

1 grplot: A Python Library for Lazy Statistical Data 2 Visualization

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Software

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Authors of papers retain copyright and release the work under a Creative Commons Attribution 4.0 International License ([CC BY 4.0](#))¹⁸ grplot.readthedocs.io.¹⁹

6 Summary

7 grplot is an open-source Python library that reduces multi-step statistical workflows to a single high-level function call. Built on top of Matplotlib ([Hunter, 2007](#)), NumPy ([Harris et al., 2020](#)), and Pandas ([McKinney, 2010](#)), and bundled with a vendored Seaborn fork ([grplot_seaborn](#)) that internally uses SciPy ([Virtanen et al., 2020](#)), it exposes a unified plot2d API that automatically handles subplot layout, axis labeling, legends, statistical annotations, tick-label number formatting (thousand separators, currency symbols, and magnitude abbreviations), and figure export to PNG, PDF, SVG, and EPS. Users specify what to plot via a plot-type string or a dictionary mapping panel positions to plot types; the library applies sensible defaults while accepting more than 100 parameters for explicit overrides at global, per-axis, or per-element granularity. As of version 1.0.6, grplot requires Python 3.10+ and is available on PyPI (v1.0.6) and conda-forge (currently distributed as v1.0.4; the conda-forge feedstock lags PyPI releases) ([Rifqialdi, 2026](#)). Full documentation is available at grplot.readthedocs.io.

20 Statement of Need

21 Producing publication-quality figures in Python typically requires orchestrating several libraries: constructing Figure/Axes objects in Matplotlib, calling Seaborn chart functions, manually setting tick formats, adding text annotations, adjusting legends, and finally saving the output. For practitioners who generate many plots routinely—data analysts, researchers, and data scientists—this boilerplate is repetitive and error-prone.

26 grplot fills this gap with a consistent imperative API. It is particularly suited to data practitioners who need reproducible, annotated figures in notebooks or technical reports without rebuilding formatting utilities for each project. It also ships two domain-specific analytic utilities—cohort retention analysis and rank-order/gain/KS/lift tables—that practitioners commonly need to reimplement from scratch.

31 State of the Field

32 Several Python libraries address statistical data visualization, each with a different scope. Matplotlib ([Hunter, 2007](#)) provides a complete 2-D graphics environment with full control over every element, but requires verbose, procedural code for even routine plots. Seaborn ([Waskom, 2021](#)) raises the abstraction level for common statistical charts while remaining tightly coupled to Matplotlib's axis-management model. Altair ([VanderPlas et al., 2019](#)) and plotnine ([Kibirige & others, 2022](#)) implement declarative grammars of graphics ([Wickham, 2016](#)) that are elegant for exploratory work but do not natively support multi-panel layout, number formatting, or annotation in a single call. Plotly ([Plotly Technologies Inc., 2015](#))

40 excels at interactive web-based visualization but is not oriented toward static, publication-ready
41 figures.

42 grplot was built rather than contributing to existing projects for three reasons. First, none of
43 the tools above offers a single end-to-end call that combines multi-panel subplot layout, chart
44 rendering, number formatting, inset statistical summaries, value-label annotations, and figure
45 export. Second, the target workflow—generating many annotated figures for notebooks and
46 technical reports—prioritizes brevity and consistency over the full configurability of Matplotlib
47 or the declarative grammar of Altair. Third, the bundled domain-specific analytics (cohort
48 and rank_order) are not available in any of the packages above and would otherwise require
49 separate, custom implementations for each project.

50 Software Design

51 Hierarchical Argument System

52 The central design challenge was exposing a large surface area of configuration (20 chart
53 types, multi-panel grids, per-axis formatting, per-element overrides) through a single function
54 without requiring users to understand its full breadth for routine use. grplot resolves this with
55 a four-level hierarchy of argument granularity:

- 56 ■ **Ordinary**: applied to the entire figure (e.g., df, figsize, Nx).
- 57 ■ **Axes**: scoped to a specific subplot by 1-based index "[i]" (1-D) or "[row,col]" (2-D
58 grid), e.g., plot, filter, title.
- 59 ■ **Axes-plot**: scoped to a specific chart layer within a subplot (e.g., hue={"[1,2]":
60 {"scatterplot": "species"}}).
- 61 ■ **Axes-axislabel**: scoped to a specific axis label within a subplot (e.g., statdesc={"[1,1]":
62 {"total_bill": "general"}}).

63 Almost all axes-axislabel arguments apply to both axes by default; prefixing with x or y
64 targets a single axis (e.g., xlim, yrot). This design deliberately trades away the lowest-level
65 Matplotlib configurability in exchange for allowing a complete, multi-panel, annotated figure
66 to be expressed in one call with consistent, predictable defaults. Full parameter documentation
67 is available in the [online documentation](#).

68 Supported Chart Types

69 grplot wraps 20 chart types across four families:

Family	Chart types
Relational	scatterplot, lineplot
Distribution	histplot, kdeplot, ecdfplot, rugplot, pieplot, treemapsplot, packedbubblesplot
Categorical	stripplot, swarmplot, boxplot, violinplot, boxenplot, pointplot, barplot, countplot, paretoplot
Regression	regplot, residplot

70 treemapsplot bundles an inline implementation of the squarified treemap layout algorithm
71 described by Laserson (2013), requiring no external squarify dependency. Any two chart
72 types may be overlaid on the same axis using + notation (e.g., "histplot+kdeplot"). Five
73 composites carry pre-tuned default values: boxplot+stripplot, violinplot+stripplot,
74 boxplot+swarmplot, violinplot+swarmplot, and stripplot+pointplot. Multiple panels
75 can be composed into grid dashboards using Nx (columns) and Ny (rows), as illustrated in
76 [Figure 1](#).

77 Vendored Seaborn Fork

78 grplot ships a vendored fork of Seaborn (grplot_seaborn) to decouple production software
 79 that embeds grplot from upstream Seaborn breaking changes. This is a deliberate stability
 80 trade-off: users gain version-independence at the cost of not automatically inheriting Seaborn
 81 upstream improvements. The fork is kept up to date with stable Seaborn releases as part of
 82 grplot maintenance.

83 Analytic Utilities

84 grplot.analytic.cohort produces a cohort retention heatmap from a customer
 85 transaction table, computing monthly retention rates in a single call (Figure 2). When
 86 display_summary=True, the underlying cohort pivot table is also printed to the notebook
 87 output for inspection.

88 grplot.analytic.rank_order produces a rank-order table with cumulative gain, KS statistic,
 89 and lift per decile from predicted probabilities and true binary labels, supporting multi-class
 90 outputs via a class selector. These utilities follow standard industry conventions and remove a
 91 common source of bespoke, error-prone reimplementation in data science notebooks.

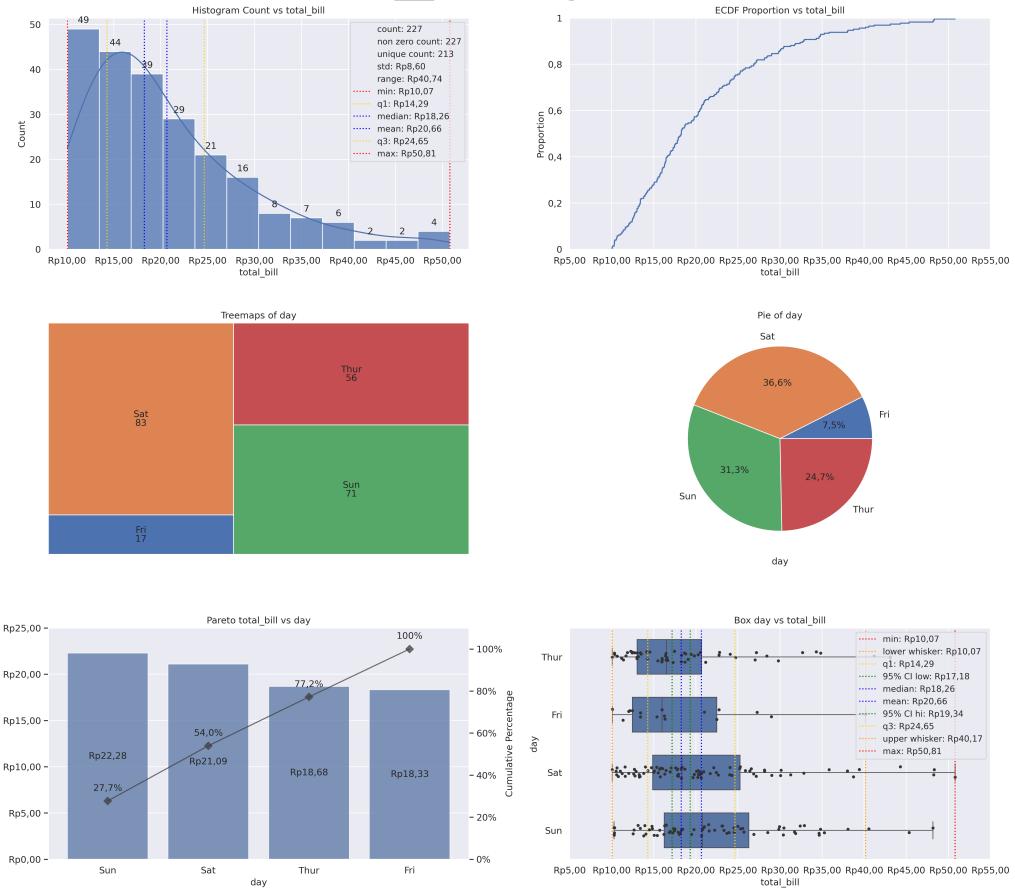


Figure 1: Six-panel 2x3 grid dashboard—histogram, ECDF, treemap, pie, Pareto, and box+strip composite—generated with a single plot2d call and a per-panel row filter applied to the Seaborn tips dataset. Tick formatting (Rp(_)), inset statistical annotation blocks, and bar-top value labels are all configured through plot2d parameters without any post-processing.

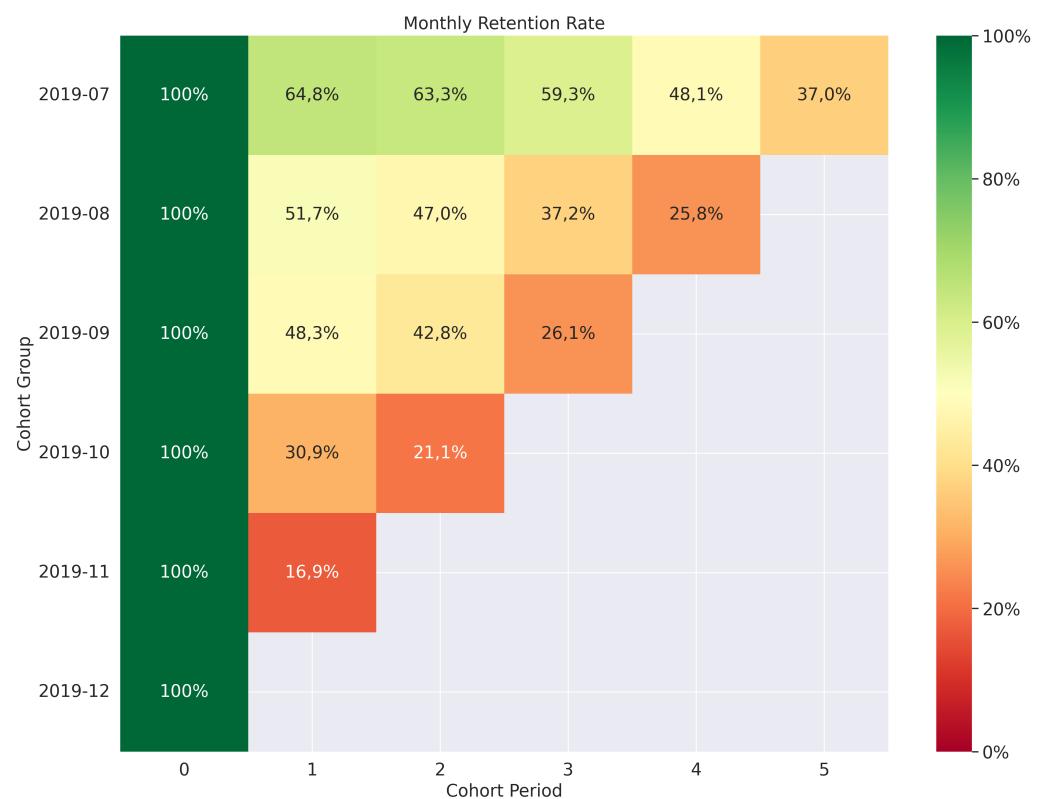


Figure 2: Monthly cohort retention heatmap produced by `grplot.analytic.cohort` from a retail transaction dataset. Rows represent cohort groups (signup month); columns represent cohort periods (months since first purchase); cell values show the percentage of customers active in each subsequent month.

92 Research Impact Statement

93 `grplot` reduces the time and code required to produce annotated, publication-ready figures in
 94 Python. By consolidating multi-step Matplotlib/Seaborn workflows into a single `plot2d` call
 95 with a hierarchical parameter system, it lowers the barrier to exploring and communicating
 96 data for data analysts, researchers, and data scientists who may not have deep expertise in
 97 lower-level graphics APIs. The bundled analytic utilities (`cohort` and `rank_order`) further
 98 accelerate common modeling-evaluation and customer-analysis workflows that practitioners
 99 would otherwise rebuild from scratch. `grplot` supports reproducibility by making figure-
 100 generation code concise, readable, and easy to version-control, and it integrates naturally into
 101 Jupyter notebook environments widely used in data science research.

102 Since its public release, `grplot` has accumulated more than 98,000 total downloads on PyPI
 103 (source: [pypi.tech](https://pypi.org/project/grplot/), retrieved 2026-02-28), ranking in the top 10% of packaged Python projects
 104 by download volume (source: ClickHouse ClickPy, retrieved 2026-02-28). An interactive [Colab](#)
 105 [documentation notebook](#) serves as a community-readiness signal: it allows practitioners to run
 106 all examples in a zero-install environment, and its existence reflects requests from potential
 107 users for a lower-friction entry point than a local installation.

108 AI Usage Disclosure

109 An AI assistant was used solely to assist with brainstorming and idea development during
 110 the writing of this paper. The tool was not used in software creation, code generation, or

¹¹¹ documentation writing. All technical content, design decisions, and architectural choices are
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