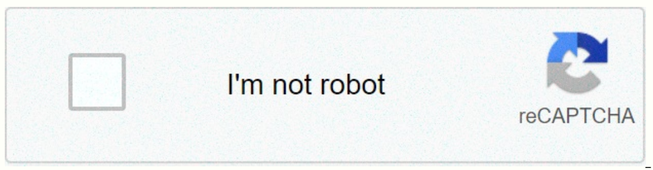

Continue

Sns heatmap styles

Heat maps display numeric tabular data where cells are colored depending on the value contained. Heat maps are great for making trends of this type of data more easily apparent, particularly when data is ordered and there is grouping. dataset: Seaborn - flights %matplotlib inline import pandas as pd import matplotlib.pyplot as plt import seaborn as sns import numpy as np plt.rcParams['figure.figsize'] = (20.0, 10.0) plt.rcParams['font.family'] = serif df = pd.pivot_table(data=sns.load_dataset(flights), index='month', values='passengers', columns='year') df.head() year 1949 1950 1951 1952 1953 1954 1955 1956 1957 1958 1959 1960 month January 11 2 115 145 171 196 204 242 284 315 340 360 417 February 118 126 150 180 196 188 233 277 301 3 18 342 391 March 132 141 178 193 236 235 267 317 356 362 406 419 April 129 135 163 181 235 227 269 313 348 348 396 461 May 121 125 172 183 229 234 270 318 355 363 420 472 Default plot <matplotlib.axes._subplots. AxesSubplot at= 0x10c53b7b8=>cmap adjusts the colormap used. I like divergent colormaps for heat maps because they provide good contrast. sns.heatmap(df, cmap='coolwarm') <matplotlib.axes._subplots. AxesSubplot at= 0x10c65d710=>center can be used to indicate at which numeric value to use the center of the colored map. Above we see most of the map using blues, then setting the center value equal to the midpoint of the data, then we can create a map where there are more equal amounts of red and blue tones. midpoint = (df.values.max() - df.values.min()) / 2 sns.heatmap(df, cmap='coolwarm', center=midpoint) <matplotlib.axes._subplots. AxesSubplot at= 0x10d448860=>Adjust the lower and upper contrast limits with vmin and vmax. Everything below Vmin will be the same color. Similarly for above vmax. midpoint = (df.values.max() - df.values.min()) / 2 sns.heatmap(df, cmap='coolwarm', center=midpoint, vmin=150, vmax=400) <matplotlib.axes._subplots. AxesSubplot at= 0x10da59a90=>Alternatively, you can set vmin and vmax to stay out of the data range to a more muted and washed midpoint = (df.values.max() - df.values.min()) / 2 sns.heatmap(df, cmap='coolwarm', center=midpoint, vmin=-100, vmax=800) <matplotlib.axes._subplots. AxesSubplot at= 0x10e038470=>robust contrast sets based on quantiles and works as an automatic contrast to choose good p values = sns.heatmap(df, cmap='coolwarm', robust=True) Label rectangles with annotations=True, who also chooses an appropriate text color p = sns.heatmap(df, cmap='coolwarm', annot=True) The annotation format can be changed with fmt – here I will change from the default scientific notation to a decimal precision p = sns.heatmap(df, cmap='coolwarm', annot=True , fmt=.1f) Any other parameters for the text, such as font size, can be passed annot_kws. p = sns.heatmap(df, cmap='coolwarm', annot=True, fmt=.1f,annot_kws={'size':16}) cbar</matplotlib.axes._subplots. AxesSubplot> </matplotlib.axes._subplots. AxesSubplot> </matplotlib.axes._subplots. AxesSubplot> </matplotlib.axes._subplots. AxesSubplot> </matplotlib.axes._subplots. AxesSubplot> </matplotlib.axes._subplots. AxesSubplot> </matplotlib.axes._subplots. AxesSubplot> be used to turn off the color bar p = sns.heatmap (df, cmap='coolwarm', annot=True, fmt=.1f, annot_kws={'size':16}, cbar=False) square forces the proportion of blocks to be equal to p = sns.heatmap(df, cmap='coolwarm', annot=True, fmt=.1f, annot_kws={'size':10}, cbar=False, square=True) xticklabels and yticklabels are boolean to turn off the p-axis labels = sns.heatmap(df, cmap='coolwarm', annot=True, fmt=.1f, annot_kws={'size':10}, cbar=False, square=True, xticklabels=False, yticklabels=False) If you want to hide certain values, pass in a binary mask = np.zeros(df.shape) [1:::2,1::2] = 1 p = sns.heatmap(df, cmap='coolwarm', annot=True, fmt=.1f, annot_kws={'size:10}, cbar=False, square=True, xticklabels=False , yticklabels=False, mask=mask) Finalize plt.rcParams['font.size'] = 20 bg_color = (0.88,0,85,0,95) plt.rcParams['figure.facecolor'] = bg_color plt.rcParams['axes.facecolor'] = bg_color fig , fig, ax = plt.subplots(1) p = sns.heatmap(df, cmap='coolwarm', annot=True, fmt=.1f, annot_kws={'size':16}, ax=ax) plt.xlabel ('Month') plt.ylabel ('Year') ax.set_ylim((0.15)) plt.text(5,12.3, Heat Map, fontsize = 95, color='', fontstyle='italic') <matplotlib.text.Text at= 0x10ec6acf8=> p.get_figure().savefig('.). /.. /figures/heatmap.png') Photo by Markus Spiske in UnsplashFor data scientists, verifying correlations is an important part of the exploratory data analysis process. This analysis is one of the methods used to decide which characteristics most affect the target variable and, in turn, are used in the prediction of this target variable. In other words, it is a commonly used method for selecting resources in machine learning. And because visualization is generally easier to understand than reading tabular data, heatmaps are typically used to visualize correlation matrices. A simple way to plot a heat map in Python is by importing and implementing the Seaborn library. From the documentation of the seaborn seaborn heatmaps are attractive to the eyes, and they tend to send clear messages about data almost immediately. That's why this correlation matrix visualization method is widely used by data analysts and data scientists. But what else can we get from the heat map besides a simple correlation matrix plot? In two words: A LOT. Surprisingly, the seaborn heatmap function has 18 arguments that can be used to customize a correlation matrix, improving how quickly insights can be derived. For the purposes of this tutorial, let's use 13 of these arguments. Let's go straight to itTo make things a little simpler for the purposes of this tutorial, let's use one of the data sets preinstalled in Seaborn. The first thing we need to do is import the Seaborn library and load the Note: If you are using Google Colab or any Anaconda package, there is no need to install Seaborn; you just need to import it. Otherwise, use this link </matplotlib.text.Text> </matplotlib.text.Text> install Seaborn.Our data, which is called Tips (a data set preinstalled in the Seaborn library), has 7 columns consisting of 3 numeric features and 4 categorical features. Each entry or line captures a type of customer (whether male or female or smoker or non-smoker) having dinner or lunch on a given day of the week. It also captures the total account amount, tip given, and a customer's table size. (For more information about pre-installed datasets in the Seaborn library, check here) One important thing to note when plotting a correlation matrix is that it completely ignores any nonnumeric column. For the purposes of this tutorial, the entire category variable has been changed to numeric variables. This is what the DataFrame looks like after you dispute. Take a look at how the data was tangled up here. As mentioned earlier, the seaborn heat map function can have 18 arguments. This is how the function looks like all arguments:sns.heatmap (data, vmin=None, vmax=None, cmap=None,center=None, robust=False, annot=None, fmt='.2g', annot_kws=None, line widths=0, linecolor='white', cbar=True, cbar_kws=None, cbar_ax=None, square=False, xticklabels='auto', yticklabels='auto', mask=None, ax=None, **kwargs)Just take a look at the code and have no idea how it works can be very overwhelming. Let's dissect it together. To better understand the arguments, let's group them into 4 categories:2. Adjustment of the shaft (the measuring bar)3. Aesthetics4. Changing the shape of the matrixThe essential argument in the function is to insert the data, since the ultimate goal is to draw a correlation. A .corr() method will be added to the data and approved as the first argument.2. Interpreting the insights only using the first argument is sufficient. For an even easier interpretation, an argument called annot=True must also be approved, which helps display the correlation coefficient.3. There are times when correlation coefficients may be running to 5 decimal digits. A good trick to reduce the displayed number and improve readability is to pass the argument fmt ='.3g'or fmt = '.1g' because by default the function displays two digits after the decimal (greater than zero) i.e. fmt='.2g'(this may not always mean that it displays two decimal places). Let's specify the default argument for fmt='.1g'. For the rest of this tutorial, let's stick to fmt='.2g'Standard axis adjustment (the measuring bar)4. The next three arguments have to do with resizing the color bar. There are times when the correlation matrix bar does not start at zero, a negative number or ends at a certain choice number—or even has a distinct center. All of this can be customized by specifying these three arguments: vmin, which is the minimum value of the bar; Vmax is the maximum value of the bar; and center= . By default, all have not been specified. Let's say we want our color bar to be between -1 to 1 and be centered on 0.An obvious change, in addition to resizing, is that the color has changed. This has to do with changing the center from No to Zero or any other number. But that doesn't mean we can't change the color back or to any other color available. Let's see how to do that. Aesthetics5. Let's change the color by specifying the cmap argument here for more information about the available color codes.6. By default, the thickness and color border of each array line are set to 0 and white, respectively. There are times when the heat map may look better with some edge thickness and a color change. This is where the linewidths and linecolor arguments apply. Let's specify the line widths and line color for 3 and black, respectively. For the rest of this tutorial, we'll go back to the default cmap, linecolor, and line widths. This can be done by passing the following arguments: cmap=None, linecolor='white' and linewidths=0; or not pass the arguments at all (what we will do).7. So far, the heat map used has its color bar displayed vertically. This can be customized to be horizontal by specifying the cbar_kws8. There may also be cases where a heat map may be better off not having a color bar. This can be done by specifying cbar=FalseFor the rest of this tutorial, we will display the color bar.9. Take a closer look at the shape of each matrix box above. They're all rectangular shaped. We can turn them into squares by specifying the argument to square=TrueChanging the array shape Changing the entire shape of the array from rectangular to triangular is a bit complicated. To do this, we'll need to import NumPy .triu() & .tril() methods, and then specify the seaborn heat map argument called mask=.triu() is a Method in NumPy that returns the lower triangle of any array given to it, while .tril() returns the top triangle of any array given to it. The idea is to pass the correlation matrix to the NumPy method and then pass this to the mask argument in order to create a mask in the heat map array. Let's see how this works below. First using the np.trui() method then using the np.tril() method we discovered 13 ways to customize our seaborn heat map to a correlation matrix. The remaining 5 arguments are rarely used because they are very specific to the nature of the data and associated objectives. Full source code for this tutorial can be found on GitHub:ReferencesLearn more about the Seaborn function using the documentation hereTo learn more about how to improve the EDA process through viewing, check out this dataquest tutorial (login required). Note from the Heartbeat is a taxpayer-driven online publication and a community dedicated to exploring the emerging intersection of mobile mobile app development machine learning. We are committed to supporting and inspiring developers and engineers from all walks of life. Editorially independent, heartbeat is sponsored and published by Fritz AI, the machine learning platform that helps developers teach devices to see, hear, feel and think. We pay our taxpayers, and we don't sell ads. If you want to contribute, go to our call for taxpayers. You can also sign up for our weekly newsletters (Deep Learning Weekly and Fritz AI Newsletter), join us at Slack and follow Fritz AI on Twitter for all the news in mobile machine learning. Learning.

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