

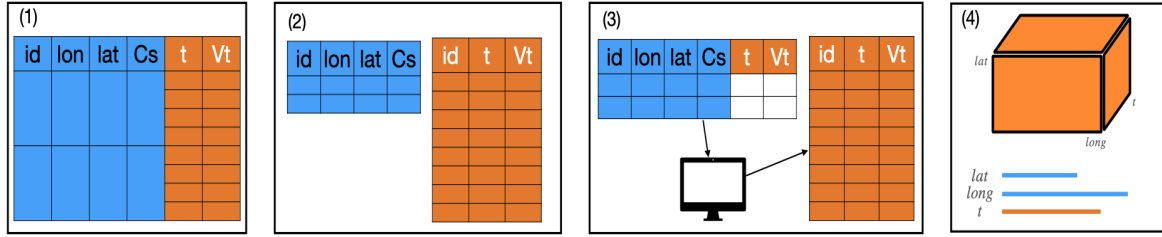


Figure 1: Illustration of incoming data formats for spatio-temporal data. (1) Data comes in as a single table; (2) Separate tables for spatial and temporal variables; (3) A single table with all the parameters used to query the database and a separate table for queried data; and (4) Cubical data in array or NetCDF format.

2. Cubble data structure

2.1. Spatio-temporal data in the wild

Spatio-temporal data don't usually come to the analysts in various forms. Figure 1 groups them into four categories. Despite whichever form the data is in, all the forms have a group identifier, **key**, a time column, **t**, and variables that either various across group, i.e. `lon`, `lat`, `Cs`, or across time, i.e. `Vt`. These identifiers will be the building blocks for the data structure introduced below.

2.2. A new data structure: cubble

A cubble, in essence, wires the spatial and temporal dimension into a single object while provides two forms for manipulation each dimension separately.

In the nest form, Figure 2a), a cubble:

- defines each group in a row,
- displays the group-related variables in columns, and
- nests all the time-related variables into a column called `ts`.

In the long form, Figure 2b), a cubble:

- defines the combination of group and timestamp as a row
- displays time-related variables, along with the group identifier in columns, and
- stores group-related variables as a attributes called `spatial`.

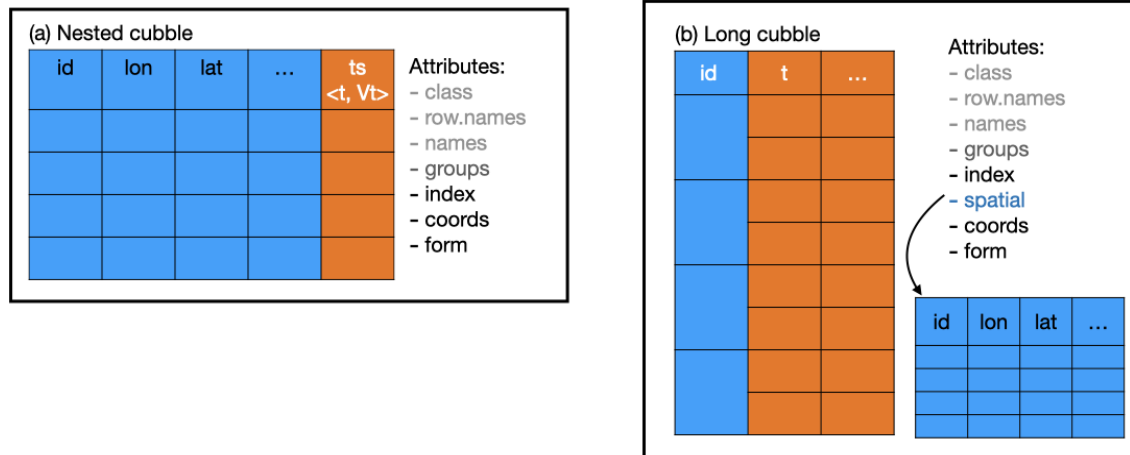


Figure 2: Illustration of nested and long cubble.

2.3. Create a cubble in the nested form

To create a cubble, you can use `as_cubble` with proper supply of `key`, `index`, and `coords`. [`key` defines whether a variable is spatial or temporal by looking at whether it varies across `key`. For example, `lat` is a spatial variable since for one `id` there's only one `lat` value. `index` and `coords` prescribes the temporal index and spatial coordinates used in the data. These are common variables that should present in the point pattern spatio-temporal data.] The cubble created by default is in the nested form.

```
R> (cubble_nested <- climate_flat %>%
+   as_cubble(key = id, index = date, coords = c("long", "lat")))

# cubble:   id [5]: nested form
# bbox:     [115.97, -32.94, 133.55, -12.42]- check gap on long and lat
# temporal: date [date], prcp [dbl], tmax [dbl], tmin [dbl]
#   id      lat long elev name      wmo_id ts
#   <chr>    <dbl> <dbl> <dbl> <chr>    <dbl> <list>
# 1 ASN00009021 -31.9 116. 15.4 perth airport 94610 <tibble [366 x 4]>
# 2 ASN00010311 -31.9 117. 179  york          94623 <tibble [366 x 4]>
# 3 ASN00010614 -32.9 117. 338  narrogin    94627 <tibble [366 x 4]>
# 4 ASN00014015 -12.4 131. 30.4 darwin airport 94120 <tibble [366 x 4]>
# 5 ASN00015131 -17.6 134. 220  elliot     94236 <tibble [366 x 4]>
```

In the cubble header, you can read the key variable + number, bbox, and also the name of variable nested in the `ts` column. Here in this example, the temporal variables are precipitation, `prcp`, maximum temperature, `tmax`, and minimum temperature, `tmin`.

In this structure, the nested form is suitable for manipulating the spatial dimension of the data and this would include manipulating variables that 1) are inherently spatial and 2) summarise the temporal variables by `key`. Under the hood, the nested cubble is built on top

of the rowwise dataframe (`rowwise_df`). This is design to simplify the code when working with the temporal variables - they are nested into the list-column `ts`.

2.4. Stretch a nested cubble into the long form

The verb `stretch()` switch the cubble from the nested form into a long form. Under the hood, it first extracts the spatial variables into a separate tibble to store in the attribute `spatial` and then unnests the `ts` column to show the temporal content:

```
R> (cubble_long <- cubble_nested %>% stretch(ts))

# cubble:  date, id [5]: long form
# bbox:    [115.97, -32.94, 133.55, -12.42]- check gap on long and lat
# spatial: lat [dbl], long [dbl], elev [dbl], name [chr], wmo_id [dbl]
   id      date      prcp  tmax  tmin
   <chr>    <date>    <dbl> <dbl> <dbl>
1 ASN00009021 2020-01-01      0  31.9  15.3
2 ASN00009021 2020-01-02      0  24.9  16.4
3 ASN00009021 2020-01-03      6  23.2   13
4 ASN00009021 2020-01-04      0  28.4  12.4
5 ASN00009021 2020-01-05      0  35.3  11.6
6 ASN00009021 2020-01-06      0  34.8  13.1
7 ASN00009021 2020-01-07      0  32.8  15.1
8 ASN00009021 2020-01-08      0  30.4  17.4
9 ASN00009021 2020-01-09      0  28.7  17.3
10 ASN00009021 2020-01-10      0  32.6  15.8
# ... with 1,820 more rows
```

Notice here that the third line in the header is changed to reflect the spatial variables stored. This is a format suitable for computing time-wise variables.

2.5. Tamp a long cubble back to the nested form

Manipulation on the spatial and temporal dimension can be an iterative process. Many times, we may decide to go back to the nested form after some temporal manipulation. The verb to switch a long cubble back to the nested form is `tamp()`:

```
R> (cubble_back <- cubble_long %>% tamp())

# cubble:  id [5]: nested form
# bbox:    [115.97, -32.94, 133.55, -12.42]- check gap on long and lat
# temporal: date [date], prcp [dbl], tmax [dbl], tmin [dbl]
   id      lat  long  elev name      wmo_id ts
   <chr>    <dbl> <dbl> <dbl> <chr>    <dbl> <list>
1 ASN00009021 -31.9  116.  15.4 perth airport  94610 <tibble [366 x 4]>
2 ASN00010311 -31.9  117.  179  york          94623 <tibble [366 x 4]>
3 ASN00010614 -32.9  117.  338  narrogin      94627 <tibble [366 x 4]>
```

```
4 ASN00014015 -12.4 131. 30.4 darwin airport 94120 <tibble [366 x 4]>
5 ASN00015131 -17.6 134. 220 elliot 94236 <tibble [366 x 4]>
```

2.6. Migrate spatial variables to a long cubble

As an output to be supplied to further visualisation or modelling, analysts would usually like the spatial and temporal variables to be in the same table. `migrate()` moves the spatial variables in the attribute `spatial` into the long form cubble.

```
R> (cubble_long %>% migrate(long, lat))

# cubble:  date, id [5]: long form
# bbox:    [115.97, -32.94, 133.55, -12.42]- check gap on long and lat
# spatial: lat [dbl], long [dbl], elev [dbl], name [chr], wmo_id [dbl]
  id      date      prcp  tmax  tmin  long  lat
  <chr>   <date>   <dbl> <dbl> <dbl> <dbl> <dbl>
1 ASN00009021 2020-01-01    0  31.9  15.3  116. -31.9
2 ASN00009021 2020-01-02    0  24.9  16.4  116. -31.9
3 ASN00009021 2020-01-03    6  23.2  13    116. -31.9
4 ASN00009021 2020-01-04    0  28.4  12.4  116. -31.9
5 ASN00009021 2020-01-05    0  35.3  11.6  116. -31.9
6 ASN00009021 2020-01-06    0  34.8  13.1  116. -31.9
7 ASN00009021 2020-01-07    0  32.8  15.1  116. -31.9
8 ASN00009021 2020-01-08    0  30.4  17.4  116. -31.9
9 ASN00009021 2020-01-09    0  28.7  17.3  116. -31.9
10 ASN00009021 2020-01-10    0  32.6  15.8  116. -31.9
# ... with 1,820 more rows
```

2.7. Support on hierarchical structure

```
switch_key()
```

2.8. Integrating into a tidy workflow

Building from an underlying `tbl_df` structure, it is natural to implement methods available in `dplyr` to `cubble`. Supported methods in the `cubble` with `dplyr` generics includes: `mutate`, `filter`, `summarise`, `select`, `arrange`, `rename`, `left_join`, `group_by`, `ungroup`, and the slice family (`slice_head`, `slice_tail`, `slice_sample`, `slice_min` and `slice_max`) **into a table**.

`cubble` is also compatible with `tsibble` in the sense that the original list-column can be a `tbl_ts` object. Duplicates and gaps should be first checked before structuring the data into a cubble. If the input data is a `tsibble` object, the long form cubble is also a `tsibble` where users can directly apply time series operations.

3. Examples

3.1. Australia precipitation pattern in 2020

Forming a cubble + basic tidyverse verbs - Vig 2 Aggregation - Vig 4

3.2. Matching precipitation and river level in Victoria water gauges

Matching - Vig 3

4. Conclusion

5. Old stuff

Many spatial and spatio-temporal data structures have been developed by the R-spatial team for both raster and vector spatial data. For vector spatial data, which is the focus of this paper, `sf` (?) represents spatial vector information with simple features: points, lines, polygons and their multiples. Various `st_` function are designed to manipulate these features based on their geometric relationships. For spatio-temporal data, `stars` (Pebesma 2021) can represent both raster and vector data using multi-dimensional array. However, the underlying array structure can be difficult to operate for data analysts who are more familiar with a flat 2D data frame structure used by the tidyverse ecosystem.

In the temporal aspect, the `tsibble` (?) structure and its tidyverts ecosystem have provided a [...] workflow to work with temporal data. In a `tsibble` structure, temporal data is characterised by `index` and `key` where `index` is the temporal identifier and `key` is the identifier for multiple series, which could be used as a spatio identifier. However, a `tsibble` object, by construction, always requires the `index` in its structure. This makes it less appealing for spatio-temporal data since the output of calculated spatio-specific variables (i.e. features of each series) don't have the time dimension. Analysts will either need to have an additional step to join this output to the original `tsibble` or operate with variables stored in two separate objects. In addition, the long form structure of a `tsibble` object means spatio variables (i.e. longitude, latitude, and features of each series if joined back to the `tsibble`) of each spatio identifier will be repetitively recorded at each timestamp. This repetition is unnecessary and would inflate the object size for long series.

6. A new data structure for spatio-temporal data

The main difficulty and challenge

The main difficulty in visualising this type of data is to show information in both space and time dimension with the proper level of details without information overflow. This would sometimes require aggregating the time dimension into the proper level or slicing the data into a reasonable number of subset for display. In this sense, a data structure that regulates the manipulation spatio-temporal data will benefit the analysis workflow. While many implementations focus on manipulating and visualising pure spatial or temporal data, there are not sufficient tools to deal with spatio-temporal data. The purpose of this paper is to introduce a spatio-temporal vector data structure for data analysis in R.

To work with spatio-temporal data, analysts can choose to either work separately on each dimension or join the two sets together, however, each approach has its own problem: While it is natural to work separately on each sheet (since spatial and temporal operations usually don't overlap), analysts will need to manually keep the other data frame up to date. For example, the following pseudo code illustrates the scenario where once the spatial dataset is filtered for those within Victoria, the temporal dataset needs to be manually updated to reflect this spatial filter.

```
R> spatial_new <- spatial %>% filter(SITES_IN_VICTORIA)
R> temporal_new <- temporal %>% filter(id %in% spatial_new$id)
```

If analysts choose to join the spatial and temporal data together, the joined dataset could be too large since each spatial variable will be repeated at each time stamp for each site. Also,

recordings of the site ID from different data sources can be slightly different from each other, causing a painful checking and cleaning of site IDs before the join.

7. Create a cubble

The creation of a cubble requires the site identifier (*key*), as well as the spatial (*coords*) and temporal (*index*) identifier. `climate_flat` is already a tibble and it uses *id* to identify each station, *date* as the time identifier, and `c(long, lat)` as the spatial identifier. To create a cubble for this data, use:

```
R> climate_flat %>% as_cubble(key = id, index = date, coords = c(long, lat))

# cubble:   id [5]: nested form
# bbox:     [115.97, -32.94, 133.55, -12.42]- check gap on long and lat
# temporal: date [date], prcp [dbl], tmax [dbl], tmin [dbl]
  id          lat long elev name          wmo_id ts
<chr>        <dbl> <dbl> <dbl> <chr>        <dbl> <list>
1 ASN00009021 -31.9  116.  15.4 perth airport  94610 <tibble [366 x 4]>
2 ASN00010311 -31.9  117.  179  york          94623 <tibble [366 x 4]>
3 ASN00010614 -32.9  117.  338  narrogin      94627 <tibble [366 x 4]>
4 ASN00014015 -12.4  131.  30.4 darwin airport  94120 <tibble [366 x 4]>
5 ASN00015131 -17.6  134.  220  elliot      94236 <tibble [366 x 4]>
```

Most of the time, spatio-temporal data doesn't come into this form and analysts need to query the climate variables based on station metadata. **This is also a problem illustrated in Section 3.5 in @tidydata. Here we provide a structured way to query this data based on the row-wise operator and nested list.** For this type of task, one can structure a metadata into a tibble and use row-wise operator to query the climate variables into a nested list. As an example here we demonstrate the workflow to find the 5 closest stations to Melbourne. We first create a station data frame with the 5 target stations.

```
# A tibble: 5 x 8
  id          lat long elev name          wmo_id dist city
<chr>        <dbl> <dbl> <dbl> <chr>        <dbl> <dbl> <chr>
1 ASN00086038 -37.7  145.  78.4 essendon airport  95866  10.8 melbourne
2 ASN00086282 -37.7  145.  113. melbourne airport  94866  20.1 melbourne
3 ASN00086077 -38.0  145.  12.1 moorabbin airport  94870  21.9 melbourne
4 ASN00088162 -37.4  145.  528. wallan (kilmore gap)  94860  48.1 melbourne
5 ASN00087113 -38.0  144.  10.6 avalon airport  94854  48.8 melbourne
```

We can query the climate information into a nested list named *ts* for each station with the `rowwise()` operator. To create a cubble, supply the same identifiers as with the first example.

```
R> sydmel_climate <- stations %>%
+   rowwise() %>%
+   mutate(ts = list(meteo_pull_monitors(id,
+                                         date_min = "2020-01-01",
+                                         date_max = "2020-12-31",
+                                         var = c("PRCP", "TMAX", "TMIN"))) %>%
+     select(-id))) %>%
+   as_cubble(key = id, index = date, coords = c(long, lat))
```

```
# cubble:   id [5]: nested form
# bbox:     [144.47, -38.03, 145.1, -37.38]
# temporal: date [date], prcp [dbl], tmax [dbl], tmin [dbl]
  id      lat  long  elev name      wmo_id  dist city  ts
  <chr>    <dbl> <dbl> <dbl> <chr>    <dbl> <dbl> <chr> <list>
1 ASN00086038 -37.7  145.  78.4 essendon airport    95866  10.8 melbo~ <tibbl~
2 ASN00086282 -37.7  145. 113.  melbourne airport    94866  20.1 melbo~ <tibbl~
3 ASN00086077 -38.0  145.  12.1 moorabbin airport    94870  21.9 melbo~ <tibbl~
4 ASN00088162 -37.4  145. 528.  wallan (kilmore gap)  94860  48.1 melbo~ <tibbl~
5 ASN00087113 -38.0  144.  10.6 avalon airport    94854  48.8 melbo~ <tibbl~
```

Below are the how the nested and long form look like for Australia climate data, which records daily precipitation, maximum and minimum temperature for 55 stations across Australia from 2015- 2020. Notice that each station forms a group in both forms and specifically, the nested and long form have a underlying `rowwise_df` and `grouped_df` respectively.

With a cubic framework on mind, different types of manipulation with cubble can be thought of as slicing the cube in various way. The table below shows how some `dplyr` verbs are mapped into the operation in a cubble. With the existing grouping on the station, additional grouping can be added with `group_by` and removed with `ungrouped`. [talk about why it is useful]

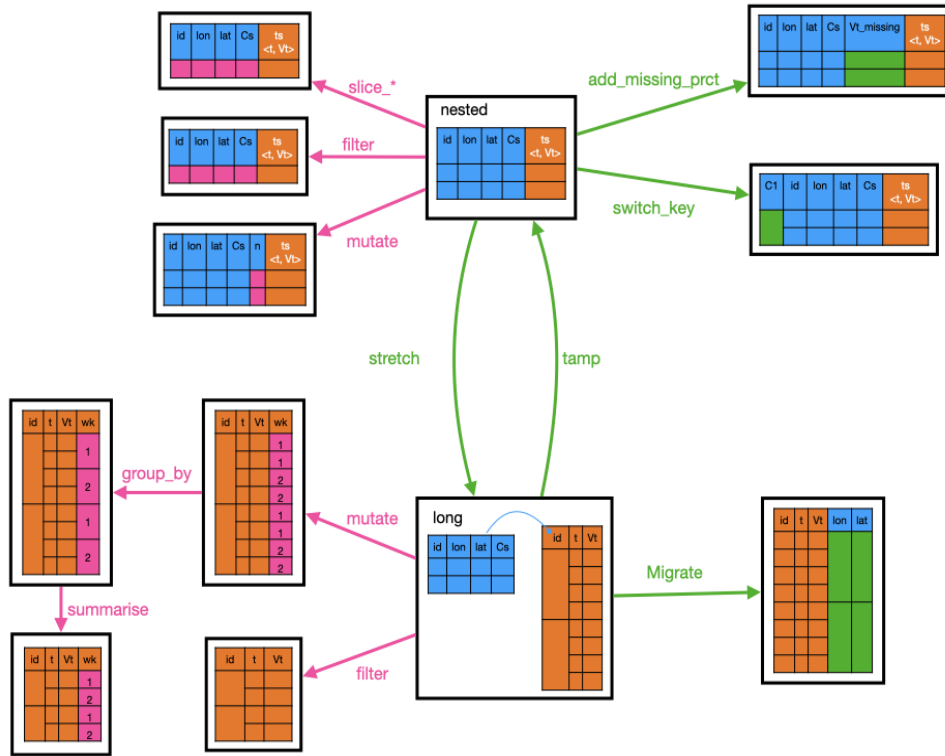


Figure 3: Cubble operations

7.1. Cubble operations

Basics

- **stretch:** nest to long form
- **tamp:** long to nest form
- **migrate:** move selected spatial variables to the long form.
- **add_dscrb_prct:** summary stats for missingness

dplyr compatibility:

- mutate, filter, summarise, select, arrange
- group and ungroup: group_by, ungroup
- slice family

Combine two cubbles

- match river and weather gauges data

- involve combining two cubbles
- join operations combine the two together by appending more rows but what we really want is to bind rows.
- bind rows also doesn't work since we want to bind only when there's a matching???
- introduce `bind_join`

Hierarchical structure in cubble

- hierarchical is common.
- Given examples.
- Essence: switch between different levels
- introduce `switch_key`

8. Examples

Daily climate data (precip, tmax, and tmin) from RNOAA - lots of stations across Australia

An exploratory data analysis questions: What's the climate profile look like in Australia

- General features: Any general trend/ fluctuation in precip, tmax, and tmin?
- Local features: Any station stands out from the crowd?

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