Extending ggplot2 for linked and dynamic web graphics

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Abstract

The web is the most popular medium for sharing interactive data visualizations thanks to the portability of the web browser and the accessibility of the internet. Unfortunately, creating interactive web graphics often requires a working knowledge of numerous web technologies that are foreign to many people working with data. As a result, web graphics are rarely used for exploratory data analysis where quick iteration between different visualizations is of utmost importance. This is the core strength of ggplot2, a popular data visualization package for R, the world's leading open-source statistical programming language. The conceptual framework behind ggplot2 is based on the grammar of graphics, which lays a foundation for describing any static graphic as a small set of independent components. Perhaps the most fundamental component is the mapping from abstract data to the visual space, sometimes referred to as the aesthetic mapping. We propose adding two new aesthetics to the grammar, which together are sufficient for elegantly describing both animations and certain classes of coordinated linked views. We implement this extension in the open-source R package animint, which converts ggplot2 objects to interactive web visualizations via D3.

Keywords: Animation, Linked Views, Statistical graphics, Exploratory data analysis, Web technologies

1 Introduction

The world's leading open source statistical programming language, R, has a rich history of interfacing with computational tools for the use of people doing data analysis and statistics research (R Core Team 2017). Understanding R's core audience is important, as they typically want to maximize their time working on data analysis problems, and minimize time spent learning computational tools. R excels in this regard, as it is designed specifically for interactive use, where users can quickly explore their data using highly expressive interfaces. Another key player in R's success story is its packaging infrastructure, which provides tools for distributing entire research compendium(s) (code, data, documentation, auxiliary documents, etc) (Gentleman and Lang 2004).

One of the most widely used R packages is ggplot2, a data visualization package inspired by the grammar of graphics (Wickham 2009, Wilkinson et al. (2006)). In fact, Donoho (2015) writes: "This effort may have more impact on today's practice of data analysis than many highly-regarded theoretical statistics papers". In our experience, ggplot2 has made an impact thanks to its foundation in the grammar of graphics, carefully chosen defaults, and overall usability. This helps data analysts rapidly iterate and discover informative visualizations – an essential task in exploratory data analysis (EDA). When dealing with high-dimensional data, however, it is often useful to produce interactive and/or dynamic graphics, which ggplot2 does not inherently support.

Interactive graphics toolkits in R have been used for decades to enhance the EDA workflow, but these approaches are often not easy to reproduce or distribute to a larger audience. It is true that most graphics generated during EDA are ultimately not useful, but sometimes, understanding gained during this phase is most easily shared via the interactive graphics themselves. Thus, there is value in being able to easily share, and embed interactive graphics inside a larger report. Unfortunately, this is typically hard, if not impossible, using traditional interactive graphics toolkits. As a result, there is a large disconnect between the visualization tools that we use for exploration versus presentation.

We aim to narrow this gap in visualization tools by extending ggplot2's grammar of graphics implementation for interactive and dynamic web graphics. Our extension allows one to create animated transitions and perform dynamic queries via direct manipulation of linked views like those described in Ahlberg, Williamson, and Shneiderman (1991) and Buja et al. (1991). A conceptual model for our extension is provided in Section 3.1 and Section 3.2. In Section 3.3, we demonstrate our extension with an example. In Section 3.4, we outline design decisions made in our implementation in the R package animint. In Section 4, we provide a sense of the scope of our system and its performance limitations through a handful of examples. In Section 5, we conduct a comparison study by replicating examples with other leading systems. Finally, in Section 7, we discuss future work and limitations of our current system.

2 Related work

We aim to provide a system which empowers ggplot2 users to go beyond the confines of static graphics with minimal friction imposed upon their current workflow. We acknowledge that numerous systems which support similar visualization techniques exist outside of the R ecosystem, but we intentionally focus on R interfaces since the surrounding statistical computing environment is crucial for enabling an efficient EDA workflow.

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+, Qt, or Java GUI frameworks (Lawrence and Temple Lang 2010, Lawrence and Sarkar (2016a), Lawrence and Sarkar (2016b), 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, anyone wishing to extend or alter the core functionality needs a deep understanding of base graphics and SVG.

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, if one wanted to use this interface to add interactivity to a ggplot2 plot, they must know and understand the grid naming scheme ggplot2 uses internally and hope it does not change down the road. 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 3.2. 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 us track positions between frames, which is useful in many scenarios, such as the touring example discussed in Section 5.1.

Tours are 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 tool for touring data and has support for interactive techniques such as linking, zooming, panning, and identifying (Cook and Swayne 2007). The R package rggobi (Wickham et al. 2008) provides an R interface to ggobi's graphical interface, but unfortunately, the software requirements for installation and use of this toolchain are heavy and stringent. 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 heavy and stringent software requirements which limits the portability and accessibility of the software.

Another R package for interactive graphics which draws design inspiration from the grammar of graphics is ggvis (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 requires special web server softwares, even when the interaction logic could be handled entirely client-side. As we outline in Section 3.4, our system does not require a web server, but can also be used inside shiny web applications, when desired.

3 Extending the layered grammar of graphics

In this section, we propose an extension to the layered grammar of graphics (Wickham 2010), which enables declarative expression of animations and dynamic queries via direct manipulation. In the ggplot2 system, 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 easily understood 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"):

```
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 (Andreas Buja and McDonald 1988, 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 in Ahlberg, Williamson, and Shneiderman (1991) and Buja et al. (1991).

3.1 Direct manipulation of dynamic queries

Cook and Swayne (2007) use SQL queries to formalize the direct manipulation methods discussed in Ahlberg, Williamson, and Shneiderman (1991) and Buja et al. (1991). As it turns out, we can embed this framework inside the layered grammar of graphics with two classes of new aesthetics: one class to define a selection source and one to define a target. This is most easily seen using our animint implementation, which has a `clickSelects` aesthetic for defining the selection source (via mouse click) and a `showSelected` aesthetic for defining the target. Here we use animint to create a linked view between a bar chart and a scatter plot, where the user can click on bars to control the points shown in the scatterplot, as shown in the video in Figure 1. As a result, we can quickly see how the relationship among tip amount and total bill amount depends on whether the customer is smoker.

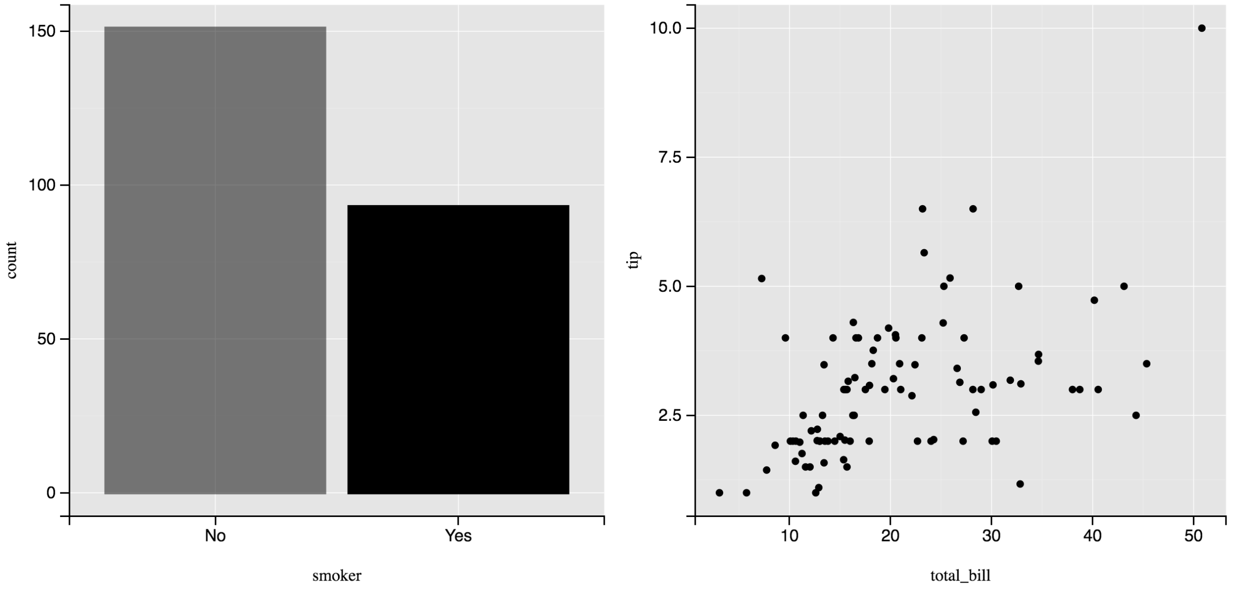


Figure 1: Linked dynamic querying via direct manipulation using animint. A video demonstration can be viewed online at https://vimeo.com/160496419

```r
library(animint)
p1 <- ggplot() + geom_bar(
  data = reshape2::tips,
  aes(x = smoker, clickSelects = smoker)
)
p2 <- ggplot() + geom_point(
  data = reshape2::tips,
  aes(x = total_bill, y = tip,
      showSelected = smoker)
)
animint2dir(list(p1 = p1, p2 = p2))
```

In essense, the R code above allows us to use direct manipulation to dynamically perform SQL queries of the form:

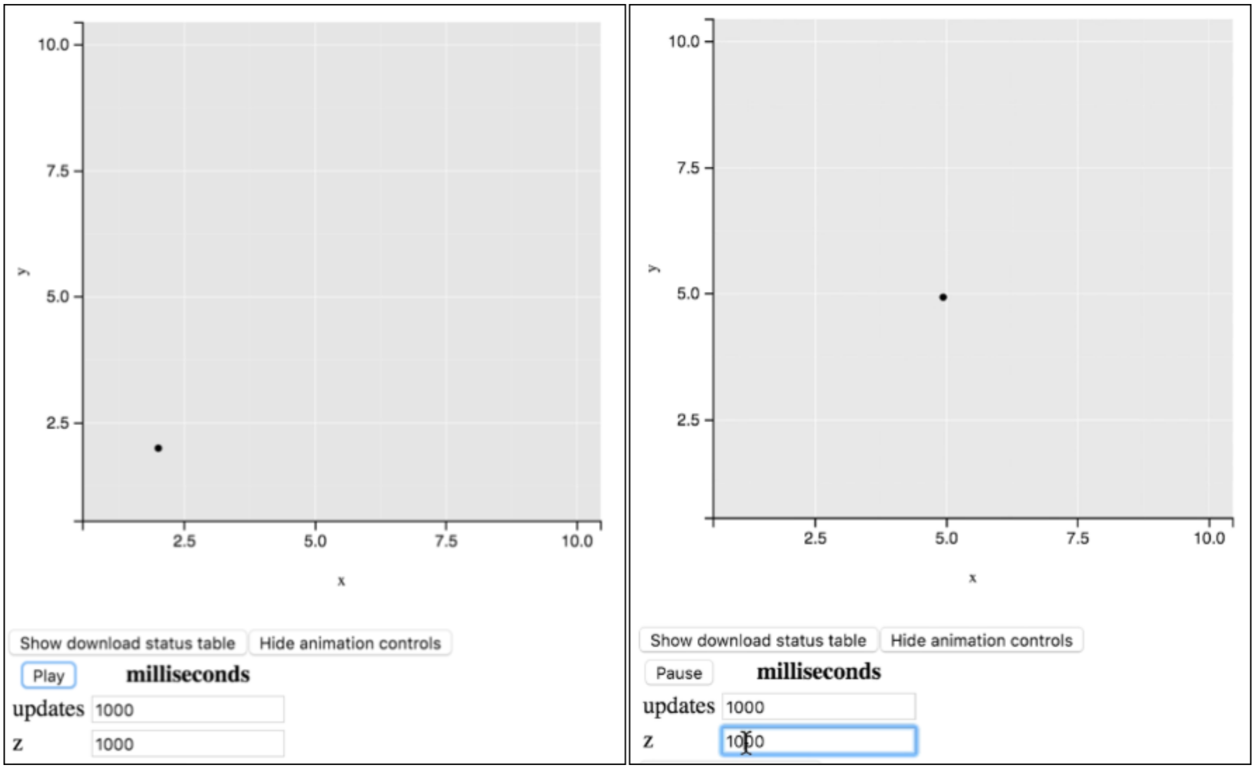
```sql
SELECT total_bill, tip FROM tips
  WHERE smoker IN clickSelects
```

In this example, `clickSelects` is either “Yes” or “No”, but as we show in later examples, `clickSelects` can also be an array of values. Although `clickSelects` is tied to a mouseclick event, this same framework supports other selection events, such as hover or click+drag. Statistically speaking, this is useful for visualizing and navigating through joint distributions conditional upon discrete values. In this sense, our extension is closely related to trellis displays and linked scatterplot brushing (Becker, Cleveland, and Shyu 2010, 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 Adding animation

In some sense, the `showSelected` aesthetic splits the layer into subsets – one for every unique value of the `showSelected` variable. The `clickSelects` aesthetics provides a mechanism to alter the visibility of those subset(s) via direct manipulation, but our system also provides a mechanism for automatically looping through selections to produce animation(s). We achieve this by reserving the name `time` to specify which variable to select as well as the amount of time to wait before changing the selection (in milliseconds). We also reserve the name `duration` to specify the amount of time used to smoothly transition between frames (with linear easing). The code below was used to generate Figure 2 which demonstrates a simple animation with smooth transitions between 10 frames of a single point. Note that the resulting web page has controls for interactively altering the `time` and `duration` parameters.

```r
d <- data.frame(v = 1:10)
plotList <- list(
  plot = ggplot() + geom_point(
    data = d, aes(x = v, y = v, showSelected = v)
  ),
  time = list(variable = "v", ms = 1000),
  duration = list(v = 1000)
)
```



milliseconds
updates 1000
z 1000

milliseconds
updates 1000
z 1000

Figure 2: Two frames from an animation of one marker moving from (1, 1) towards (10, 10). A video of the animation with smooth transitions can be viewed online at https://vimeo.com/160505146

```
animint2dir(plotList)
```

3.3 World Bank example

Figure 3 shows an interactive animation of the World Bank data set created with our animint implementation (World Bank 2012). The visualization helps us explore the change in the relationship between life expectancy and fertility over time for 205 countries. By default, the year 1979 and the countries United States and Vietnam are selected, but readers are encouraged to watch the video of the animation and/or interact the visualization using a web browser.[1] In the interactive version, the selected value of the year variable is automatically incremented every few seconds, using animation to visualize yearly changes in the relationship

[1] http://bl.ocks.org/tdhock/raw/8ce47eebb3039263878f/

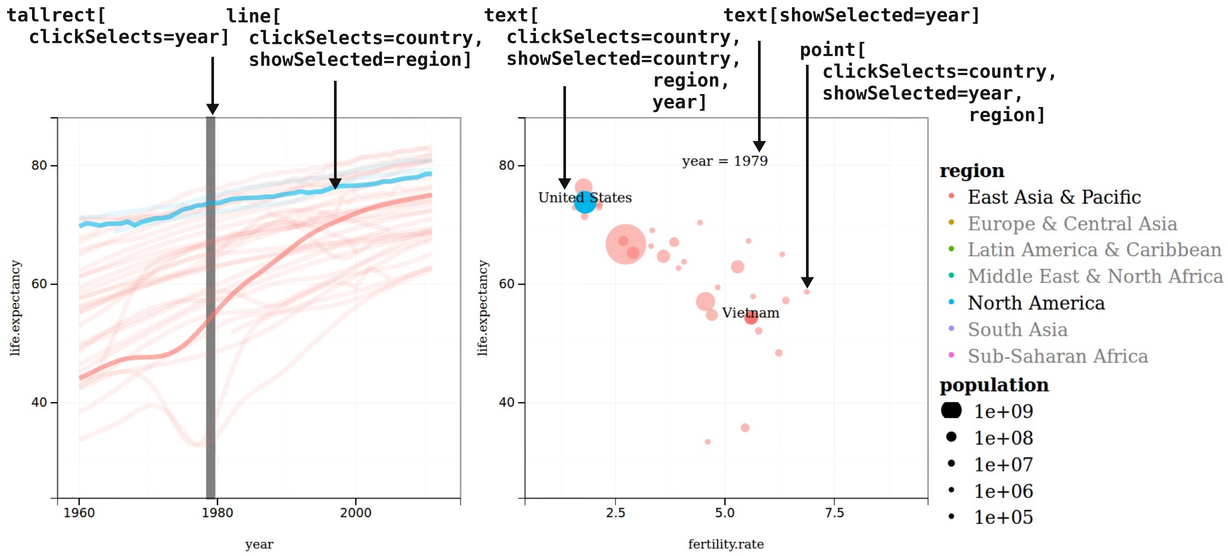
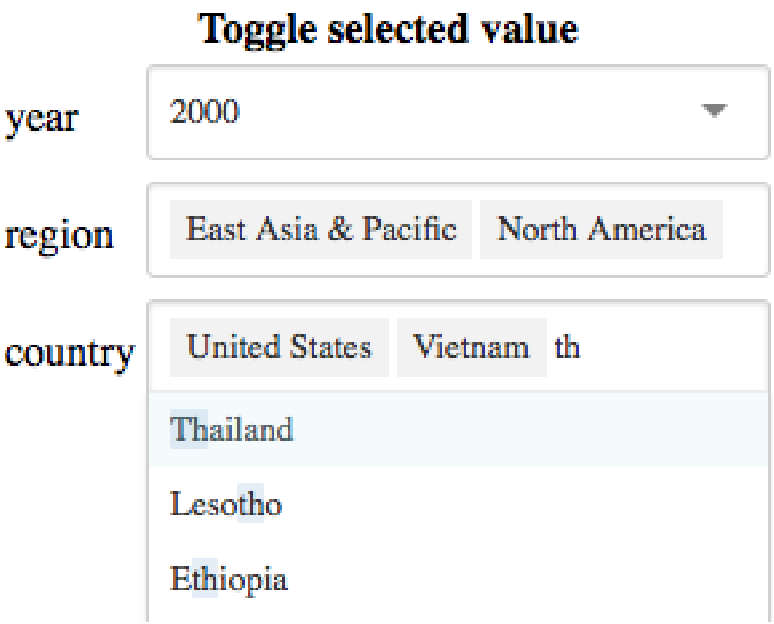


Figure 3: An interactive animation of World Bank demographic data of several countries, designed using `clickSelects` and `showSelected` keywords (top). Left: a multiple time series from 1960 to 2010 of life expectancy, with bold lines showing the selected countries and a vertical grey tallrect showing 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}

between life expectancy and fertility rate.

When viewing the interactive version of Figure 3, suppose we wish to select Thailand. Direct manipulation is not very useful in this case since it is not easy to identify and select Thailand based on graphical marks on a plot. For this reason, animint also provides dropdown menu(s) for each selection variable to aid the selection process. Figure 4 shows what the user sees after typing "th" in the search box. Note that these dropdowns support selection of multiple values and coordinate sensibly with selections made via direct manipulation.

We anticipate that some ggplot2 users will be able to reverse engineer the animint code which creates Figure 3, 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 a figure that exists in your head into computer code. Note that, in the left hand plot of Figure 3, we have a time series of the life expectancy where each line is a country (i.e., we `group` by country) and



Toggle selected value

year 2000

region East Asia & Pacific North America

country United States Vietnam th

Thailand

Lesotho

Ethiopia

Figure 4: Animint provides a menu to update each selection variable. In this example, after typing “th” the country menu shows the subset of matching countries.

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. 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.

```
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 3, 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)
)
```

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)
)
```

Now that we have defined the plots in Figure 3, we can set the `time` and `duration` options (introduced in Section 3.2) to control the animation parameters. Our animint implementation also respects a `selector.types` option which controls whether or not selections for a given variable can accumulate and a `first` option for controlling which values are selected by default. [2] By default, supplying the list of plots and additional options to `animint2dir()` will write all the files necessary to render the visualization to a temporary directory and prompt a web browser to open an HTML file.

```
viz <- list(
  timeSeries = timeSeries,
  scatterPlot = scatterPlot,
  time = list(variable = "year", ms = 3000),
  duration = list(year = 1000),
  selector.types = list(
    year = "single",
    country = "multiple",
    region = "multiple"
  ),
```

[2] We maintain a complete list of (animint specific) options here – https://github.com/tdhock/animint/wiki/Advanced-features-present-animint-but-not-in-ggplot2

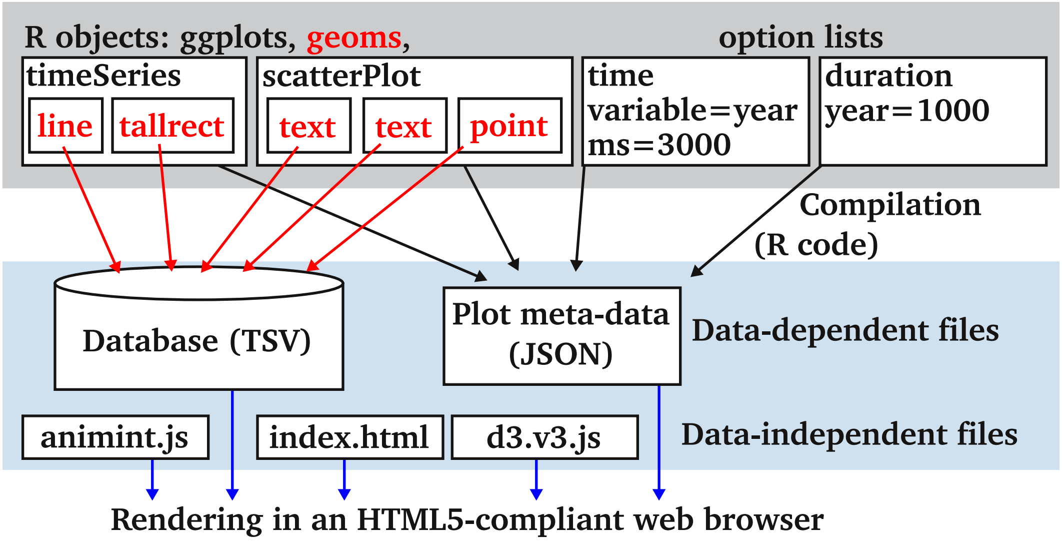


Figure 5: A schematic explanation of compilation and rendering in the World Bank visualization. Top: the interactive animation is a list of 4 R objects: 2 ggplots and 2 option lists. Center: animint R code compiles data in ggplot geoms to a database of TSV files (→). It also compiles plot meta-data including ggplot aesthetics, animation time options, and transition duration options to a JSON meta-data file (→). Bottom: those data-dependent compiled files are combined with data-independent JavaScript and HTML files which render the interactive animation in a web browser (→).

```
    first = list(
      country = c("United States", "Vietnam")
    )
)
animint2dir(viz)
```

3.4 Implementation details

As shown in Figure 5, the animint system is implemented in 2 parts: the compiler and the renderer. The compiler is implemented in about 2000 lines of 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.

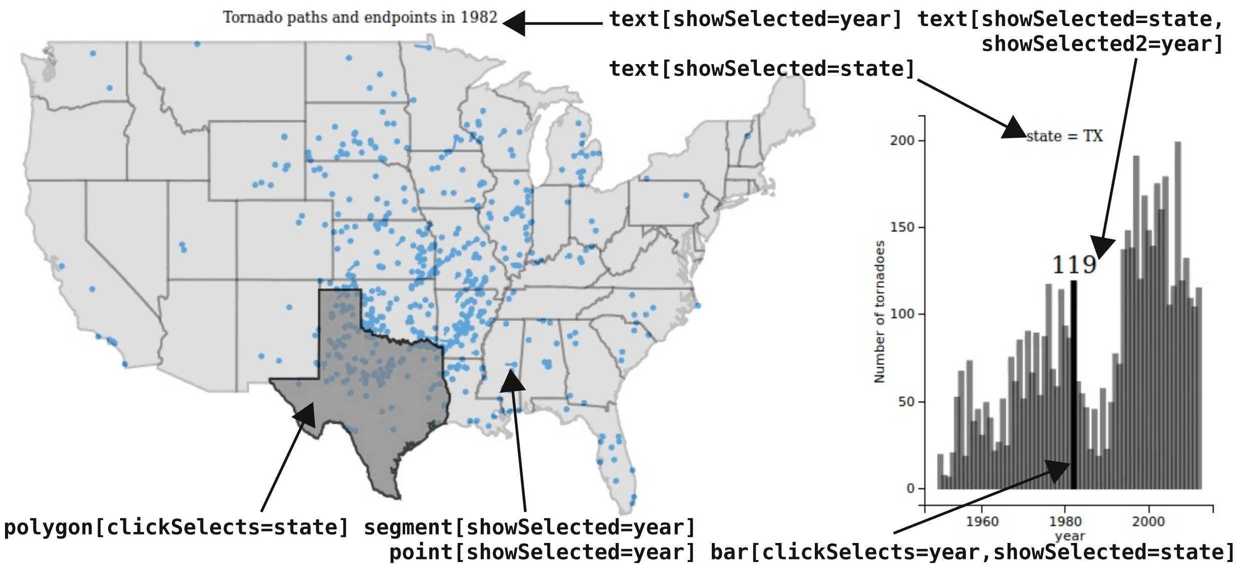
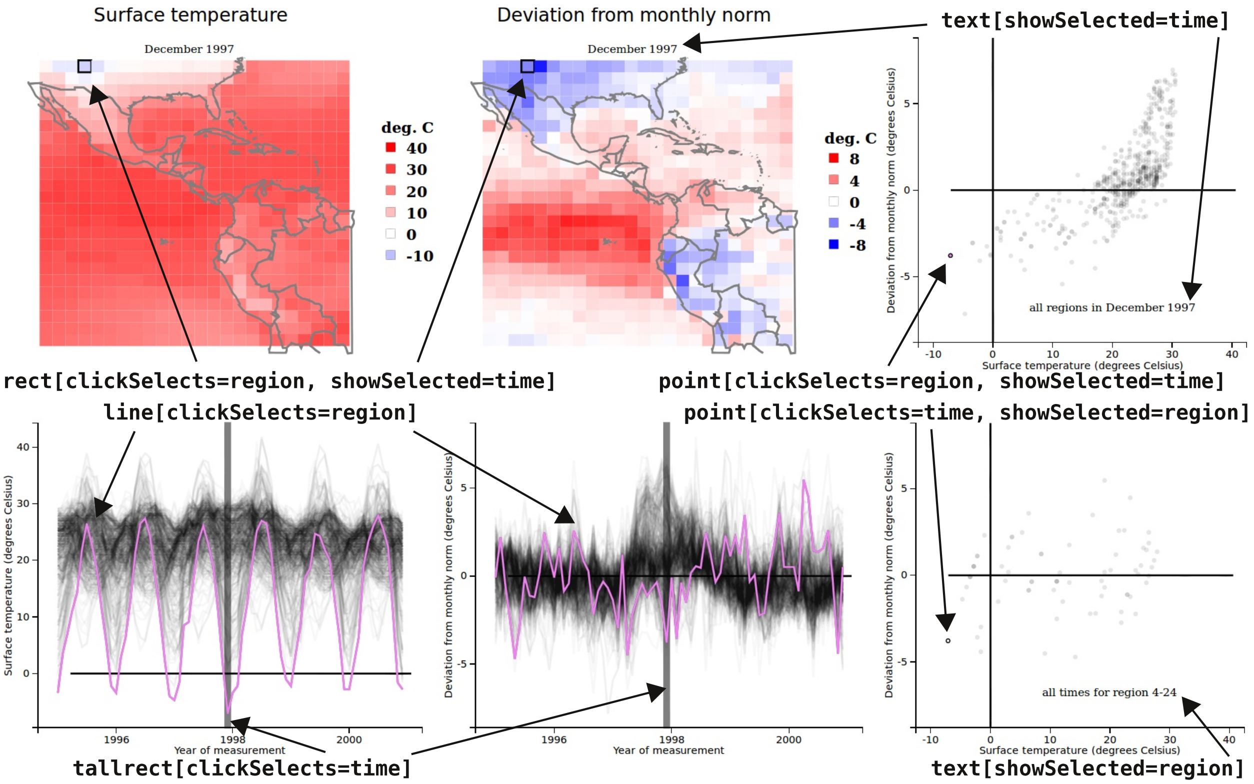


Figure 6: Interactive animation of tornadoes recorded from 1950 to 2012 in the United States. Left: map of the lower 48 United States with tornado paths in 1982. The text shows the selected year, and clicking the map changes the selected state, currently Texas. Right: time series of tornado counts in Texas. Clicking a bar changes the selected year, and the text shows selected state and the number of tornadoes recorded there in that year (119 tornadoes in Texas in 1982).



text[showSelected=time]

rect[clickSelects=region, showSelected=time]

point[clickSelects=region, showSelected=time]

line[clickSelects=region]

point[clickSelects=time, showSelected=region]

tallrect[clickSelects=time]

text[showSelected=region]

Figure 7: 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.

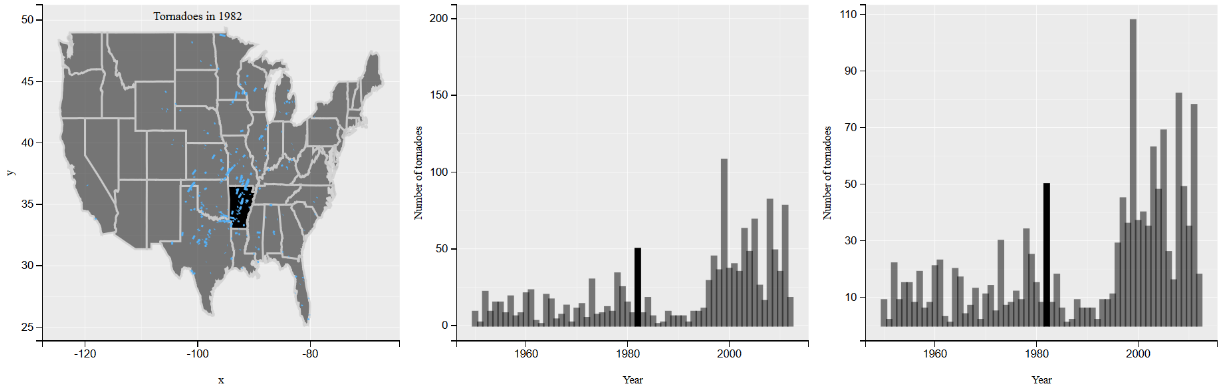


Figure 8: Interactive animation of tornadoes in the United States from 1950 to 2012. In this view, the year 1982 and state of Arkansas are selected, so tornado paths from 1982 are displayed on the map and the tornado counts represent Arkansas. The middle and right panel display the same data, but use different scaling: the middle panel reflects the 'global' range (US) while the right panel reflects the 'local' range (Arkansas). Futhermore, when an axis update is triggered, they smoothly transition from one state to next (preserving object constancy in the axis ticks). This helps the viewer better perceive/understand how the range has changed from one state to the next. The interactive version of this chart may be viewed here https://bl.ocks.org/faizan-khan-iit/raw/b3912f21ec2750f96e8d1bd4b66463b2/#year={1982}state={AR}

The compiler scans the aesthetics in the ggplots to determine how many selection variables are present, and which geoms to update after a selection variable is updated. It uses ggplot2 to automatically calculate the axes scales, legends, labels, backgrounds, and borders. It outputs this information to the JSON plot meta-data file.

The compiler also uses ggplot2 to convert data variables (e.g. life expectancy and region) to visual properties (e.g. y position and color). The data for each layer/geom are saved in several TSV files, one for each combination `showSelected` values. Thus for large data sets, the web browser only needs to download the subset of data required to render the current selection (Heer 2013).

When repeated data would be saved in each of the TSV files, an extra common TSV file is created so that the repeated data only need to be stored and downloaded once. In that case, the other TSV files do not store the common data, but are merged with the common data after downloading. This method for constructing the TSV file database was developed to minimize the disk usage of animint, particularly for ggplots of spatial maps as in Figure 6.

animint also supports axes updates for both x and y axes for selected geoms. The idea is that when the user selects a subset of data to be displayed in a plot, the axes are re-calculated so that the displayed data covers the whole of the viewing area in the plot, as shown in Figure 8. The axes updates currently work only for single selection variables, as the axes ranges are computed in the compiler and stored in the JSON plot meta-data file. The renderer uses these stored ranges to update the axes scales everytime the displayed subset of data changes. Calculating all the subset combinations in the compiler for multiple selection variables is not efficient, in which case it would be beneficial to shift this computation to the renderer itself.

Finally, the rendering engine (`index.html`, `d3.v3.js`, and `animint.js` files) is copied to the plot directory. The `animint.js` renderer is implemented in about 2200 lines of JavaScript/D3 code that renders the TSV and JSON data files as SVG in a web browser. Importantly, animation is achieved by using the JavaScript `setInterval()` function, which updates the `time` selection variable every few seconds. Since the compiled plot is just a directory of files, the interactive plots can be hosted on any web server. The interactive plots can be viewed by opening the `index.html` page in any modern web browser.

4 Exploring performance & scope with examples

This section attempts to demonstrate a range of visualizations that are supported by animint with more examples. Figure 6 shows an interactive animation of tornadoes observed in the United States between 1950 and 2012. At any moment in time, the user can simultaneously view the spatial distribution of tornadoes in the selected year over all states, and see the trend over all years for the selected state. Clicking a state on the map updates the time series bars to show the tornado counts from that state. Clicking a bar on the time series updates the spatial distribution of tornadoes in the selected year. Figure 7 shows an interactive animation of climate time series data observed in Central America. Two maps display the spatial distribution of two temperature variables, which are shown over time in corresponding the time series plots below. Scatterplots also show the relationships between the two temperature variables for the selected time and region. Clicking any of the plots updates all 6 of them. The `clickSelects` and `showSelected` aesthetics make it easy to design this set of 6 linked plots in only 87 lines of code.

Summary statistics describing complexity and performance of examples in this paper, as well as other animint examples, are displayed in Table 1. The climate data visualization has noticeably slow animations, since it displays about 88,980 geometric elements at once (http://bit.ly/QcUrhn). We observed this slowdown across all browsers, which suggested that there is an inherent bottleneck when rendering large interactive plots in web browsers using JavaScript and SVG. Another animint with a similar amount of total rows is based on the evolution data (http://bit.ly/O0VTS4), but since it shows less data onscreen (about 2,703 elements), it exhibits faster responses to interactivity and animation.

Animint is still useful for creating interactive but non-animated plots when there is not a time variable in the data. In fact, 7 of the 11 examples in Table 1 are not animated. For example, linked plots are useful to illustrate complex concepts such as a change point detection model in the breakpoints data (http://bit.ly/1gGYFIV). The user can explore different model parameters and data sets since these are encoded as animint interaction variables.

Table 1: Characteristics of 11 interactive visualizations designed with animint. The interactive version of these visualizations can be accessed via http://members.cbio.ensmp.fr/~thocking/animint/. From left to right, we show the data set name and Figure number in this paper (Figure), the lines of R code (LOC) including data processing but not including comments (80 characters max per line), the amount of time it takes to compile the visualization (seconds), the total size of the uncompressed TSV files in megabytes (MB), the total number of data points (rows), the median number of data points shown at once (onscreen), the number of data columns visualized (vars), the number of `clickSelects`/`showSelected` variables (int), the number of linked panels (plots), if the plot is animated.

Figure	LOC	seconds	MB	rows	onscreen	vars	int	plots	animated?
worldPop	17	0.2	0.1	924	624	4	2	2	yes
WorldBank 3	20	2.3	2.1	34132	11611	6	2	2	yes
evolution	25	21.6	12.0	240600	2703	5	2	2	yes
change	36	2.8	2.5	36238	25607	12	2	3	no
tornado 6	39	1.7	6.1	103691	16642	11	2	2	no
prior	54	0.7	0.2	1960	142	12	3	4	no
compare	66	10.7	7.9	133958	2140	20	2	5	no
breakpoints	68	0.5	0.3	4242	667	13	2	3	no
climate 7	84	12.8	19.7	253856	88980	15	2	6	yes
scaffolds	110	56.3	78.5	618740	9051	30	3	3	no
ChIPseq	229	29.9	78.3	1292464	1156	44	4	5	no

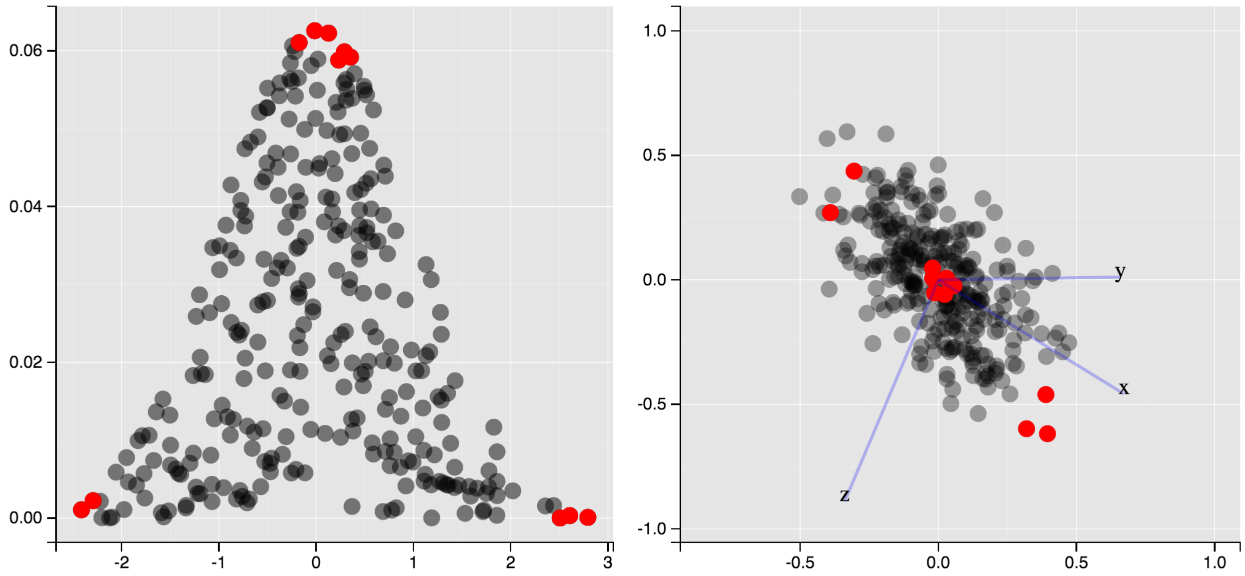


Figure 9: Linked selection in a grand tour with animint. A video demonstration can be viewed online at https://vimeo.com/160720834

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 9 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).

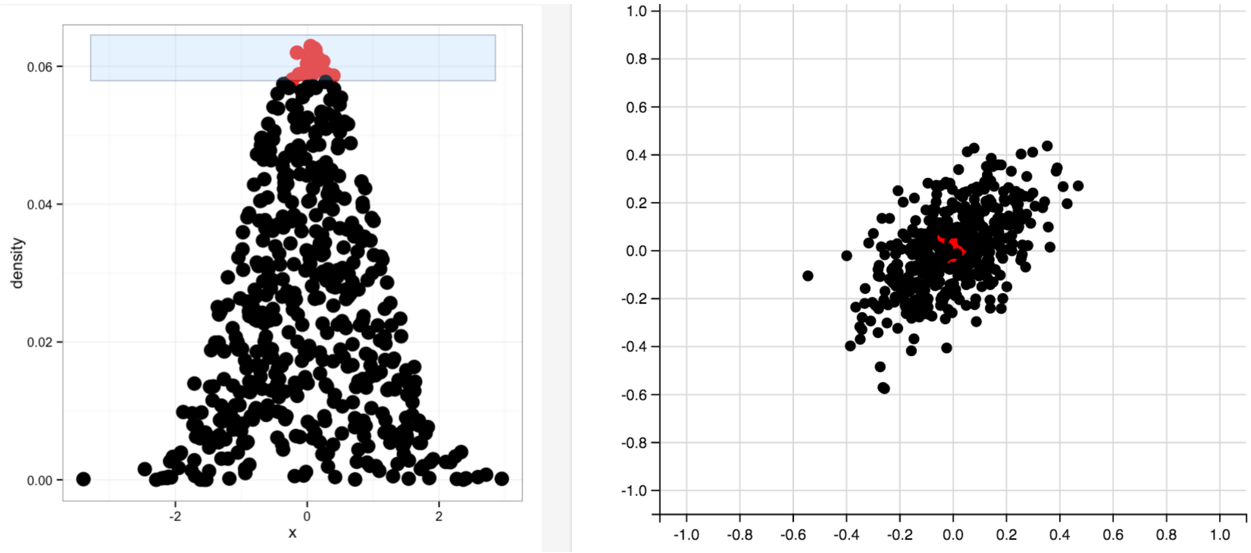


Figure 10: Linked selection in a grand tour with ggvis and shiny. A video demonstration can be viewed online at https://vimeo.com/160825528

When touring data, it is generally useful to link low-dimensional displays with the tour itself. The video in Figure 9 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 10 which implements the same touring example using the R packages ggvis and shiny. The brush in Figure 10 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 10 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 9 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 3.4, our current animint implementation requires every subset of data to be precomputed before render time. For 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 3 using ggvis+shiny (see http://bit.ly/1SsJKlN) and Tableau (see http://bit.ly/worldBank-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 3 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 User feedback and observations

By working with researchers in several fields of research, we have created a wide variety of interactive visualizations using animint. Typically, the researchers have a complex data set that they wish to visualize, but they do not have the expertise or time to create an interactive data visualization. The animint system made it easy to collaborate with the various domain experts, who were able to provide us with annotated sketches of the desired plots, which we then translated to animint R code. In this section we share comments and constructive criticism that we have obtained from our users.

6.1 User perspective

For the `prior` data visualization (http://bit.ly/1peIT7t), the animint user is a machine learning researcher who developed an algorithm and applied it to 4 benchmark data sets. He wanted to explore how his algorithm performed, in comparison to a baseline learning algorithm. He appreciated the intuition about his algorithm's performance that he learned from the interactive plots: "Interactive plotting allows us to explore all relationships of our high-dimensional dataset and gives us an intuitive understanding of the performance of our proposed algorithm. An intuitive understanding of the results is important since it shows under which conditions our proposed method works well and provides avenues for further research."

Another user from a machine learning background found the interactive plots useful for presenting his work: "the 'regularization path' is a difficult concept to demonstrate in my research. The animint (http://bit.ly/1gVb8To) helped greatly by rendering an interactive plot of regularization path, likelihood, and graph at the same time and illustrating their connections. It also reveals an interesting phenomenon that maximizing the testing likelihood actually gives many false positives."

In another application, the animint user was a genomics researcher: "viewing and exploring my complex intestinal microbiome dataset in animint allowed me to grasp the patterns and relationships between samples at an almost intuitive level. The interactive aspect of it was very helpful for browsing through the dataset."

Finally, users also appreciated the simple web interface, and the detail that is possible to show in interactive plots, but impossible to show in publications: "… the web interface is simple and easy to use. It also enables us to publish more detailed interactive results on our website to accompany the results presented in publications."

6.2 Developer perspective

R users, and in particular ggplot2 users, have found that animint is easy to learn and use. One statistics Ph.D. student writes, "animint is a fantastic framework for creating interactive graphics for someone familiar with R and ggplot2's grammar of graphics implementation. The API is very intuitive and allows one to quickly bring their static graphics to life in a way that facilitates exploratory data analysis."

7 Limitations and future work

A number of limitations 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 (http://bit.ly/animint-shiny).

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, 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 should be added, that wouldn't require additional extensions to the grammar of graphics, such as: zooming, panning, and plot resizing.

8 Conclusion

Our R package animint extends ggplot2's layered grammar of graphics implementation for a declarative approach to producing interactive and dynamic web graphics. By adding two 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.

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