Plotting with categorical data

- We previously learned how to use scatterplots and regression model fits to visualize the relationship between two variables and how it changes across levels of additional categorical variables.
- However, what if one of the main variables you are interested in is categorical? In this case, the scatterplot and regression model approach wont work. There are several options, however, for visualizing such a relationship, which we will discuss in this tutorial.

- Its useful to divide seaborns categorical plots into two groups: those that show the full distribution of observations within each level of the categorical variable, and those that apply a statistical estimation to show a measure of central tendency and confidence interval.
- The former includes the functions `stripplot()`, boxplot(), and violinplot(), while the latter includes the functions `barplot()`, `countplot()`, and `pointplot()`.
- These functions all share a basic API for how they accept data, although each has specific parameters that control the particulars of the visualization that is applied to that data.

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Much like the relationship between regplot() and lmplot(), in seaborn there are both relatively low-level and relatively high-level approaches for making categorical plots. The functions named above are all low-level in that they plot onto a specific matplotlib axes. There is also the higher-level factorplot(), which combines these functions with a FacetGrid to apply a categorical plot across a grid of figure panels.

It is easiest and best to invoke these functions with a DataFrame that is in tidy format, although the lower-level functions also accept wide-form DataFrames or simple vectors of observations. See below for examples.

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```
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib as mpl
import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="whitegrid", color_codes=True)
np.random.seed(sum(map(ord, "categorical")))
titanic = sns.load_dataset("titanic")
tips = sns.load_dataset("tips")
iris = sns.load_dataset("iris")
```

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Distributions of observations within categories

- The first set of functions shows the full distribution of the quantitative variable within each level of the categorical variable(s).
- These generalize some of the approaches we discussed in the chapter to the case where we want to quickly compare across several distributions.

Categorical scatterplots A simple way to show the distribution of some quantitative variable across the levels of a categorical variable uses stripplot(), which generalizes a scatterplot to the case where one of the variables is categorical:

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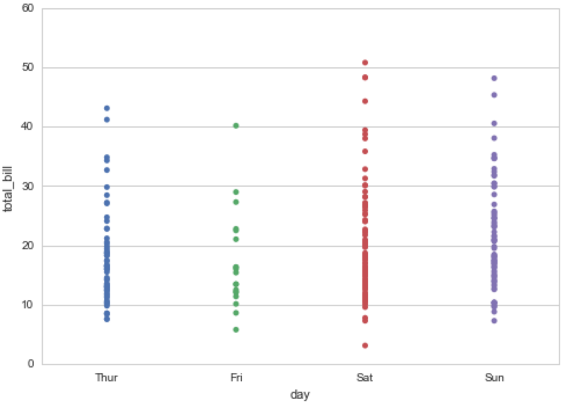
```
sns.stripplot(x="day", y="total_bill", data=tips);
```



- Its also possible to add a nested categorical variable with the hue paramater.
- Above the color and position on the categorical axis are redundent, but now each provides information about one of the two variables:

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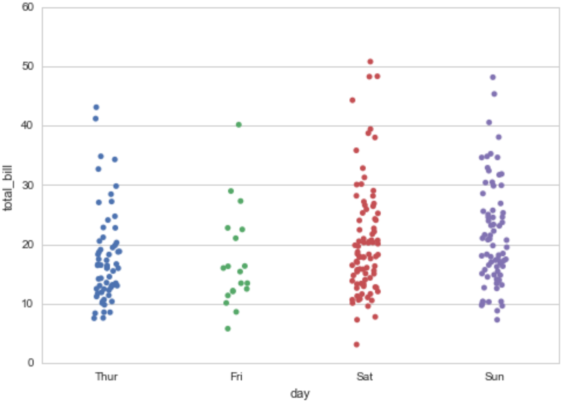
```
sns.stripplot(x="day", y="total_bill", hue="time", data
```



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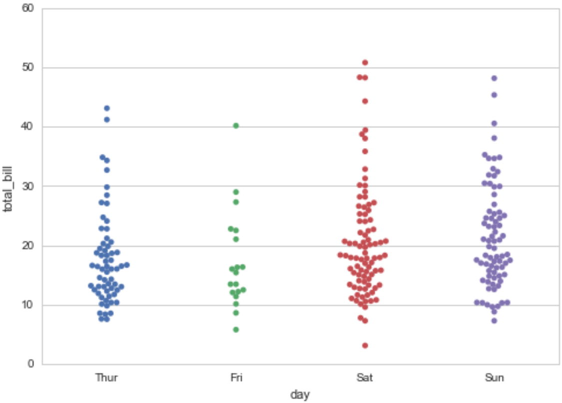
```
sns.stripplot(x="size", y="total_bill", data=tips.sort(
```



With these plots, its often helpful to put the categorical variable on the vertical axis (this is particularly useful when the category names are relatively long or there are many categories):

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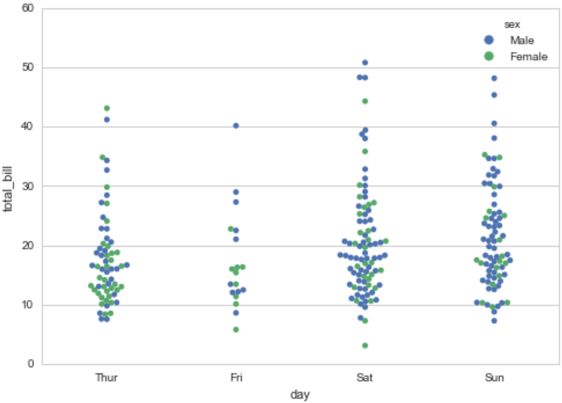
```
sns.stripplot(x="total_bill", y="day", hue="time", data
```

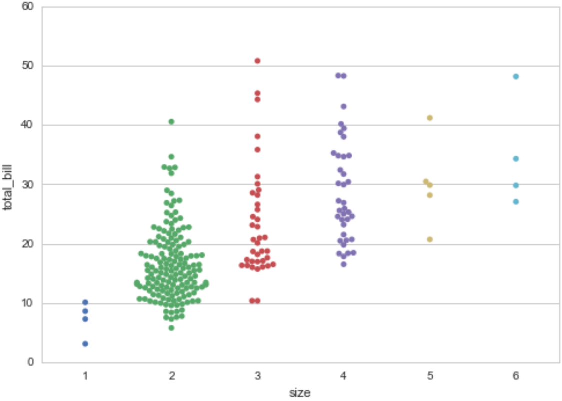


Boxplots

- At a certain point, the categorical scatterplot approach becomes limited in the information it can provide about the distribution of values within each category.
- There are several ways to summarize this information in ways that facilitate easy comparisons across the category levels.

- The first is the familiar `boxplot()`. This kind of plot shows the three quartile values of the distribution along with extreme values.
- The whiskers extend to points that lie within 1.5 IQRs of the lower and upper quartile, and then observations that fall outside this range are displayed independently.
- Importantly, this means that each value in the boxplot corresponds to an actual observation in the data:

```
sns.boxplot(x="day", y="total_bill", hue="time", data=tips)
```



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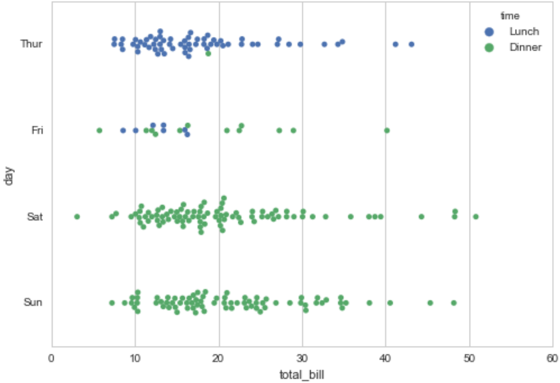
Violinplots A different approach is a violinplot(), which combines a boxplot with the kernel density estimation procedure described in the distributions tutorial

```
sns.violinplot(x="total_bill", y="day", hue="time", dat
```



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- This approach uses the kernel density estimate to provide a better description of the distribution of values.
- Additionally, the quartile and whikser values from the boxplot are shown inside the violin.
- Because the violinplot uses a KDE, there are some other parameters that may need tweaking, adding some complexity relative to the straightforward boxplot:

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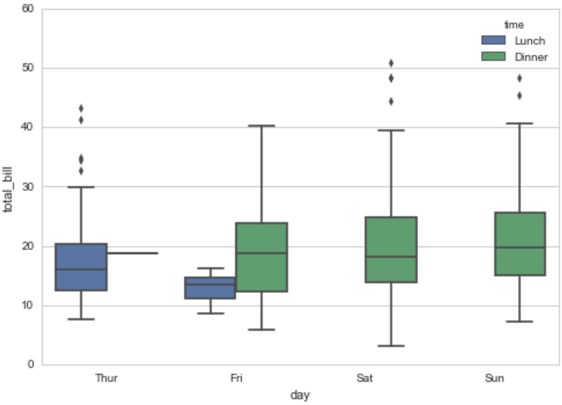
```
sns.violinplot(x="total_bill", y="day", hue="time", dat
bw=.1, scale="count", scale_hue=False);
```



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Its also possible to split the violins when the hue parameter has only two levels, which can allow for a more efficient use of space:

```
sns.violinplot(x="day", y="total_bill", hue="sex", data
```

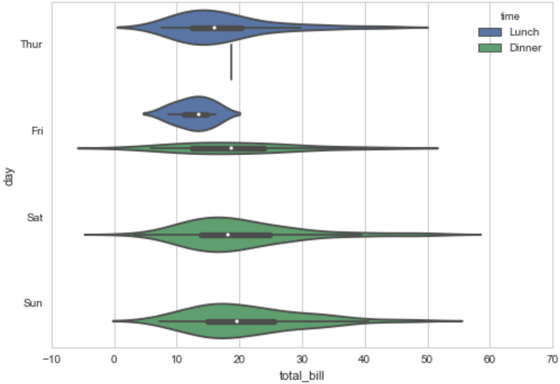

Figure:

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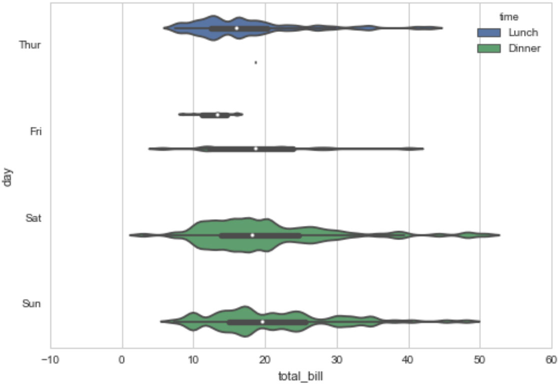
Finally, there are several options for the plot that is drawn on the interior of the violins, including ways to show each individual observation instead of the summary boxplot values:

```
sns.violinplot(x="day", y="total_bill", hue="sex", data=ti
split=True, inner="stick", palette="Set3");
```



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It can also be useful to combine `stripplot()` with `violinplot()` or `boxplot()` to show each observation along with a summary of the distribution:

```
sns.violinplot(x="day", y="total_bill", data=tips, inner=No
sns.stripplot(x="day", y="total_bill", data=tips, jitter=Tr
```