Extending ggplot2 for linked and animated web graphics

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Abstract

Interactive web graphics are great for communication and knowledge sharing, but are difficult to leverage during the exploratory phase of a data science workflow. Even before the web, interactive graphics helped data analysts quickly gather insight from data, discover the unexpected, and develop better model diagnostics. Web technologies, however, are not designed to fit inside an exploratory data analysis (EDA) workflow where rapid iteration between data manipulation, modeling, and visualization must occur. We propose the R package **animint** for rapid creation of linked and animated web graphics through a simple extension of **ggplot2**'s implementation of the Grammar of Graphics. The extension uses the existing **ggplot2** code, and leverages a simple API for describing animations and graphical queries between multiple linked views in a standalone web page.

Keywords: Animation, Multiple linked views, Statistical graphics, Exploratory data analysis, Web technologies, Grammar of graphics

1 Introduction

For more than a half century now, statisticians have designed, built, and used interactive graphics for exploring high-dimensional data and better informing their modeling process. In fact, the ASA maintains a video library (http://stat-graphics.org/movies/) to document and demonstrate applications of instrumental interactive statistical graphics systems such as `PRIM-9` (Fisherkeller and Tukey 1988), `Data Viewer` (Andreas Buja and McDonald 1988), `XGobi` (Swayne, Cook, and Buja 1998), `GGobi` (D. Cook and Swayne 2007), and `Mondrian` (Theus 2002). These, as well as other influential systems, such as `LISP-STAT` (Tierney 1990) and `MANET` (Unwin A. 1996), all have a rich support for accomplishing a wide variety of statistical analysis tasks, and most were developed before the web browser had rich graphics support.

All of these systems, as well as some more modern systems, such as **rggobi** (Duncan Temple Lang 2016), **iplots** (Urbanek 2011), **loon** (Waddell and Oldford 2018), etc, require a heavy set of computational dependencies in order to view or interact with graphics. These requirements grant the freedom to leverage libraries with sophisticated statistical functionality on-demand, but it limits the ability to share or embed such graphics in a larger document. Some of these systems allow users to create the graphics from the command-line, which as Unwin and Hofmann (2009) points out, allows power users to combine the strengths of a programming interface (e.g., precise, repeatable, fast, and extensible) with the strengths of a graphical interface (e.g., intuitive, forgiving, and easy-to-use). Web technologies can certainly be used to build a similar class of system, but in order to capitalize on the key strength of web technologies (e.g., accessible, portable, and composable), we must be mindful if which technologies we're requiring in such a system, and minimize those requirements whenever possible.

Generally speaking, web graphics that use purely client-side technologies (i.e., `HTML`, `SVG`, `CSS`, and `JavaScript`) are desired over client-server web applications because of their relative ease of distribution and maintenance. This is why many web-based graphing libraries work entirely with client-side technologies, like Vega (Trifacta 2014) and plotly.js (Plotly 2015). Unfortunately, client-side technologies are not particularly well-suited for statistical computation, which we often want to leverage via dynamic controls in an interactive statistical graphics system. In this scenario, it often makes sense to introduce a client-server infrastructure to leverage functionality that is not natively supported by web browsers (e.g., R, python, etc).

Focusing just on the R language, there are now numerous ways to develop web applications, including the R package **shiny** (RStudio 2013), which makes it easy for R users to take their existing scripting workflow and wrap a web interface around it. **Shiny** is great for quickly prototyping interactive webpages that re-execute R code on-demand, but that flexibility comes at the cost of requiring a complex web server framework, which can be hard to scale, maintain, and secure sensitive information. Unfortunately, all too often, a web application framework is used to implement linked and animated graphics that could more easily be described with an idiomatic R interface which produces a purely client-side result.

There are now a large number of R packages that interface with purely client-side graphing libraries and give users the option of embedding these graphics in a larger web application. In fact, this is a large enough use case that the R package **htmlwidgets** (Vaidyanathan et al. 2018) was created to make it easier to get these interfaces to work seamlessly in any context (e.g., **shiny**, **rmarkdown**, RStudio, R prompt, Jupyter notebook, etc). In our experience, these R packages rarely provide a way to describe linked views in R and produce a purely client-side result, which we view as a powerful workflow for exploratory web graphics.

We propose an extension of **ggplot2**'s layered Grammar of Graphics API to create interactive web graphics that don't require server-side technologies. The core idea lies in attaching metadata to graphical marks that can be used to hide/show subsets of data. The resulting framework is quite similar to what D. Cook, Buja, and Swayne (2007) describe as brushing in multiple linked views as a database query. The assignment of data to graphical marks is done through *aesthetic mappings*, which is a term the Grammar of Graphics uses for mapping data to visual attributes (e.g., color, shape, x, y, etc). Typically aesthetic mappings are visual, meaning they can be easily seen in a static graphic, but our proposed variable mappings are more conceptual, meaning that they can't easily be seen, but can be used to control certain interactive properties. To give a small example, Figure 1 depicts a graphical query made by assigning sensible metadata to graphical marks via the `clickSelects` and `showSelected` aesthetics.

Table 1: New features that animint adds to the grammar of graphics.

Feature	Type	Description
`clickSelects`	aesthetic	value(s) to select on click
`showSelected`	aesthetic	value(s) attached to mark(s) that determine when they are shown
`key`	aesthetic	value(s) attached to mark(s) for smooth transitions.
`tooltip`	aesthetic	information to display on hover
`href`	aesthetic	URL link to open on click
`first`	option	what value(s) should be selected by default?
`time`	option	delay between animation frames.
`duration`	option	to specify smooth transitions.
`selector.types`	option	should selections accumulate?
`selectize`	option	include a dropdown widget to set selection value(s) indirectly?

In addition to graphical queries, our extension supports a number of other interactive features, including animation, tooltips, and hyperlinks. A summary of these extensions and relevant additional options are provided in Table 1. There are a number of other options specific to our implementation in the R package **animint** which are described in the supplemental materials.

2 Related work

It is important to acknowledge that **ggplot2** is built on top of the R package **grid**, a low-level graphics system, which is now bundled with R itself (R Core Team 2017). Neither **grid**, nor **base** R graphics, have strong support for handling user interaction, which creates a need for add-on packages. There are a number of approaches these packages take to rendering, each with their own benefits and drawbacks. Traditionally, they build on low-level R interfaces to graphical systems such as GTK+ (Lawrence and Temple Lang 2010), Qt (Lawrence and Sarkar 2016), or Java GUI frameworks (Urbanek 2016). In general, the resulting system can be very fast and flexible, but sharing and reproducing output is usually a problem due to the heavy software requirements. Although there may be sacrifices in performance, using the modern web browser as a canvas is more portable, accessible, and composable (graphics can be embedded within larger frameworks/documents).

Base R does provide a Scalable Vector Graphics (SVG) device, `svg()`, via the Cairo graphics API (Cairo 2016). The R package **SVGAnnotation** provides functionality to post-process `svg()` output in order to add interactive and dynamic features (Nolan and Lang 2012). This is a powerful approach, since in theory it can work with any R graphic, but the package is self-described as a proof-of-concept which reverse-engineers poorly-structured `svg()` output. As a result, it is not straightforward to extend this system for linked data visualizations with advanced functionality (multiple layers, multiple plots, multiple selection variables).

The lack of well-structured SVG for R graphics motivated the **gridSVG** package which provides sensible structuring of SVG output for grid graphics (Murrell and Potter 2015). This package also provides some low-level tools for animating or adding interactive features, where grid objects must be referenced by name. As a result, use of this interface to add interactivity to a **ggplot2** plot requires understanding of the grid naming scheme **ggplot2** uses internally. An interface where interactivity can be expressed by referencing the data to be visualized, rather than the building blocks of the graphics system, would be preferable since the former interface is decoupled from the implementation and does not require knowledge of grid.

In terms of the animation API, the R package **gganimate** is very similar to our system (Robinson 2016). It directly extends **ggplot2** by adding a new aesthetic, named `frame`, which splits the data into subsets (one for each unique value of the frame variable), produces a static plot for each subset, and uses the **animation** package to combine the images into a key frame animation (Xie 2013). This is quite similar but not as flexible as our system's support for animation, which we fully describe in Section 3.4. Either system has the ability to control the amount of time that a given frame is displayed, but our system can also animate the transition between frames via the `d3.transition()` API (Bostock, Oglevetsky, and Heer 2011). Smooth transitions help the animation viewer track positions between frames, which is useful in many scenarios, such as the touring example discussed in Section 5.1. The **tweenr** package provides similar smooth transitions, by computing data values in R that interpolate between animation frames (in **animint**, these calculations are performed in the web browser).

The **ggvis** package is similar to our system in that is also inspired by the Grammar of

Graphics (Chang and Wickham 2015). It does not directly extend **ggplot2**, but instead provides a brand new purely functional interface which is designed with interactive graphics in mind. It currently relies on Vega to render the SVG graphics from JSON (Trifacta 2014), and the R package **shiny** to enable many of its interactive capabilities (RStudio 2013). The interface gives tremendous power to R users, as it allows one to write R functions to handle user events. This power does come with a cost, though, as sharing and hosting **ggvis** graphics typically require special web server softwares, even when the interaction logic could be handled entirely client-side.

The tour is a useful visualization technique for exploring high-dimensional data which requires interactive and dynamic graphics. The open-source software ggobi is currently the most fully-featured toolkit for touring data and has support for interactive techniques such as linking, zooming, panning, and identifying (D. Cook and Swayne 2007). The R package **rggobi** (Duncan Temple Lang 2016) provides an R interface to ggobi's graphical interface, but it unfortunately has many software requirements. Furthermore, sharing the interactive versions of these graphics are not possible. The R package **cranvas** aims to be the successor to ggobi, with support for similar interactive techniques, but with a more flexible interface for describing plots inspired by the Grammar of Graphics (Xie et al. 2013). **Cranvas** also has many software requirements which limits its portability and accessibility.

Another R package for interactive graphics is **iplots** (Urbanek 2011), which has several important differences compared to **animint**. Brushing/highlighting of linked iplots is supported for single-layer plots such as scatterplots or barplots, but it is not easy to define new multi-layer interactive plots. Furthermore since iplots does not use the Grammar of Graphics, it is difficult to create legends and multi-panel plots. Finally since iplots requires compiled C++ code for rendering on the local machine, its graphics are not as easy to share as **animint** graphics which can be viewed in a web browser.

3 Extending the layered grammar of graphics

In this section, we describe in detail our extension of **ggplot2**'s layered grammar of graphics implementation (Wickham 2010). In **ggplot2**, there are five essential components that define a layer of graphical makings: data, mappings (i.e., aesthetics), geometry, statistic, and position. These simple components are easy to understand in isolation and can be combined in many ways to express a wide array of graphics. For a simple example, here is one way to create a scatterplot in **ggplot2** of variables named `<X>` and `<Y>` in `<DATA>`:

```r
ggplot() + layer(
  data = <DATA>,
  mapping = aes(x = <X>, y = <Y>),
  geom = "point",
  stat = "identity",
  position = "identity"
)
```

For every geometry, **ggplot2** provides a convenient wrapper around `layer()` which provides sensible defaults for the statistic and position (in this case, both are "identity"):

```r
ggplot() + geom_point(
  data = <DATA>,
  aes(x = <X>, y = <Y>)
)
```

A single **ggplot2** plot can be comprised of multiple layers, and different layers can correspond to different data. Since each graphical mark within a **ggplot2** layer corresponds to one (or more) observations in `<DATA>`, aesthetic mappings provide a mechanism for mapping graphical selections to the original data (and vice-versa) which is essential to any interactive graphics system (Wickham et al. 2010). Thus, given a way to combine multiple **ggplot2** plots into a single view, this design can be extended to support a notion of multiple linked views, as those discussed by Ahlberg, Williamson, and Shneiderman (1991) and Buja et al. (1991).

3.1 Linking views via aesthetic mappings

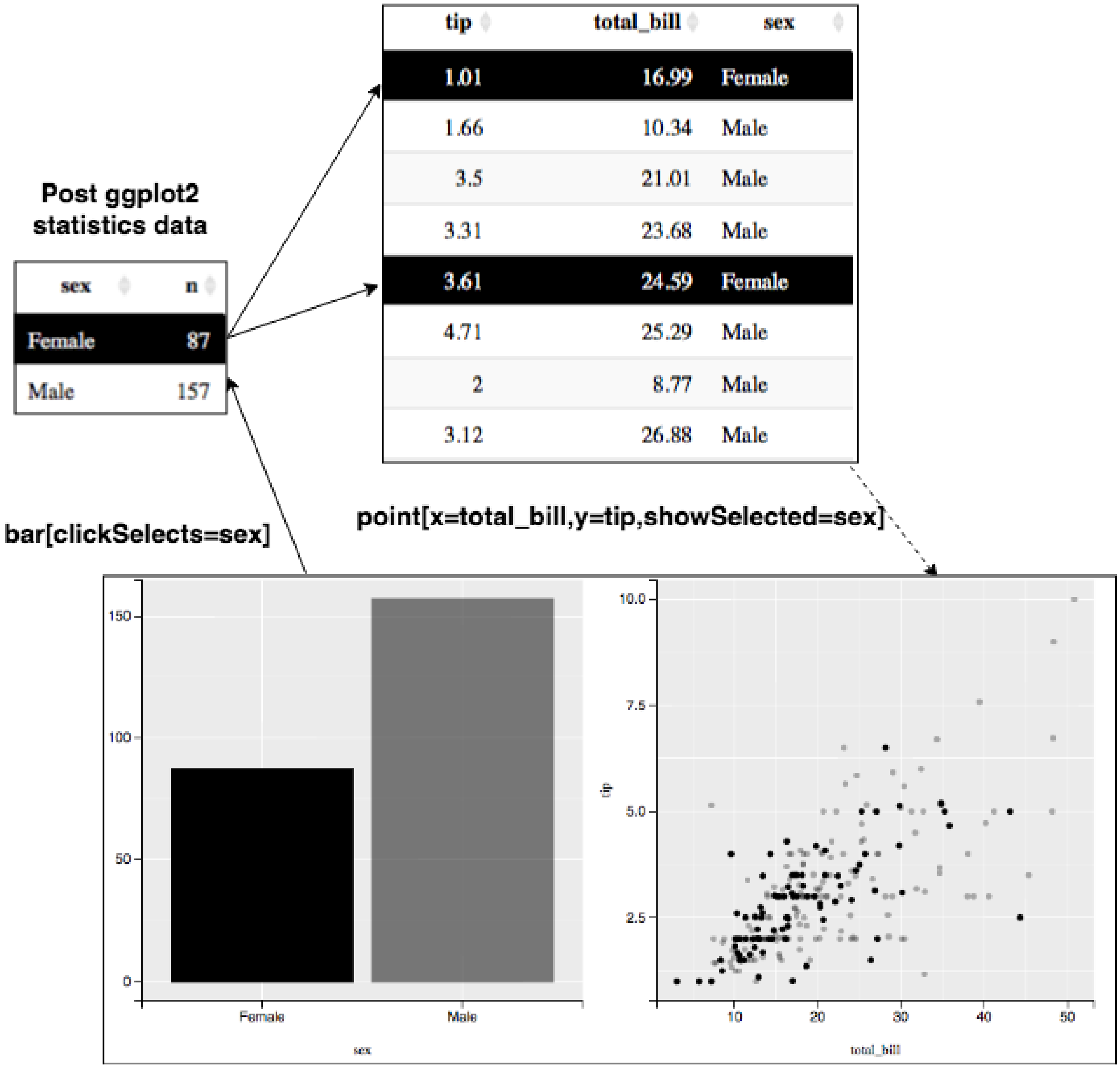
D. Cook and Swayne (2007) use SQL queries to formalize the linked views infrastructure discussed in Ahlberg, Williamson, and Shneiderman (1991) and Buja et al. (1991). We use a similar approach to show how aesthetic mappings can be used to assign data values to graphical marks via **ggplot2** to support similar graphical queries. It's worth noting that, since these aesthetics effectively define a set of database queries that are known at print time, these queries can be made by direct manipulation of graphical marks and/or indirect manipulation via a dropdown widget, as discussed in Section **??**. It's also worth noting that these aesthetics could be defined in such a way that they are not solely restricted to any particular user event (e.g. mouse click), but for sake of demonstration, we restrict focus to our **animint** implementation, which has `clickSelects` and `showSelected` aesthetics. Consider the R code below which uses these aesthetics to describe the interactive graphic shown in Figure 1[1].

```r
data(tips, package = "reshape2")
bar <- ggplot(tips) +
  geom_bar(aes(x = sex, clickSelects = sex))
scatter <- ggplot(tips) +
  geom_point(aes(x = total_bill, y = tip), alpha = 0.3) +
  geom_point(aes(x = total_bill, y = tip, showSelected = sex))
```

The `clickSelects` aesthetic is used to declare a geom which can be clicked to set selection value(s). For the example in Figure 1, we declare a bar with `clickSelects=sex` and refer to the current set of selection value(s) as `selected_sex`. The value of `selected_sex` can take on any subset of the unique values of `sex`, and in this case, the unique values are `Male` and `Female`. The selection set, `selected_sex`, is then used to select subsets of data for geoms with the `showSelected=sex` aesthetic. In this case there is a geom point with `showSelected=sex`, so clicking on a bar results in an update to the displayed subset of points.

In the R code above, the `geom_bar()` layer in the left-hand plot is linked to the 2nd

[1] Interactive versions of all of the figures mentioned in this paper can be found at http://members.cbio.mines-paristech.fr/~thocking/animint-paper-figures/



sex	n
Female	87
Male	157

tip	total_bill	sex
1.01	16.99	Female
1.66	10.34	Male
3.5	21.01	Male
3.31	23.68	Male
3.61	24.59	Female
4.71	25.29	Male
2	8.77	Male
3.12	26.88	Male

Figure 1: A graphical query of tips data set. Left: the `clickSelects` aesthetic designates a clickable geom bar that can change a selection variable. Right: the `showSelected` aesthetic designates a geom point that responds by showing only the data which corresponds to the current selection.

geom_point() layer in the right-hand plot since the clickSelects and showSelected aesthetics are mapped to a common variable, sex. Note how the first geom_point() layer does not have a showSelected mapping, but has a bit of alpha transparency, so all the data is shown in light gray, and the current selection is portrayed in black. In other words, when a bar is clicked, in order to update the second layer of points, our system performs an SQL query of the form:

```
SELECT * FROM tips
  WHERE sex IN selected_sex
```

In this example, selected_sex is either Male or Female (a single selected value), but as we show in later examples, a selection set can also be multiple values. Although the clickSelects aesthetic is tied to a mouse click event, other aesthetics could easily be created to support other selection events, such as hover or click+drag. Statistically speaking, this type of interaction is useful for navigating through joint distributions conditional upon discrete values. In this sense, our extension is closely related to trellis displays (Becker, Cleveland, and Shyu 2010) and linked scatterplot brushing (Becker and Cleveland 1987). The major differences are that our conditioning is layer-specific (not plot-specific), is not tied to a particular geometry, and can be controlled through direct manipulation or animation controls.

3.2 World Bank example

This section uses the linking framework introduced in the previous section to visualize a more complex data set provided by the World Bank. The interactive version of Figure 2 fosters exploration of the relationship between life expectancy and fertility rate over time for 205 countries. The year 1979 and the countries United States and Vietnam are selected in the static version of Figure 2, but readers are encouraged to change the selection by clicking on the interactive version, which is provided in the supplementary materials. The interactive version also makes use of additional animation options (explained later in Section 3.4), allowing us to visualize the evolution of the relationship between life expectancy and fertility rate.

We anticipate that some **ggplot2** users will be able to reverse engineer the code which creates

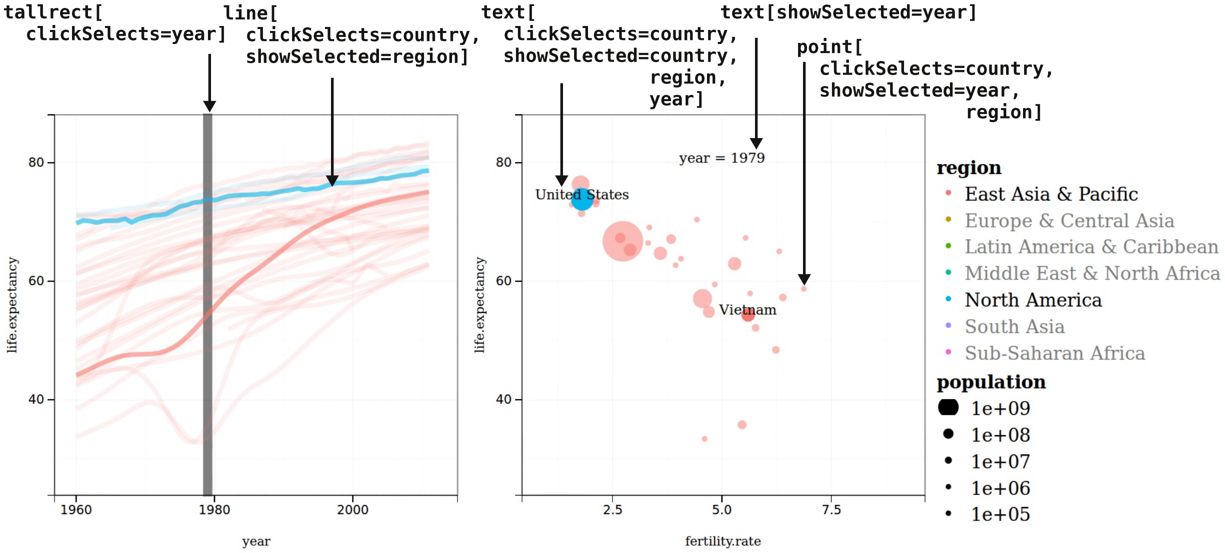


Figure 2: An interactive animation of World Bank demographic data of several countries, designed using `clickSelects` and `showSelected` aesthetics (top). Left: a multiple time series from 1960 to 2010 of life expectancy, with bold lines showing the selected countries and a vertical grey tallrect showing the selected year. Right: a scatterplot of life expectancy versus fertility rate of all countries. The legend and text elements show the current selection: year=1979, country={United States, Vietnam}, and region={East Asia & Pacific, North America}

Figure 2, simply by looking at it. In fact, this is a big reason why **ggplot2** is so widely used: it helps minimize the amount of time required to translate an idea for a figure into computer code. Note that, in the left-hand plot of Figure 2, we have a time series of the life expectancy where each line is a country (i.e., we `group` by country) and lines are colored by region. By clicking on a line, we also want the country label to appear in the right-hand plot, so we also need to set `clickSelects=country`. Lastly, by setting `showSelected=region`, we can hide/show lines by clicking on the color legend entries.

```r
timeSeries <- ggplot() + geom_line(
  data = WorldBank,
  aes(x = year, y = life.expectancy,
      group = country, color = region,
      clickSelects = country,
      showSelected = region)
)
```

We want to provide a visual cue for the selected year in the time series, so in the code below we add some tall rectangles to the time series plot. These tall rectangles will also serve as a way to directly modify the selected year. The tallrect geometry is a special case of a rectangle that automatically spans the entire vertical range, so we just have to specify the horizontal range via `xmin` and `xmax` aesthetics. Also, since the layered grammar of graphics allows for different data in each layer, we supply a data frame with just the unique years in the entire data for this layer.

```r
years <- data.frame(year = unique(WorldBank$year))
timeSeries <- timeSeries + geom_tallrect(
  data = years,
  aes(xmin = year - 0.5, xmax = year + 0.5,
      clickSelects = year)
)
```

As for the right-hand plot in Figure 2, there are three layers: a point layer for countries, a text layer for countries, and a text layer to display the selected year. By clicking on a point, we want to display the country text label and highlight the corresponding time series on the left-hand plot, so we set `clickSelects=country` in this layer. Furthermore, we only want to show the points for the selected year and region, so we also need `showSelected=year` and `showSelected2=region`.

```
scatterPlot <- ggplot() + geom_point(
  data = WorldBank,
  aes(x = fertility.rate, y = life.expectancy,
      color = region, size = population,
      clickSelects = country,
      showSelected = year,
      showSelected2 = region)
)
```

Note that any aesthetics containing the substring `showSelected` (including `showSelected2`) are interpreted as `showSelected` variables, and combined together using the intersection operation. In the example above, that means that a point will be drawn for the currently selected combination of year and region, as in the following SQL query,

```
SELECT * FROM WorldBank
  WHERE year   IN selected_year
  AND   region IN selected_region
```

Below, the text layer for annotating selected countries is essentially the same as the point layer, except we map the country name to the `label` aesthetic.

```
scatterPlot <- scatterPlot + geom_text(
  data = WorldBank,
  aes(x = fertility.rate, y = life.expectancy,
      label = country,
      showSelected = country,
      showSelected2 = year,
      showSelected3 = region)
)
```

Lastly, to help identify the selected year when viewing the scatterplot, we add another layer of text at a fixed location.

```
scatterPlot <- scatterPlot + geom_text(
  data = years, x = 5, y = 80,
  aes(label = paste("year =", year),
      showSelected = year)
)
```

In summary, this section shows an example of how the proposed `clickSelects` and `showSelected` aesthetics can be used with several different geoms (line, point, text, tallrect), each of which can potentially display a different data set. In each case we use `clickSelects` to declare a geom for which clicking changes the value of a selection variable, and we use `showSelected` to declare a geom which responds to such changes by updating the set of displayed data. In the next sections, we further explain how to link ggplots and add animation.

3.3 Linking and multiple selection

Linking is declared in R code by putting ggplots with common `clickSelects` and `showSelected` aesthetics together in a list. For example, we can link the ggplots from the previous section by including them together in the following list:

```
viz <- list(
  timeSeries = timeSeries,
  scatterPlot = scatterPlot
)
```

Linking is accomplished because the two ggplots declared `clickSelects` and `showSelected` aesthetics that refer to common variable names (`region`, `year`, `country`). For each such selection variable, our interactive renderer updates the set of selected values in response to mouse clicks on `clickSelects` geoms, and then updates the corresponding data which is displayed for `showSelected` geoms.

Note that the viz list above can also contain rendering options, as we discuss below (see Table 1 for a summary of proposed interactive features). For example, the selector.types option controls whether or not selections for a given variable can accumulate (single or multiple selected values). This difference is also sometimes referred to as transient versus persistent selection (D. Cook and Swayne 2007).

```r
viz$selector.types <- list(
  year = "single",
  country = "multiple",
  region = "multiple"
)
```

The code above declares year as a single selection variable, which means that only a single year may be selected at a time (clicking a geom with clickSelects=year will change the selection to the corresponding year). The country and region variables are declared as multiple selection variables, which can have multiple selected values at a time (clicking a geom with clickSelects=country will add/remove that country to/from the selection set).

3.4 Animation and smooth transitions

Animation is declared using the time option, which specifies a selection variable that will be automatically updated over time, as well as a time delay in milliseconds. The code below declares the year variable to be animated every 3 seconds.

```r
viz$time <- list(variable = "year", ms = 3000)
```

Animation is useful in the World Bank data visualization because it shows how the bi-variate relationship between fertility rate and life expectancy changes over time. Animation clearly shows how many countries progress from low life expectancy and high fertility rate in early years, to high life expectancy and low fertility rate in later years.

Finally, the duration option specifies the amount of time used to smoothly transition between selections (with linear easing). Smooth transitions help the viewer track geoms before and after an update to the selection set. For example in the code below we declare a 1 second smooth transition on the year variable, in order to more easily track the points on the scatterplot.

```r
viz$duration <- list(year = 1000)
```

Note that for accurate interpretation of smooth transitions, the new key aesthetic must be specified. The key aesthetic is used to match data elements before and after the smooth transition. In the World Bank example, we would need to specify aes(key=country) for the points and text in the scatterplot.

3.5 Compiling and rendering

We have implemented the **animint** R package which enables viewing the linked interactive ggplots that we proposed in the previous sections. Supplying the viz list of ggplots and rendering options to the animint2dir() function will save all the files necessary for rendering the visualization:

```r
animint::animint2dir(viz)
```

As shown in supplementary Figure 1, the **animint** system is implemented in 2 parts: the compiler and the renderer. The compiler is implemented in R code that converts a list of ggplots and options to a JSON plot meta-data file and a tab-separated values (TSV) file database. The renderer consists of HTML and JavaScript files, which can be easily hosted along with the TSV and JSON files on any web server. The interactive plots can be viewed by opening the index.html page in any modern web browser. Note that our current implementation of **animint** depends on a fork of **ggplot2**[2] that contains some minor modifications which are needed to support interactive rendering on web pages. Additional implementation details are available in the supplementary materials.

[2] https://github.com/faizan-khan-iit/ggplot2/tree/validate-params

4 Exploring scope with examples

This section attempts to demonstrate the range of visualizations that are supported by the system we propose. In particular because of its support for interaction and animation, it excels at display of interactive maps with time-varying data. We give two such examples below.

4.1 Tornadoes in the United States

One of the strong points of the system we propose is display of multi-layer plots such as maps with time-varying data. For example, Figure 3 shows a visualization of US tornado data from 1950 to 2012. This data visualization consists of two multi-layer plots with two interaction variables, `year` and `state`.

The left plot is a map which shows state borders using a polygon with `clickSelects=state`. The currently selected state is shown using semi-transparency, and other states can be selected by clicking them. The state map plot uses geoms with `showSelected=year` to show tornado paths (segment geom) and endpoints (point geom) for the currently selected year (which is emphasized with a text geom above the map).

The right plot uses several geoms to show details for the currently selected state and year. A bar geom shows a time series of tornado counts for the selected state (`showSelected=state`), which can be clicked to change the currently selected year (`clickSelects=year`). A text geom at the top of the plot shows the currently selected state (`showSelected=state`), and a text geom at the bottom emphasizes the tornado count for the selected year (using `showSelected` variables for both `state` and `year`).

These interactions can be useful for discovering patterns in the data, and for suggesting models that can describe or predict tornado paths.

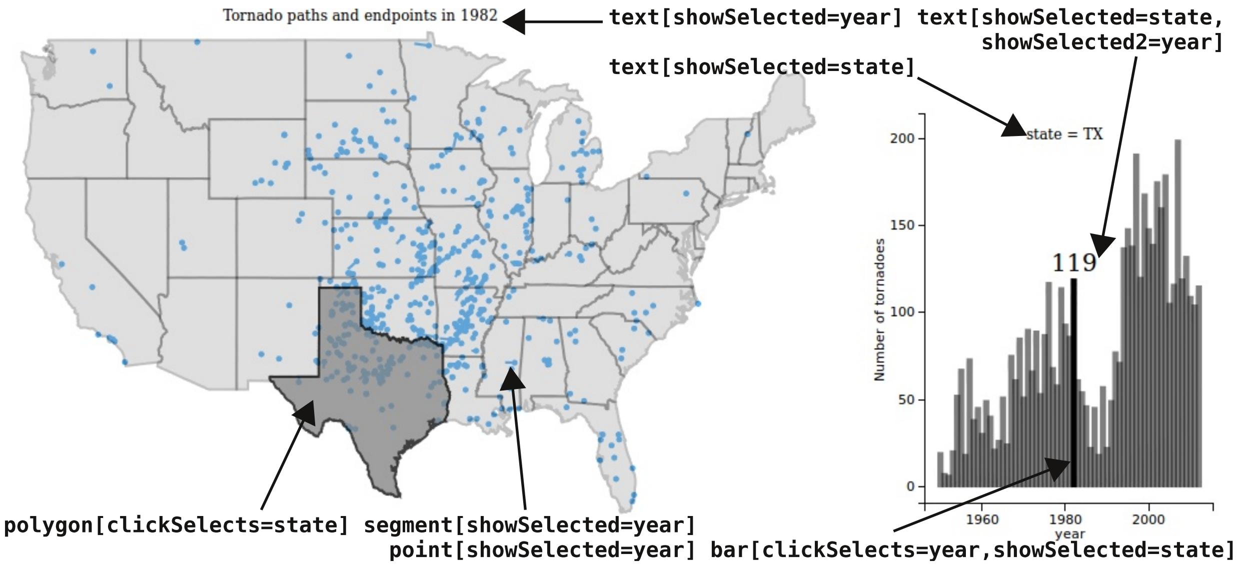


Figure 3: Interactive animation of US tornadoes from 1950 to 2012. This figure depicts a scenario where the user queried Texas (by clicking the map), and the year 1982 (by clicking the bar chart). In addition to the graphical elements being highlighted as a visual clue of what query is being made, this visualization includes dynamic text labels reflecting the query.

4.2 Central American climate data

A more complex map data visualization example is shown in Figure 4, which depicts climate time series data observed in Central America. There are two interaction variables, `time` and `region`.

Two maps in the upper left display borders of the countries in and near Central America. Unlike the previous example with US states, the country borders are static (clicking has no effect). For the currently selected time, rect geoms with `showSelected=time` show the spatial distribution of sea surface temperature as well as its deviation from the monthly norm. Since `clickSelects=region` is specified, clicking a rect changes the currently selected region, which is emphasized with a black border. These plots facilitate visualization of the spatial distribution of the climate variables, and how they change over time.

The plots below the maps use lines to show time series of the climate variables. Since `clickSelects=region` is specified, clicking a line changes the currently selected region, which is emphasized with a purple color. A semi-transparent tallrect shows the currently

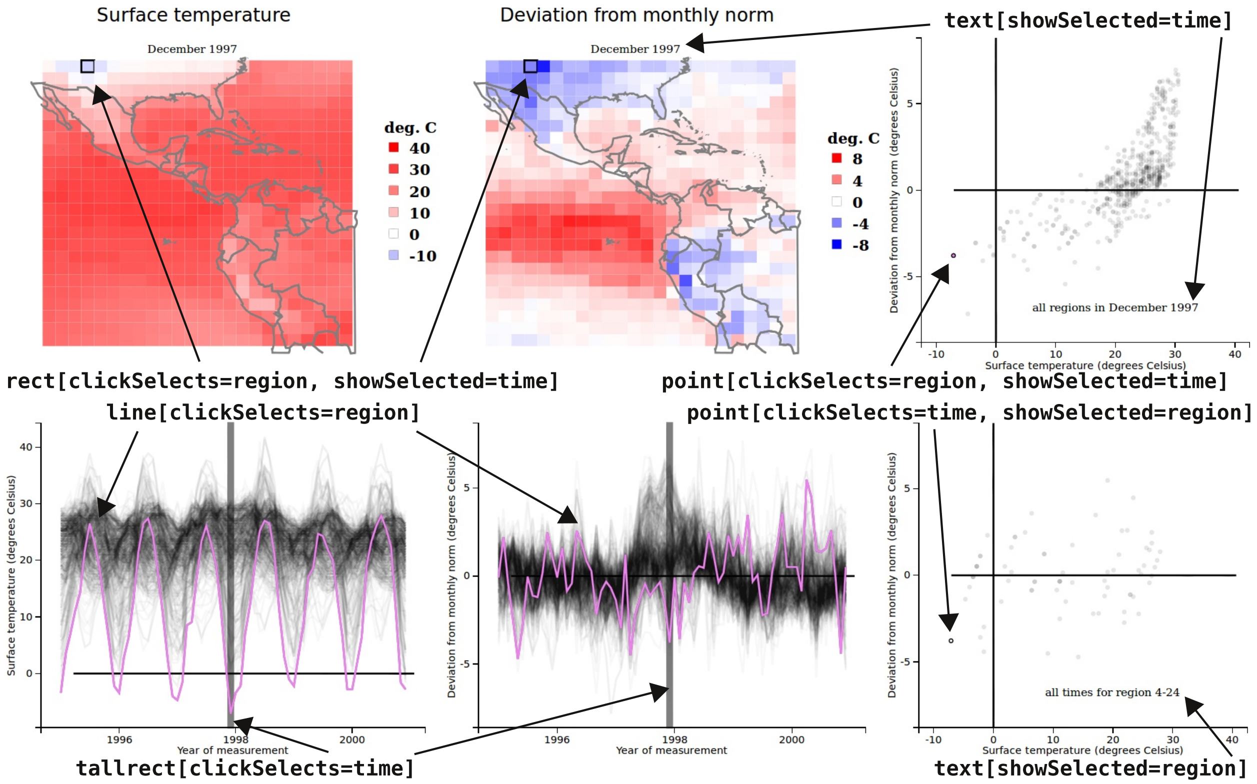


Figure 4: Visualization containing 6 linked, interactive, animated plots of Central American climate data. Top: for the selected time (December 1997), maps displaying the spatial distribution of two temperature variables, and a scatterplot of these two variables. The selected region is displayed with a black outline, and can be changed by clicking a rect on the map or a point on the scatterplot. Bottom: time series of the two temperature variables with the selected region shown in violet, and a scatterplot of all times for that region. The selected time can be changed by clicking a background tallrect on a time series or a point on the scatterplot. The selected region can be changed by clicking a line on a time series.

selected time; other tallrects can be clicked to update the time (`clickSelects=time`). These plots make it easy to select different times and regions, and to make comparisons between times and regions.

Scatterplots on the right use `showSelected` variables with point and text geoms, to show the joint distribution of the two temperature variables for the selected time (top) and region (bottom). The plots use `clickSelects` to emphasize the currently selected region (top) and time (bottom), and are useful for visualizing normality and outliers in the joint distribution.

5 Comparison study

In this section we compare our **animint** implementation with other similar leading systems by creating a given visualization in each system and discussing the pros and cons of the different approaches.

5.1 The Grand Tour

The Grand Tour is a well-known method for viewing high dimensional data which requires interactive and dynamic graphics (Asimov 1985). Figure 5 shows a grand tour of 300 observations sampled from a correlated tri-variate normal distribution. The left-hand view shows the marginal density of each point while the right-hand view "tours" through 2D projections of the 3D data. There are many ways to choose projections in a tour, and many ways to interpolate between projections, most of which can be programmed fairly easily using R and relevant add-on packages. In this case, we used the R package **tourr**, which uses the geodesic random walk (i.e., random 2D projection with geodesic interpolation) in its grand tour algorithm (Wickham et al. 2011).

When touring data, it is generally useful to link low-dimensional displays with the tour itself. The video in Figure 5 was generated with our current **animint** implementation, and points are selected via mouse click which reveals that points with high marginal density are located in the ellipsoid center while points with a low marginal density appear near the ellipsoid border. In this case, it would be convenient to also have brush selection, as we demonstrate in

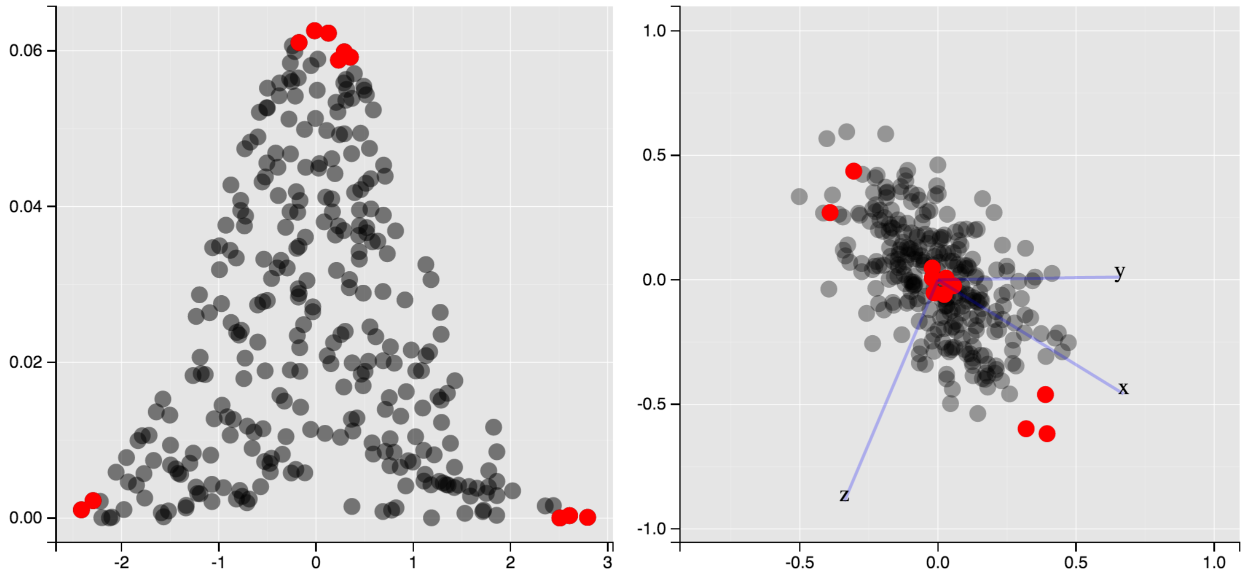


Figure 5: Linked selection in a grand tour with **animint**. A video demonstration can be viewed online at https://vimeo.com/160720834

Figure 6 which implements the same touring example using the R packages **ggvis** and **shiny**. The brush in Figure 6 is implemented with **shiny**'s support for brushing static images, which currently does not support multiple brushes, making it difficult to select non-contiguous regions.

This example helps point out a few other important differences in using **animint** versus **ggvis+shiny** to implement "multiple linked and dynamic views" as described in Ahlberg, Williamson, and Shneiderman (1991) and Buja et al. (1991). Maintaining state of the linked brush in Figure 6 requires both knowledge and clever use of some sophicated programming techniques such as closures and reactivity. It also requires knowledge of the **shiny** web application framework and a new approach to the Grammar of Graphics. On the other hand, maintaining state in Figure 5 requires a few different `clickSelects`/`showSelected` mappings. As a result, we believe **animint** provides a more elegant user interface for this application.

The touring example also helps point out important consequences of the design and implementation of these two different systems. As mentioned in Section **??**, our current **animint** implementation requires every subset of data to be precomputed before render time. For

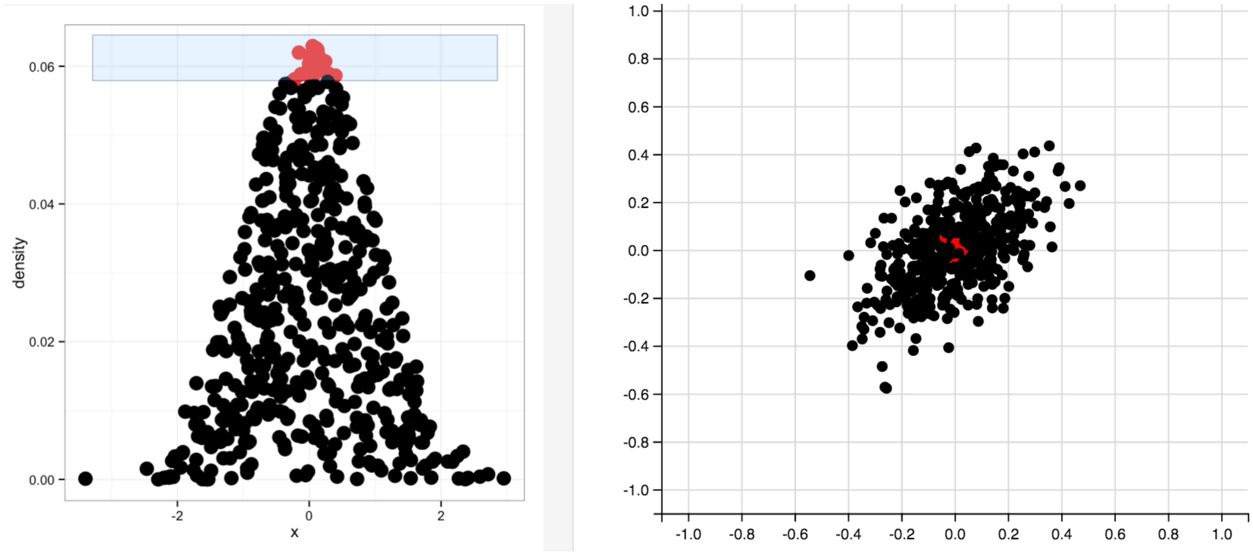


Figure 6: Linked selection in a grand tour with **ggvis** and **shiny**. A video demonstration can be viewed online at https://vimeo.com/160825528

visualizations such as tours, where it is more efficient to perform statistical computations on-the-fly, this can be a harsh restriction, but this is a restriction of our current implementation (not a restriction of the framework itself). As a result, when touring a large high-dimensional space, where many projections are needed, **ggvis+shiny** may be desirable since the projections are computed on the server and sent to the browser in real-time. This works fine when the application is running and viewed on the same host machine, but viewing such an application hosted on a remote machine can produce staggered animations since client-server requests must be performed, processed, and rendered roughly 30 times a second. Also, generally speaking, the **animint** system results a more pleasant experience when it comes to hosting and sharing applications since it doesn't require a Web Server with R and special software already installed.

5.2 World Bank example

We also recreated Figure 2 using **ggvis+shiny** and Tableau. Even as experienced **ggvis+shiny** users, we found it quite difficult to replicate this example, and were not able to completely replicate it due to a lack of a mechanism for coordinating indirect and direct manipulations. Overall the visualization is pretty similar, but lacks a few important features. In particular, there is no way to control the selected year using both the slider (indirect) and clicking on the **ggvis** plot (direct). It also lacks the ability to click on a country time series and label the corresponding point on the scatterplot. This might be possible, but we could not find a way to update a plot based on a click event on a different plot. Even with this lack of functionality, the **ggvis+shiny** is significantly more complicated and requires more code (about 100 lines of code compared to 30).

It was also impossible to completely replicate Figure 2 using Tableau essentially because the example requires a *layered* approach to the Grammar of Graphics. In particular, since graphical marks and interaction source/target(s) must derive from the same table in Tableau, it was impossible to control the clickable multiple time series and the clickable tallrects in different ways based on the two different selection variables. In other words, in Tableau, selections are managed on the plot level, but in **animint**, selections are specific to each graphical layer.

6 Limitations and future work

The system we have proposed provides linked interactive plots via the new `showSelected` and `clickSelects` aesthetics. The linking between plots is rather flexible, but is limited to interactions which are specified by the plot designer at compile-time. Our current implementation provides a visual indication of the current selection via semi-transparency of `clickSelects` geoms. In future work we would like to explore more obvious visual cues that can be used to quickly show the user the links between plots and possible interactions.

A number of limitations in our current implementation derive from the fact that some plot features are computed once during the compilation step, and remain static on a rendered plot. For example, users are unable to change variable mappings after compilation. Also, when different data subsets have very different ranges of values, it may be preferable to recompute scales when `clickSelects` selection(s) change. Some of these limitations can be resolved by adding interactive widgets to "recompile" components hard-coded in the plot meta information. In fact, **animint** makes it easy to embed visualizations inside of **shiny** web applications, and we have an example of interactively redefining variable mappings.

Our compiler also currently takes advantage of **ggplot2** internals to compute statistics and positional adjustments before rendering. As a result, statistics/positions will not dynamically recompute based on selections. In other words, using `clickSelects`/`showSelected` with non-identity statistic(s)/position(s) may not generate a sensible result. It would be possible, but a significant amount of work, to transfer these computations from the compiler to the renderer.

Another set of limitations derive from our current restriction that all subsets (corresponding to each possible selection) must be precomputed before render time. As elucidated in Section 5.1, if there is a large space of possible selections, it is impractical to precompute every subset before viewing. Therefore, for future work it would be useful if the renderer could dynamically compute subsets when new selections are made.

Our implementation is also limited to two specific types of direct manipulation: selecting graphical elements via mouse click (`clickSelects`), and showing/hiding related elements (`showSelected`). However, the framework described in Section 3.1 is not restricted to a particular event type, so `hoverSelects` and `brushSelects` aesthetics could be added, for instance. There are other types of interaction that could be added, that wouldn't require additional extensions to the Grammar of Graphics, such as: zooming, panning, and plot resizing.

7 Conclusion

We have proposed several extensions to **ggplot2**'s layered grammar of graphics in order to support a declarative approach to producing interactive and dynamic web graphics. By adding `clickSelects` and `showSelected` aesthetics to specify selection source(s) and target(s), **ggplot2** users can quickly and easily create animations with smooth transitions and perform dynamic queries via direct manipulation of linked views. As a result, **animint** is a useful tool not only for EDA, but also for the presentation and distribution of interactive statistical graphics.

Interactive figures and reproducible research statement

The source code to create this paper and its figures is online at https://github.com/tdhock/animint-paper/ and the interactive figures can be viewed at http://members.cbio.mines-paristech.fr/~thocking/animint-paper-figures/

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