Conversations in time: interactive visualisation to explore structured temporal data

by Earo Wang and Dianne Cook

Abstract Temporal data often has a hierarchical structure, defined by categorical variables describing different levels, such as political regions or sales products. Nesting of categorical variables produces a hierarchical structure. The **tsibbletalk** package is developed to allow a user to interactively explore temporal data, relative to the nested or crossed structures. It can help to discover differences between category levels, and uncover interesting periodic or aperiodic slices. The package implements a shared `tsibble` object that allows for linked brushing between coordinated views, and a shiny module that aids in wrapping time lines for seasonal patterns. The tools are demonstrated using two data examples: retail turnover and tourism in Australia.

Introduction

Temporal data typically arrives as a set of many observational units measured over time. Some variables may be categorical, indicating a hierarchy in the collection process, that may be measurements taken in different geographic regions, or types of products sold by the one company. Exploring these multiple features can be daunting. Ensemble graphics (Unwin and Valero-Mora, 2018) bundle multiple views of a data set together into one composite figure. These provide an effective approach for exploring and digesting many different aspects of temporal data. Adding interactivity to the ensemble can greatly enhance the exploration process.

This article describes new software, the **tsibbletalk** package, for exploring temporal data using linked views and time wrapping. The next section provides some background to the approach based on setting up data structures and workflow. The section following explains the mechanism for constructing interactivity, to link between multiple hiearchical data objects and hence plots. The section after this describes the set up for interactively slicing and dicing time to wrap a series on itself to investigate periodicities.

Background: tidy temporal data and workflow

The **tsibble** package (Wang et al., 2020) introduced a unified temporal data structure, referred to as a `tsibble`, to represent time series and longitudinal data in a tidy format (Wickham, 2014). A `tsibble` extends the `data.frame` and **tibble** classes with the temporal contextual metadata: `index` and `key`. The `index` declares a data column that holds time-related indices. The `key` identifies a collection of related series or panels observed over the `index`-defined period, which can comprise multiple columns. An example of a `tsibble` can be found in the monthly Australian retail trade turnover data (`aus_retail`), available in the **tsibbledata** package (O'Hara-Wild et al., 2020c), shown below. The `Month` column holds year-months as the `index`. `State` and `Industry`, together, are the identifiers for these 152 series, which form the `key`. Note that the column `Series ID` could be an alternative option for setting up the `key`, but `State` and `Industry` are more readable and informative. The `index` and `key` are "sticky" columns to a `tsibble`, forming critical pieces for fluent downstream temporal data analysis.

```
#> # A tsibble: 64,532 x 5 [1M]
#> # Key:       State, Industry [152]
#>   State                Industry                 `Series ID`    Month Turnover
#>   <chr>                <chr>                    <chr>          <mth>    <dbl>
#> 1 Australian Capital ~ Cafes, restaurants and cat~ A3349849A   1982 Apr      4.4
#> 2 Australian Capital ~ Cafes, restaurants and cat~ A3349849A   1982 May      3.4
#> 3 Australian Capital ~ Cafes, restaurants and cat~ A3349849A   1982 Jun      3.6
#> 4 Australian Capital ~ Cafes, restaurants and cat~ A3349849A   1982 Jul      4
#> 5 Australian Capital ~ Cafes, restaurants and cat~ A3349849A   1982 Aug      3.6
#> # ... with 64,527 more rows
```

In the spirit of tidy data from the **tidyverse** (Wickham et al., 2019), the **tidyverts** suite features `tsibble` as the foundational data structure, and helps to build a fluid and fluent pipeline for time series analysis. Besides **tsibble**, the **feasts** (O'Hara-Wild et al., 2020b) and **fable** (O'Hara-Wild et al.,

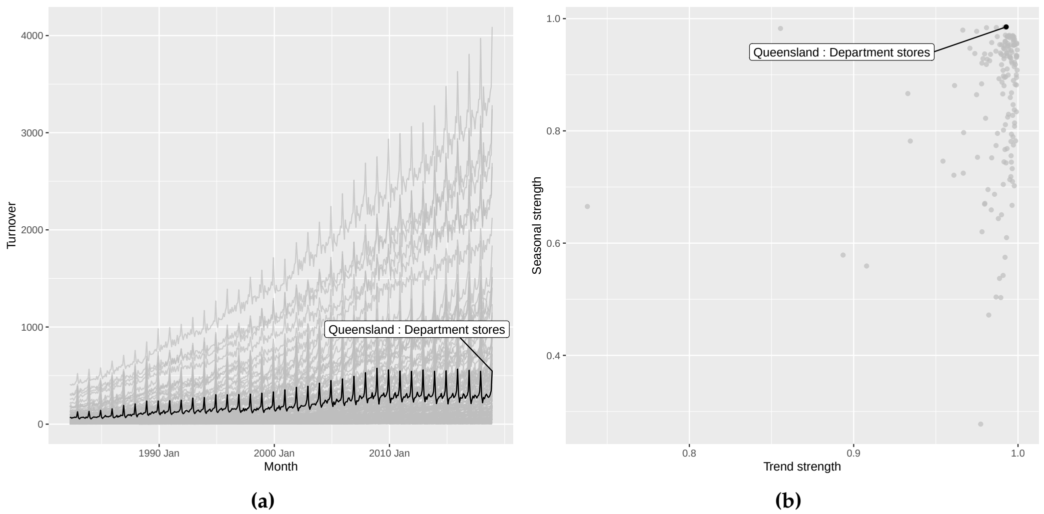


Figure 1: Plots for the `aus_retail` data, with the series of strongest seasonal strength highlighted. (a) An overlaid time series plot. (b) A scatter plot drawn from their time series features, where each dot represents a time series from (a).

2020a) packages fill the role of statistical analysis and forecasting in the **tidyverts** ecosystem. During all the steps of a time series analysis, the series of interest, denoted by the `key` variable, typically persist, through the trend modeling and also forecasting. We would typically want to examine the series across all of the keys.

Figure 1 illustrates examining temporal data with many keys. The data has 152 series coorresponding to different items in retail data. The multiple series are displayed using an overlaid time series plot, along with a scatterplot of two variables (trend versus seasonal strength) from feature space, where each series is represented by a dot. The feature space is computed using the `features()` function from **feasts**, which summarises the original data for each series using various statistical features. This function along with other **tidyverts** functions is `tsibble`-aware, and outputs a table in a reduced form where each row corresponds to a series, which can be graphically displayed as in Figure 1b.

Figure 1 has also been highlighted to focus on the one series with the strongest seasonality. To create this highlighting, one needs to first filter the interesting series from the features table, and join back to the original `tsibble` in order to examine its trend in relation to others. This procedure can soon grow cumbersome if many series are to be explored. It illustrates a need to query interesting series on the fly. Although these two plots are static, we can consider them as linked views becaause the common `key` variables link between the two data tables producing the two ploots. This motivates the work in this package, described in this paper, to enable interactivity of `tsibble` and `tsibble`-derived objects for rapid exploratory data analysis.

Overview of interactivity

There is a long history of interactive data visualisation research and corresponding systems. Within R, the systems can be roughly divided into systems utilising web technology and those that don't.

R **shiny** (Chang et al., 2020) and **htmlwidgets** (Vaidyanathan et al., 2019) provides and infrastructure connecting R with HTML elements and JavaScript that provide the interactivity. The **htmlwidgets** package makes it possible to embed JavaScript libraries into R so that users are able to write only R code to generate web-based plots. Many JavaScript charting libraries have been ported to R as HTML widgets, including **plotly** (Sievert, 2020), **rbokeh** (Hafen and Continuum Analytics, Inc., 2020), and **leaflet** (Cheng et al., 2019) for maps. Interactions between different widgets can be achieved with **shiny** or **crosstalk** (Cheng, 2020). The **crosstalk** extends **htmlwidgets** with shared R6 instances to support linked brushing and filtering across widgets, without relying on **shiny**.

Systems without the web technology include **loon** (Waddell and Oldford, 2020), based on Tcl/Tk, and **cranvas** (Xie et al.) based on Qt. They offer a wide array of pre-defined interactions, such as selecting and zooming, to manipulate plots via mouse action, keyboard strokes, and menus. The **cranvastime** package (Cheng et al.) is an add-on to **cranvas**, which provides specialised interactions for temporal data, such as wrapping and mirroring.

The techniques implemented in work described in this paper utilise web technology.

Using a shared temporal data object for interactivity

The **tsibbletalk** package introduces a shared tsibble instance built on a `tsibble`. This allows for seamless communication between different plots of temporal data. The `as_shared_tsibble()` function turns a `tsibble` into a shared instance, `SharedTsibbleData`, which is a subclass of `SharedData` from **crosstalk**). This is the object driving data transmission across multiple views. The **tsibbletalk** package aims to streamline interactive exploration of temporal data, with the focus of temporal elements and structured linking.

Linking between plots

As opposed to one-to-one linking, **tsibbletalk** defaults to categorical variable linking where selecting one or more observations in one category will broadcast to all other observations in this category. In addition, linking is also by time: within the time series plot, click on any data point, and whole line will be highlighted in response. The `as_shared_tsibble()` uses `tsibble`'s `key` variables to achieve these types of linking.

The approach can also accommodate hierarchical temporal data. When one key variable is nested within another, such as regional areas within a state, this is considered to be a hierarchical structure. These time series are referred to as hierarchical and grouped time series in the literature (Hyndman and Athanasopoulos, 2017). The `aus_retail` above is an example. Each series in the data corresponds to all possible combinations of the `State` and `Industry` variables, which means they are intrinsically crossed with each other.

The `spec` argument in `as_shared_tsibble()` constructing hybrid linking, that incorporates hierarchical and categorical linking. A symbolic formula can be passed to the `spec` argument, to incorporate structured specifications in the `key`. Adopting Wilkinson and Rogers (1973)'s notation for factorial models, the `spec` follows the `/` and `*` operator conventions to declare nesting and crossing variables, respectively. The `spec` for the `aus_retail` data is therefore specified as `State * Industry` or `Industry * State`, which is the default for the presence of multiple `key` variables. If there is a hierarchy in the data, using `/` is required to indicate the parent-child relation, for a strictly one directional `parent/child`.

To illustrate nesting and crossing we use the `tourism_monthly` dataset (Tourism Research Australia, 2020) packaged in **tsibbletalk**. It contains monthly domestic overnight trips across Australia. The `key` is comprised of three identifying variables: `State`, `Region`, and `Purpose` (of trip), in particular `State` nesting of `Region`, together crossed with `Purpose`. This specification can be translated as follows:

```
library(tsibbletalk)
tourism_shared <- tourism_monthly %>%
  as_shared_tsibble(spec = (State / Region) * Purpose)
```

There is a three-level hierarchy: the root node is implicitly Australia, and geographically disaggregated to states and lower-level tourism regions. A new handy function `plotly_key_tree()` has been implemented to help explore the hierarchy. It interprets hierarchies in the shared tsibble's `spec` as a tree view, built with **plotly**. The following code line produces the linked tree diagram (left panel of Figure 2). The visual for the tree hierarchy detangles a group of related series and provides a bird's eye view of the data organisation.

```
p_l <- plotly_key_tree(tourism_shared, height = 1100, width = 800)
```

The tree plot provides the data skeleton, upon which the rest of data can be attached. In this example, small multiples of line plots are placed at the top right of Figure 2 to explore the temporal trend across regions, by trip purpose. The shared tsibble data can be directly piped into **ggplot2** code as follows.

```
p_tr <- tourism_shared %>%
  ggplot(aes(x = Month, y = Trips)) +
  geom_line(aes(group = Region), alpha = .5, size = .4) +
  facet_wrap(~ Purpose, scales = "free_y") +
  scale_x_yearmonth(date_breaks = "5 years", date_labels = "%Y")
```

To tease apart these overlaid time series, they are funnelled through the `features()` S3 method to extract some key characteristics, including the measurements of trend and seasonality. A scatterplot is populated from these statistics for each series.

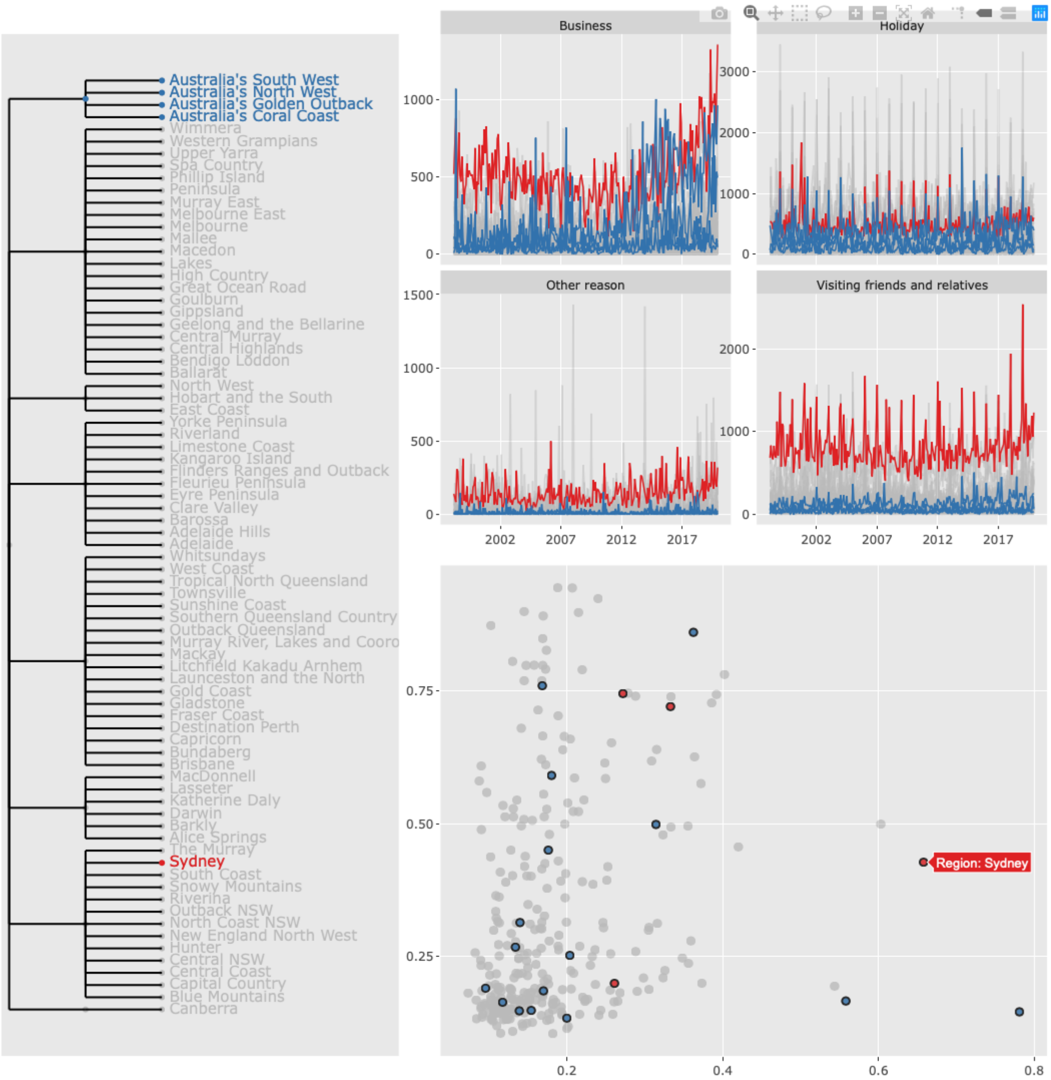


Figure 2: Coordinated views generated from the `tourism_shared` with persistent linked brushing.

```
tourism_feat <- tourism_shared %>%
  features(Trips, feat_stl)
p_br <- tourism_feat %>%
  ggplot(aes(x = trend_strength, y = seasonal_strength_year)) +
  geom_point(aes(group = Region), alpha = .8, size = 2)
```

Lastly, three graphics are composed as an ensemble of coordinated views for multi-facetted exploration, shown as Figure 2 (the interactive realisation of Figure 1). Routine functions bring about new interaction with temporal data on the client side.

```
subplot(p_l,
  subplot(
    ggplotly(p_tr, tooltip = "Region", width = 1100),
    ggplotly(p_br, tooltip = "Region", width = 1100),
    nrows = 2),
  widths = c(.4, .6)) %>%
  highlight(dynamic = TRUE)
```

Since all plots are stemmed from one shared tsibble data source, they are self-linking views. Nodes, lines, and points are hoverable and clickable. Given the `spec`, clicking either one element in any plot highlights all points that match the `Region` category, briefly "categorical linking". In Figure 2, when hovering and selecting the circle associated with "Sydney" in the scatter plot, all data records with shared values of "Sydney" listen and react to this interaction via self updating in red. In order for comparison with other regions or states, press the "Shift" key to enable persistent selection, and simultaneously select the parent node on the tree, saying "Western Australia", to include all the children by switching to the blue colour. The domestic tourism sees Sydney as one of the most popular destinations in realm of business and friends visiting over years. Despite of relatively weaker performance in Western Australia, Australia's North West region sees the strongest upward trend, bypassing Sydney in some years.

In summary, shared tsibble data nicely bridges between the **crosstalk** and **tidyverts** ecosystems for temporal data over their common term "key". The `as_shared_tsibble()` provides a symbolic user interface for effortless construction of a hybrid of hierarchical and categorical linkings. And the `plotly_key_tree()` in turn decodes the specification to plot a tree for data overview and navigation, accompanied with more detailed plots.

Slicing and dicing time

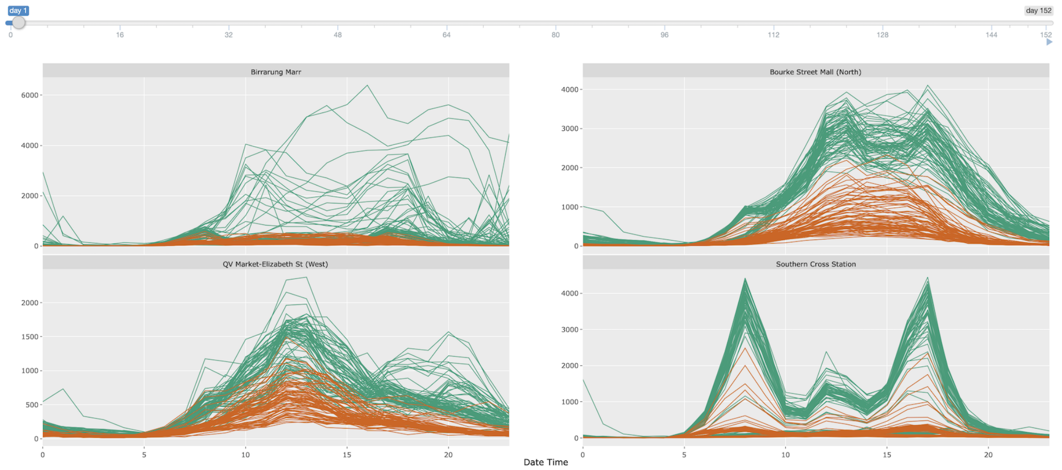
The shared tsibble data leverages the `key` attribute to converse with many coordinated views, with or without **shiny**. On the other hand, a second critical attribute–`index`–lays the foundational temporal context that augments the conversation. When temporal data are plotted and stretched against the entire span like Figure 1a, it puts emphasis on the trend perception. Yet to digest periodic/aperiodic patterns, data should be wrapped over relative time units that are origin-less, such as one quarter or one day.

The city of Melbourne has sensors installed to count hourly tallies of pedestrians in order to capture downtown daily rhythms (City of Melbourne, 2020). Figure 3 shows the first five months of 2020 foot traffic at four locations, with the depiction of three pronounced slices in time. Figure 3a unfolds all counts from January to May on their absolute time line, facetted by four sensors. On March 16, Melbourne went to the stage three lockdown due to COVID-19, seeing a significant decline in traffic volume across the city. These lines are then folded into daily and weekly sections, shown as Figure 3b and 3c respectively. Seasonal variations have been popped out to viewers, complementing the not-just-magnitude-drop story. The pre-lockdown period is coloured with dark green and lockdown with orange.

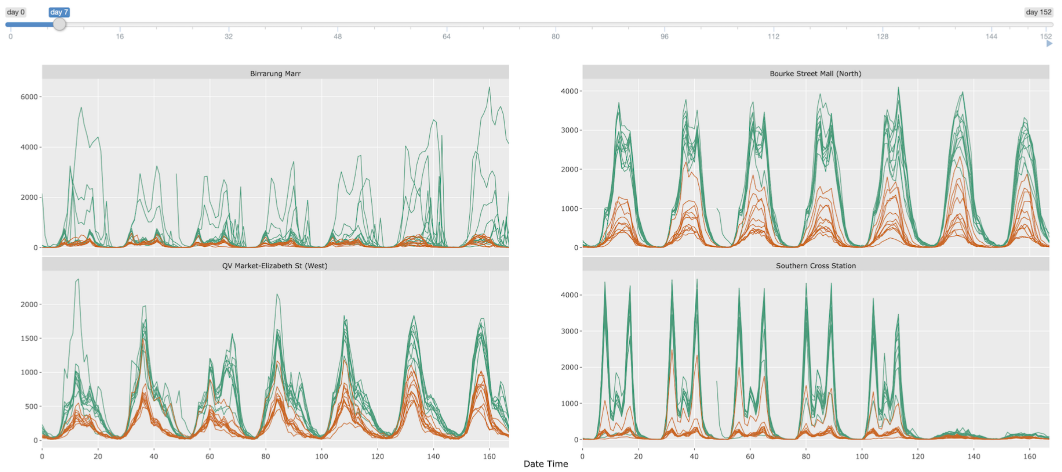
The wrapping procedure involves slicing time indices into seasonal periods of interest and their corresponding time dices. For example, hourly pedestrian data can be decomposed into 24-hour blocks grouped by all respective days, like Figure 3b. Figure 3 suggests that there could be more than one eye-catching slices out of many possible combinations, and thus repeated wrappings can be unwieldy. To visually locate a salient slice, the **tsibbletalk** package implements a shiny module, a pair of UI and server functions, to automate this wrapping procedure.

This shiny module, decoupled to `tsibbleWrapUI()` and `tsibbleWrapServer()`, presents a clean interface and forms a resusable piece in a shiny application. A shiny module provides the vehicle in modularising shiny applications for both users and developers. Like all shiny modules, the first argument in both functions requires a user-supplied session id that must be unique. The UI function `tsibbleWrapUI()` simply shows a slider that animates or controls the number of periods to be diced.

(a) Initial overview state



(b) 1-day state



(c) 7-day state, anchoring to Monday

Figure 3: The shiny module for wrapping the `pedestrian20` data.

The workhorse is certainly the server function `tsibbleWrapServer()`, encapsulating the algorithm that transforms data and sends messages to update the plot accordingly. The `plot` argument expects a `ggplot` or `plotly` object, where one can plot data using either lines or other graphical elements (such as boxplots). As the function name suggests, a (shared) tsibble is needed to start the engine, and thereby the time `index` can be retrieved for dissection. The `period` option semantically takes a desired number of seasonal periods to be shifted, for example data shifted by "1 day", "2 days", or "1 week", etc. In other words, the `period` defines the grind level. For date-times (represented by `POSIXt`), the granularity ranges from fine "day" to coarse "year". The following code snippet generates Figure 3.

```
p_line <- pedestrian20 %>%
  ggplot(aes(x = Date_Time, y = Count, colour = Lockdown)) +
  geom_line(size = .3) +
  facet_wrap(~ Sensor, scales = "free_y") +
  labs(x = "Date Time") +
  scale_colour_brewer(palette = "Dark2") +
  theme(legend.position = "none")

ui <- fluidPage(
  tsibbleWrapUI("dice")
)
server <- function(input, output, session) {
  tsibbleWrapServer("dice", ggplotly(p_line, height = 700), period = "1 day")
}
shinyApp(ui, server)
```

Upon running the shiny application, Figure 3a corresponds to the initial state, with the slider incremented by 1-day unit. The "play" button near the end of slider begins animating the slicing and dicing process by walking through all 24 hours by 152 days. Alternatively, users can drag the handler to poke around certain slices themselves.

In response to the slider input, the plot will be updated and loaded with newly transformed data. At its core, keeping the application as performant as possible is the top priority. Without completely redrawing the plot, the `plotlyProxy()` react method is invoked internally for talking to shiny. The underlying tsibble data is being called back and processed in R. Only transformed data gets fed back to the shiny server, along with reseting the x-axis ranges and breaks. The rest plot configurations, such as marks, y-axes, and layouts, are properly cached.

The new shiny module exploits the temporal aspect for a tsibble object, exposed by the `index` attribute. It allows users to slide through relative periods to digest seasonal behaviours, with slick user experience.

Summary

Close to the heart of the **tsibbletalk** package is blending the best bits from **tsibble**, **crosstalk**, **plotly**, and **shiny**.

The `as_shared_tsibble()` turns a `tsibble` object to a shared data class, with an option to express any nesting and crossing structures from the `key` attribute. If nesting is found in the data, the `plotly_key_tree()` creates an interactive hierarchical tree to help with data overview. This sets the stage for hierarchical and categorical linking between multi-views from one shared tsibble.

A new shiny module, `tsibbleWrapUI()` and `tsibbleWrapServer()`, provides a lens for looking at temporal aspects for a `tsibble`, in particular seasonal or cyclical variations. The slicing and dicing technique efficiently wrap time lines for user-defined plots. The `plotlyProxy()` react method makes it possible to send wrapped data to the server and amend the plot straight way.

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Earo Wang
The University of Auckland
Department of Statistics

`earo.wang@auckland.ac.nz`

Dianne Cook
Monash University
Department of Econometrics and Business Statistics

`dicook@monash.edu`