**autoplotly - Automatic Generation of Interactive Visualizations for Popular Statistical Results**

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**Abstract** The autoplotly package provides functionalities to automatically generate interactive visualizations for many popular statistical results supported by ggfortify package with plotly and ggplot2 style. The generated visualizations can also be easily extended using ggplot2 and plotly syntax while staying interactive.

**Background**

With the help of base graphics, grid graphics, and lattice graphics (Sarkar, 2008), R users already have many plotting options to choose from. Each has their own unique customization and extensibility options. Nowadays, ggplot2 has emerged as a popular choice for creating visualizations (Wickham, 2009) and provides a strong programming model based on a “grammar of graphics” which enables methodical production of virtually any kind of statistical chart. The ggplot2 package provides a suit of succinct syntax and independent components and makes it possible to describe a wide range of graphics. It’s based on an object-oriented model that is modular and extensible, which becomes a widely used framework for producing statistical graphics in R.

The distinct syntax of ggplot2 makes it a definite paradigm shift from base and lattice graphics and presents a somewhat steep learning curve for those used to existing R charting idioms. Many industry R users, especially the users that build web applications in R by leveraging shiny (Chang et al., 2017) package, may not be satisfied with static plots. Those web applications often involve user interactions so that users can dive into the plots, explore areas of interest, and select relevant data points for more details. ggiraph (Gohel, 2017) is an extension of ggplot2 that provides building blocks for users to build interactive plots and when used within a shiny application, elements associated with an id can be selected and manipulated on client and server sides. There are also other packages such as d3r (Bostock et al., 2017) and plotly (Sievert et al.) built on top of Javascript visualization frameworks that are totally isolated from ggplot2 but become popular building blocks for creating interactive visualizations in R.

Often times users only want to quickly iterate the process of exploring data, building statistical models, and visualizing the model results, especially the models that focus on common tasks such as clustering and time series analysis. Some of these packages provide default base plot visualizations for the data and models they generate. However, they look out-of-fashion and these components require additional transformation and clean-up before using them in ggplot2 and each of those transformation steps must be replicated by others when they wish to produce similar charts in their analyses. Creating a central repository for common/popular transformations and default plotting idioms would reduce the amount of effort needed by all to create compelling, consistent and informative charts. The ggfortify (Tang et al., 2016) package provides a unified ggplot2 plotting interface to many statistics and machine-learning packages and functions in order to help these users achieve reproducibility goals with minimal effort. ggfortify package has a very easy-to-use and uniform programming interface that enables users to use one line of code to visualize statistical results of many popular R packages using ggplot2 as building blocks. This helps statisticians, data scientists, and researchers avoid both repetitive work and the need to identify the correct ggplot2 syntax to achieve what they need. Users are able to generate beautiful visualizations of their statistical results produced by popular packages with minimal effort.

The autoplotly (Tang) package is an extension built on top of ggplot2, plotly, and ggfortify to provide functionalities to automatically generate interactive visualizations for many popular statistical results supported by ggfortify package with plotly and ggplot2 style. The generated visualizations can also be easily extended using ggplot2 and plotly syntax while staying interactive.
Software Architecture

The autoplotly package calls ggfortify’s autoplot() method that invokes an registered S3 generic functions \(^1\) for the applied object to create the visualizations with pplot2 style. Next, the generated ggplot object is translated to plotly object with interactive graphical components leveraging plotly::ggplotly. Additional clean-up and correction are then performed due to the feature parity between plotly and ggplot2 that results in redundant and corrupted components. For example, if we want to generate interactive visualization for principal components analysis results produced from prcomp(...), the following will be executed in order:

- autoplotly(prcomp(...)) - calls autoplotly’s main function
- autoplot.prcomp(prcomp(...)) - invokes the registered S3 generic function
- ggplotly(autoplot.prcomp(prcomp(...))) - translates ggplot object to plotly object

The final object is of class plotly with the corresponding ggplot object as one of its attributes. It can be easily extended using either plotly or ggplot2 style. When additional ggplot2 elements or components are applied, for example:

```r
p <- autoplotly(prcomp(iris[c(1, 2, 3, 4)]), data = iris,
                 colour = 'Species', label = TRUE, label.size = 3, frame = TRUE)
```

```r
p <- p +
    ggplot2::ggtitle("Principal Components Analysis") +
    ggplot2::labs(y = "Second Principal Components", x = "First Principal Components")
```

The above example adds title and axis labels to the originally generated plot. When `+` <-function(e1,e2) operator is applied to a ggplot element as the second argument e2, e.g. ggplot2::ggtitle(...), the ggplot object that we attached to the output of autoplotly() earlier will be used as the first argument e1, borrowing ggplot2’s extensibility.

\[1\] http://adv-r.had.co.nz/S3.html

![PCA with custom plotly style annotation element.](image)

**Figure 1:** PCA with custom plotly style annotation element.

Similarly, if we are adding plotly interactive components, the plotly object from the output of autoplotly() \(p\) will be used instead. The following code adds a custom plotly annotation element placed to the center of the plot with an arrow, as shown in Figure 1:
p <- autoplotly(prcomp(iris[c(1, 2, 3, 4)]), data = iris, colour = 'Species', frame = TRUE)

p %>% layout(annotations = list(
  text = "Example Text",
  font = list(
    family = "Courier New, monospace",
    size = 18,
    color = "black"),
  x = 0,
  y = 0,
  showarrow = TRUE))

 autoplotly re-exports plotly::subplot() to enable users to stack multiple interactive plots generated via autoplotly() together. Some statistical results produce multiple plots, e.g. lm() fitted model objects, which are given extra attention and additional manipulations are performed in order to make sure users can choose whether to share axis labels, change margins, and change layout strategy while keeping the interactive control of multiple sub-plots independently.

The snapshots of the interactive visualizations generated via autoplotly() can be exported using a simple export() function, e.g. export(p, "~/tmp/result.png"). It builds on top of RSelenium (Harrison, 2017) for exporting WebGL plots and uses webshot (Chang, 2017) for non-WebGL formats such as JPEG, PNG, PDF, etc.

Illustrations

As demonstrated earlier, autoplotly package provides a autoplotly() function to work with objects of different classes produced from various popular statistical packages. This section highlights some of the example of automatic interactive visualizations from different types of statistical results.

Principal component analysis

The autoplotly() function works for the two essential classes of objects for principal component analysis (PCA) obtained from stats package: stats::prcomp and stats::princomp, for example:

autoplotly(prcomp(iris[c(1, 2, 3, 4)]), data = iris, frame = TRUE, colour = 'Species')

The above example automatically plots the PCA results from stats package. autoplotly() accepts parameters such as frame to draw the boundaries for each flower species and colour to indicate the column name to use to color each data points, as shown in Figure 2.

Users can hover the mouse over to each point in the plot to see more details, such as principal components information and the species this particular data point belongs to, as shown in Figure 3.

Users can also use the interactive selector to drag and select an area to zoom in, as shown in Figure 4, and zoom out by double clicking anywhere in the plot.

Forecasting

Forecasting packages such as forecast (Hyndman, 2015), changepoint (Killick et al., 2016), strucchange (Zeileis et al., 2002), and dlm (Petris, 2010), are popular choices for statisticians and researchers. Interactive visualizations of predictions and statistical results from those packages can be generated automatically using the functions provided by autoplotly with the help of ggfortify.

The autoplotly function automatically plots the change points with optimal positioning for the AirPassengers data set found in the changepoint package using the cpt.meanvar function, shown in Figure 5.

library(changepoint)
autoplotly(cpt.meanvar(AirPassengers))

The autoplotly function automatically plots the original and smoothed line from Kalman filter function in dlm package as shown in Figure 6.

library(dlm)
form <- function(theta){
Figure 2: PCA with colors and boundary for each flower species.

Figure 3: PCA with colors and boundary for each principal component.
Figure 4: Zoom in using interactive selector.

Figure 5: Change points with optimal positioning for AirPassengers.
```r
dlmModPoly(order = 1, dV = exp(theta[1]), dW = exp(theta[2]))
}
model <- form(dlmMLE(Nile, parm = c(1, 1), form)$par)
filtered <- dlmFilter(Nile, model)
autoplotly(filtered)
```

**Figure 6:** Smoothed time series by Kalman filter.

Additionally, `autoplotly` plots the optimal break points where possible structural changes happen in the regression models built by the `strucchange::breakpoints`, shown in Figure 7.

```r
library(strucchange)
autoplotly(breakpoints(Nile ~ 1), ts.colour = "blue", ts.linetype = "dashed",
cpt.colour = "dodgerblue3", cpt.linetype = "solid")
```

### Clustering

The `autoplotly` package also supports various objects like `cluster::clara`, `cluster::fanny`, `cluster::pam`, `stats::kmeans`, and `lfda::lfda`, from the `cluster` (Maechler et al., 2015) and `lfda` (Tang and Li, 2016) packages. It automatically infers the object type and generate interactive plots of the results from those packages with a single function call. Users can specify `frame = TRUE` to easily draw the clustering boundaries as seen in Figure 8 and the following code:

```r
library(cluster)
autoplotly(fanny(iris[-5], 3), frame = TRUE, frame.type = "norm")
```

By specifying `frame.type`, users are able to draw boundaries of different shapes. The different frame types can be found in `type` option in `ggplot2::stat_ellipse`.

### Splines

The `autoplotly()` function can also automatically generate interactive plots for results produced by `splines`, such as B-spline basis points visualization for natural cubic spline with boundary knots shown in Figure 9.

```r
library(splines)
autoplotly(ns(diamonds$price, df = 6))
```
Figure 7: Optimal break points with possible structural changes.

Figure 8: Fuzzy clustering of the data into 3 clusters.
Figure 9: B-spline basis points for natural cubic spline with boundary knots.

Users can also stack multiple plots generated from autoplotly() together in a single view using subplot(), two interactive splines visualizations with different degree of freedom are stacked into one single view in the following example, as shown in Figure 10:

```r
library(splines)
subplot(
  autoplotly(ns(diamonds$price, df = 6)),
  autoplotly(ns(diamonds$price, df = 3)), nrows = 2, margin = 0.01)
```

Note that the interactive control of those two plots are independent. In other words, you can control two sub-plots separately without affecting each other. Additional options for subplot() are available to select whether to share axises, titles, and which layout of the plots to adopt, etc.

**Linear models**

The autoplotly() function is able able to interpret lm fitted model objects and allows the user to select the subset of desired plots through the which parameter (just like the plot.lm function). The which parameter allows users to specify which of the subplots to display. Many plot aesthetics can be changed by using the appropriate named parameters. For example, the colour parameter is for coloring data points, the smooth.colour parameters is for coloring smoothing lines and the ad.colour parameters is for coloring the auxiliary lines, as demonstrated in Figure 11 and the following code:

```r
autoplotly(
  lm(Petal.Width ~ Petal.Length, data = iris),
  which = c(4, 6),
  colour = "dodgerblue3",
  smooth.colour = "black", smooth.linetype = "dashed",
  ad.colour = "blue", label.size = 3, label.n = 5,
  label.colour = "blue")
```

**Future development**

autoplotly already supports a wide range of statistical results from many popular packages. However, with recent advancements in distributed systems and hardwares, many new frameworks have become
Figure 10: Multiple splines visualizations with different degree of freedom.

Figure 11: Linear model results.
more and more popular to researchers with the help of those optimizations and advancements, such as xgboost (Chen et al., 2017) for scalable gradient tree boosting, tensorflow (Allaire and Tang, 2017), tfestimators (Cheng et al., 2017), and keras (Allaire and Chollet, 2017) for machine learning that take advantages of hardware accelerations. We’d like to support more types of statistical results from more modern and scalable frameworks.

We welcome suggestions and contributions from others. With this package, researchers will hopefully spend less time focusing on learning ggplot2 syntax or interactive visualization packages like plotly. Instead they can spend more time on their work and research. The source code of the package is located on Github https://github.com/terrytangyuan/autoplotly where users can test out development versions of the package and provide feature requests, feedback and bug reports. We encourage you to submit your issues and pull requests to help us make this package better for the R community.

Summary

The autoplotly package provides functionalities to automatically generate interactive visualizations for many popular statistical results supported by ggfortify package with plotly and ggplot2 style. The generated visualizations can also be easily extended using ggplot2 and plotly syntax while staying interactive. This package allows users to spend more time on their research instead of learning ggplot2 syntax or interactive visualization packages like plotly.

Bibliography

J. Allaire and F. Chollet. keras: R Interface to ‘Keras’, 2017. URL https://CRAN.R-project.org/package=keras. R package version 2.1.2. [p10]

J. Allaire and Y. Tang. tensorflow: R Interface to ‘TensorFlow’, 2017. URL https://CRAN.R-project.org/package=tensorflow. R package version 1.4.3. [p10]

M. Bostock, K. Russell, G. Aisch, and A. Pearce. d3r: ‘d3.js’ Utilities for R, 2017. URL https://CRAN.R-project.org/package=d3r. R package version 0.7.1. [p1]

W. Chang. webshot: Take Screenshots of Web Pages, 2017. URL https://CRAN.R-project.org/package=webshot. R package version 0.5.0. [p3]

W. Chang, J. Cheng, J. Allaire, Y. Xie, and J. McPherson. shiny: Web Application Framework for R, 2017. URL https://CRAN.R-project.org/package=shiny. R package version 1.0.5. [p1]

T. Chen, T. He, M. Benesty, V. Khotilovich, and Y. Tang. xgboost: Extreme Gradient Boosting, 2017. URL https://CRAN.R-project.org/package=xgboost. R package version 0.6-4. [p10]

H.-T. Cheng, L. Hong, M. Ispir, C. Mewald, Z. Haque, I. Polosukhin, G. Roumpos, D. Sculley, J. Smith, D. Soergel, Y. Tang, P. Tucker, M. Wicke, C. Xia, and J. Xie. Tensorflow estimators: Managing simplicity vs. flexibility in high-level machine learning frameworks. In Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pages 1763–1771, New York, NY, USA, 2017. ACM. ISBN 978-1-4503-4887-4. doi: 10.1145/3097983.3098171. URL http://doi.acm.org/10.1145/3097983.3098171. [p10]

D. Gohel. ggiraph: Make ‘ggplot2’ Graphics Interactive, 2017. URL https://CRAN.R-project.org/package=ggiraph. R package version 0.4.2. [p1]

J. Harrison. Rselenium: R Bindings for ‘Selenium WebDriver’, 2017. URL https://CRAN.R-project.org/package=Rselenium. R package version 1.7.1. [p3]

R. J. Hyndman. forecast: Forecasting functions for time series and linear models, 2015. URL http://github.com/robjhyndman/forecast. R package version 6.2. [p3]

R. Killick, K. Haynes, and I. A. Eckley. changepoint: An R package for changepoint analysis, 2016. URL http://CRAN.R-project.org/package=changepoint. R package version 2.2.1. [p3]

M. Maechler, P. Rousseeuw, A. Struyf, M. Hubert, and K. Hornik. cluster: Cluster Analysis Basics and Extensions, 2015. R package version 2.0.3 — For new features, see the ‘Changelog’ file (in the package source). [p6]

G. Petris. An R package for dynamic linear models. Journal of Statistical Software, 36(12):1–16, 2010. URL http://www.jstatsoft.org/v36/i12/. [p3]
D. Sarkar. *Lattice: Multivariate Data Visualization with R*. Springer, New York, 2008. URL http://lmdvr.r-forge.r-project.org. ISBN 978-0-387-75968-5. [p.1]

C. Sievert, C. Parmer, T. Hocking, S. Chamberlain, K. Ram, M. Corvellec, and P. Despouy. *plotly: Create Interactive Web Graphics via ‘plotly.js’*. [p.1]

Y. Tang. *autoplotly: Automatic Generation of Interactive Visualizations for Popular Statistical Results*. URL https://github.com/terrytangyuan/autoplotly. R package version 0.1.0. [p.1]

Y. Tang and W. Li. *lfda: An r package for local fisher discriminant analysis and visualization*. arXiv preprint arXiv:1612.09219, 2016. URL https://arxiv.org/abs/1612.09219. [p.6]

Y. Tang, M. Horikoshi, and W. Li. *ggfortify: Unified interface to visualize statistical result of popular r packages*. The R Journal, 8, 2016. URL https://journal.r-project.org/. [p.1]

H. Wickham. *ggplot2: Elegant Graphics for Data Analysis*. Springer Science & Business Media, 2009. [p.1]

A. Zeileis, F. Leisch, K. Hornik, and C. Kleiber. *strucchange: An R package for testing for structural change in linear regression models*. Journal of Statistical Software, 7(2):1–38, 2002. URL http://www.jstatsoft.org/v07/i02/. [p.3]

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