KEY_Practice21_ImprovingPlots_2

July 15, 2019

1 Improving Plots II

As always, let's begin by importing our necessary packages and reading in/previewing our data. In this practice we will continue to explore the titanic dataset.

[0]:
```
# import packages
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

[2]:
```
# read in titanic data
titanic = sns.load_dataset("titanic")
# preview data
titanic.head()
```

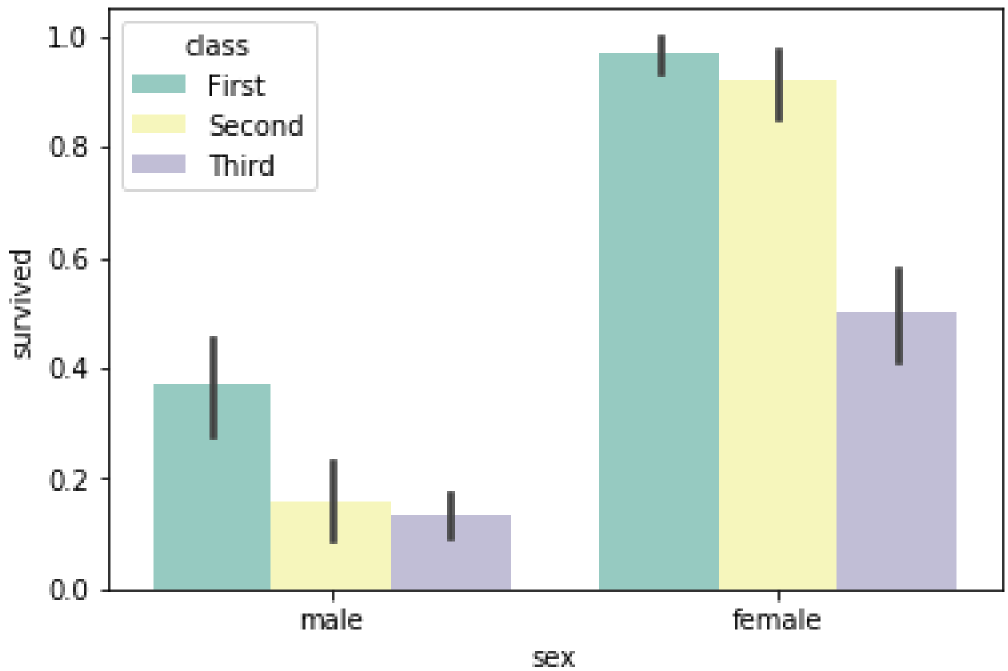
[2]:
```
   survived  pclass     sex   age  ...  deck  embark_town  alive  alone
0         0       3    male  22.0  ...   NaN  Southampton     no  False
1         1       1  female  38.0  ...     C    Cherbourg    yes  False
2         1       3  female  26.0  ...   NaN  Southampton    yes   True
3         1       1  female  35.0  ...     C  Southampton    yes  False
4         0       3    male  35.0  ...   NaN  Southampton     no   True

[5 rows x 15 columns]
```

1.1 Bar Charts

Generate a barplot of survived (y-axis) across sex (x-axis), stratified by class. Choose your favorite color palette.

[3]:
```
# barplot of sex vs survived stratified by class
sns.barplot(x="sex", y = 'survived', hue = "class", palette =␣
↪"Set3",data=titanic)
```

[3]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4e3babd1d0>
```

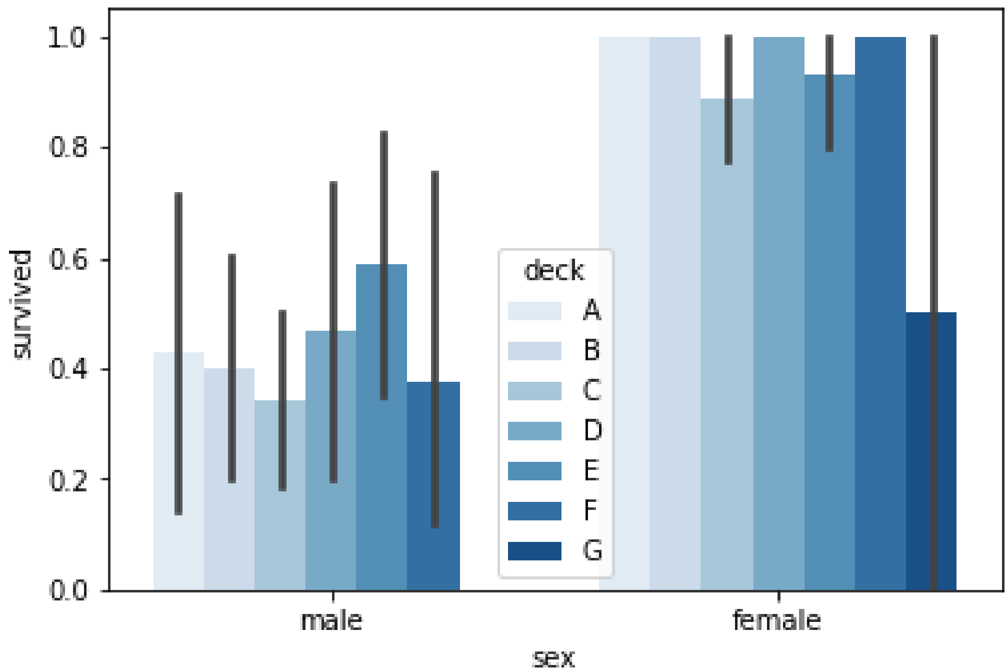


What do you notice about the y-axis in this plot? How can we interpret this? **`survived` is interpreted as numeric by seaborn, so it computes the average for each bar. This can be interpreted as *survival rate* for each group.**

Let's make the same plot, but this time stratified by `deck`. What kind of color palette is appropriate here?

[4]:
```
# barplot of sex vs survived stratified by class
sns.barplot(x="sex", y = 'survived', hue = "deck", palette =␣
↪"Blues",data=titanic)
```

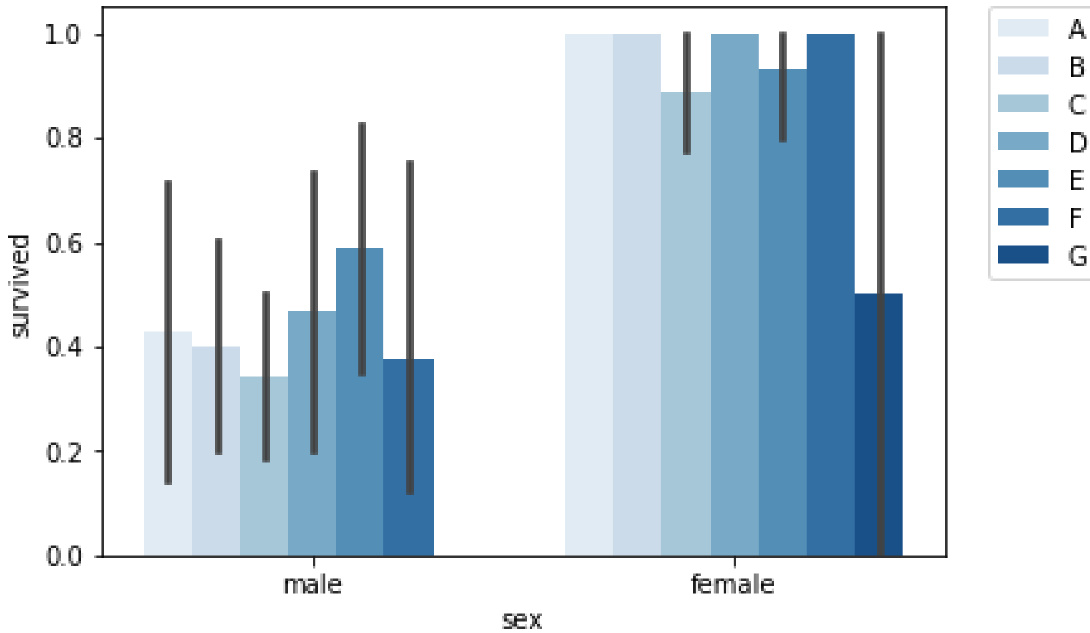
[4]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4e391a1ef0>
```



Hm, the legend is covering up some of the plot - can you find the line from Lesson 21 that we used to move the legend outsise the plot borders?

[5]:
```
# barplot of sex vs survived stratified by class
sns.barplot(x="sex", y = 'survived', hue = "deck", palette =␣
 ↪"Blues",data=titanic)
plt.legend(bbox_to_anchor=(1.05, 1), loc=2, borderaxespad=0.)
```

[5]:
```
<matplotlib.legend.Legend at 0x7f4e3916c4e0>
```



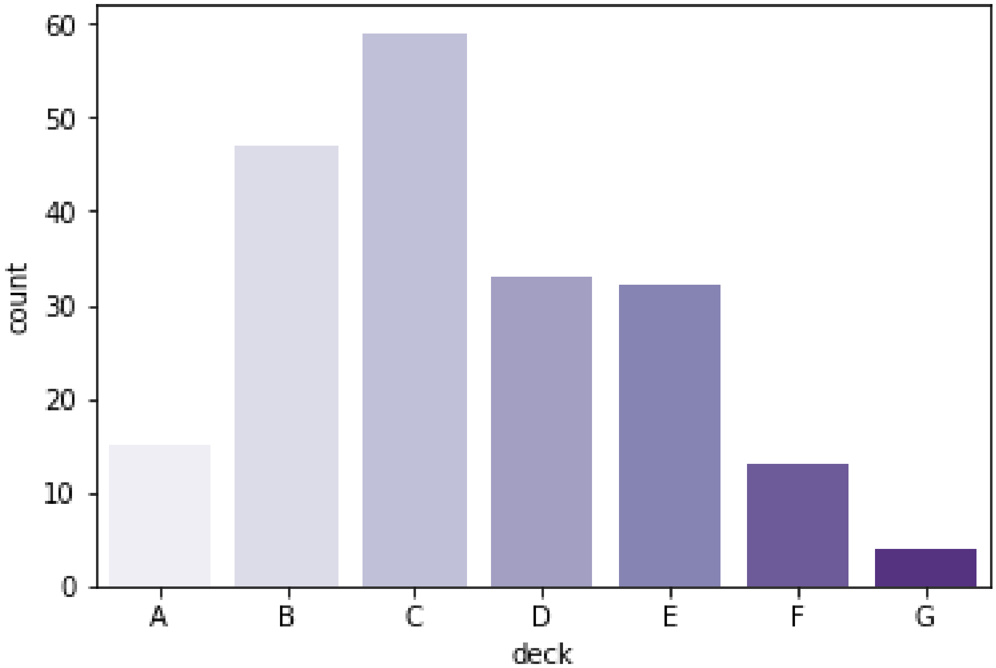
How does our interpretation of the results change here? Because we have stratifed by more groups, there are fewer data points that fall into each bar. Beacuse of this, the survival rates and *inflated* compared to what we saw in the earlier plot, especially for the male groups. This is something you must consider when deciding how to present your data in plots.

1.2 Count Plots

Generate a count plot to visualize the distribution the `deck` variable across all passengers in our data set. Choose a sequential color palette.

[6]:
```
# count plot of deck
sns.countplot(x="deck", palette = "Purples", data=titanic)
```

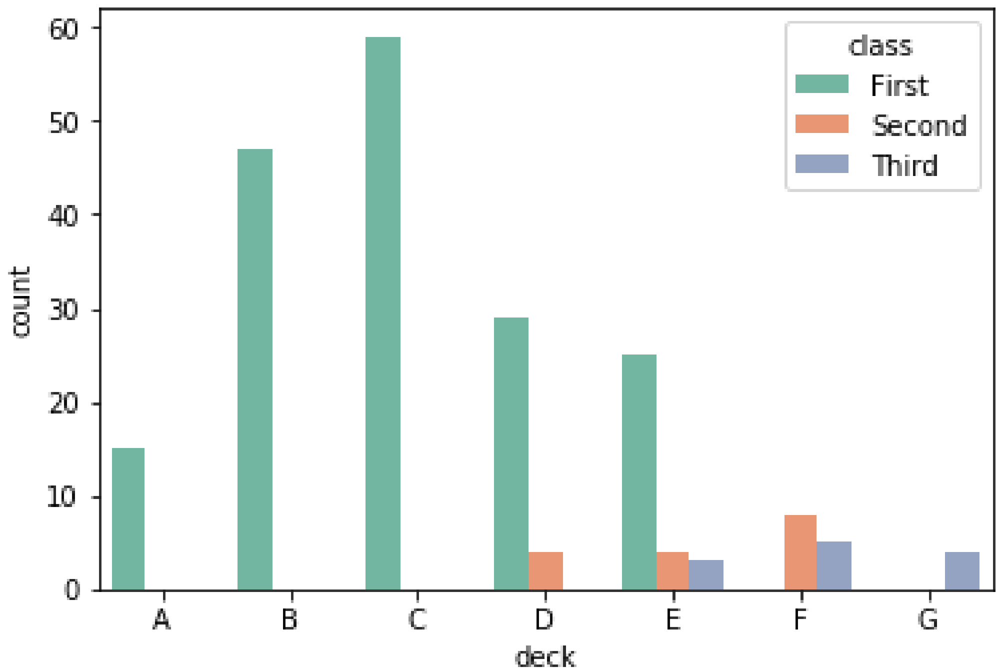
[6]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4e391397f0>
```



Now stratify your plot using the `class` variable. What kind of color palette is appropriate now?

[7]:
```
# count plot of deck stratified by class
sns.countplot(x="deck", hue = "class", palette = "Set2", data=titanic)
```

[7]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f4e39139a90>`



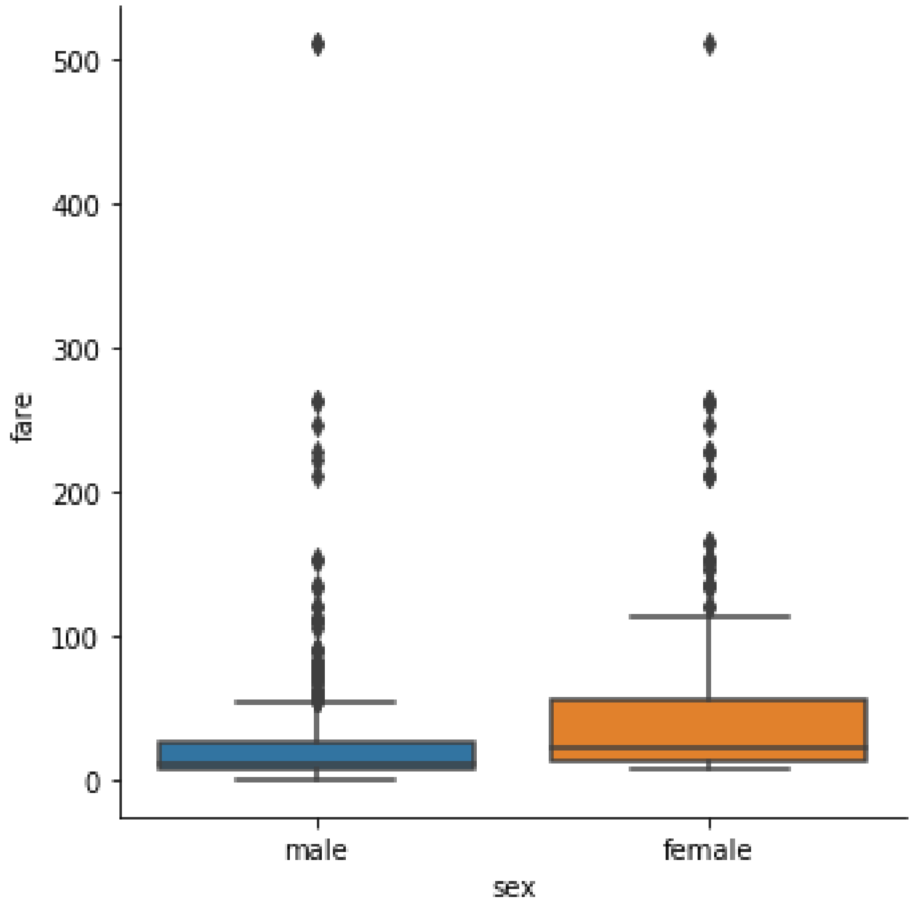
Cool! Now we can see that deck E is the only deck that housed all three classes of passengers.

1.3 Boxplots +

Generate a boxplot of fares across sexes.

[8]:
```
# boxplot of fare across sex
sns.catplot(x = "sex", y="fare", kind="box", data=titanic)
```

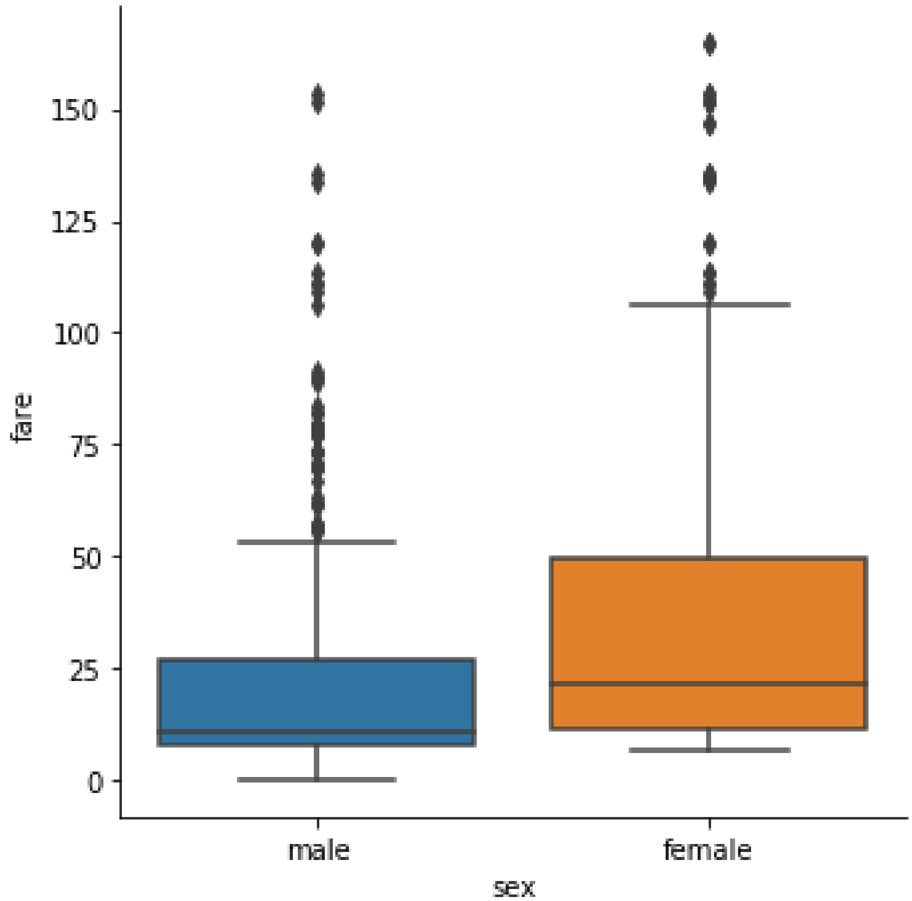
[8]:
```
<seaborn.axisgrid.FacetGrid at 0x7f4e3bb036a0>
```



Based on this plot it looks like there are some outliers that are really smushing the bulk of our data towards the bottom of the plot, making it difficult to interpret. Let's try to remove these outliers by subsetting our `titanic` pandas DataFrame. Create a new DataFrame `titanic_subset` that contains only the rows where `fare` < 200 and generate the same plot for `titanic_subset`.

[9]:
```
# subset where fare < 200
titanic_subset = titanic.query("fare < 200")
# boxplot of fare across sex for subset
sns.catplot(x = "sex", y="fare", kind="box", data=titanic_subset)
```

[9]:
```
<seaborn.axisgrid.FacetGrid at 0x7f4e38f2d240>
```

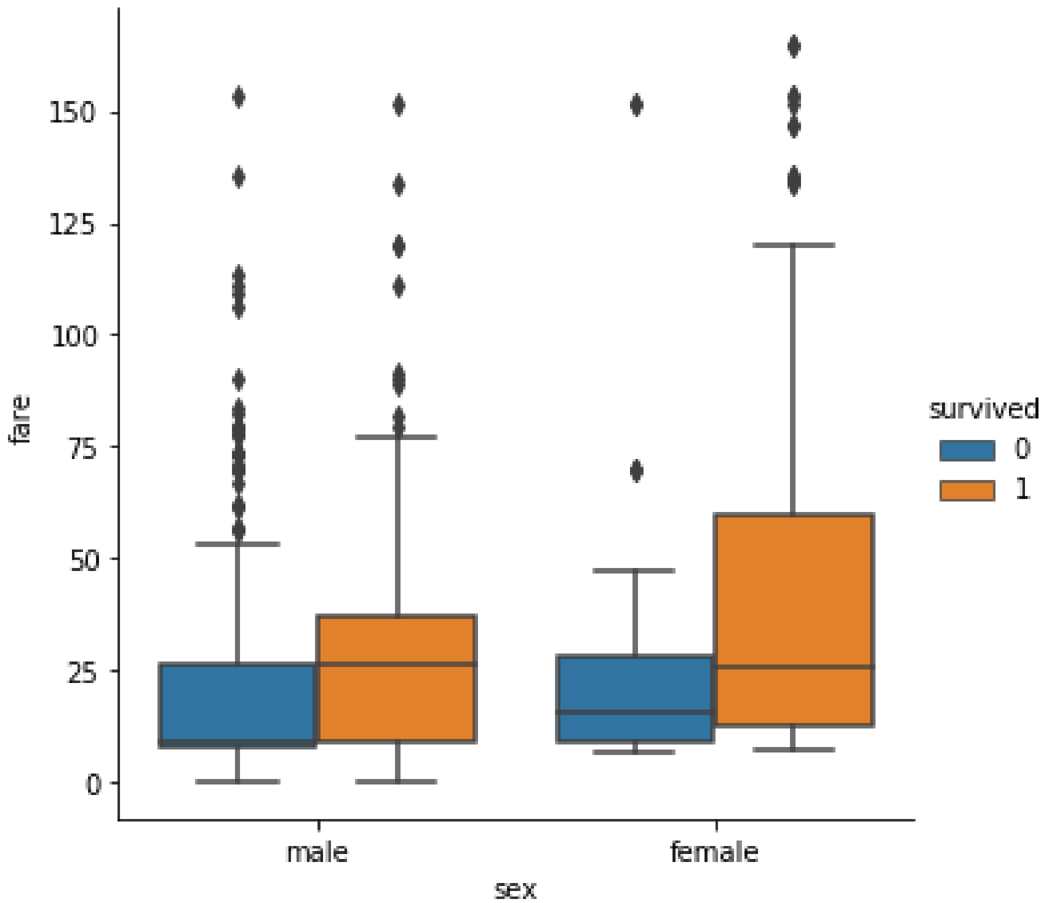


That looks much better, though there are still several high-fare outliers. We will just keep this in mind as we interpret our further analyses.

Let's generate the same boxplot, but this time stratified by `survived`.

[10]:
```
# boxplot of fare across sex stratified by survived for subset
sns.catplot(x = "sex", y="fare", hue = "survived", kind="box",␣
↪data=titanic_subset)
```

[10]:
```
<seaborn.axisgrid.FacetGrid at 0x7f4e3914bcf8>
```

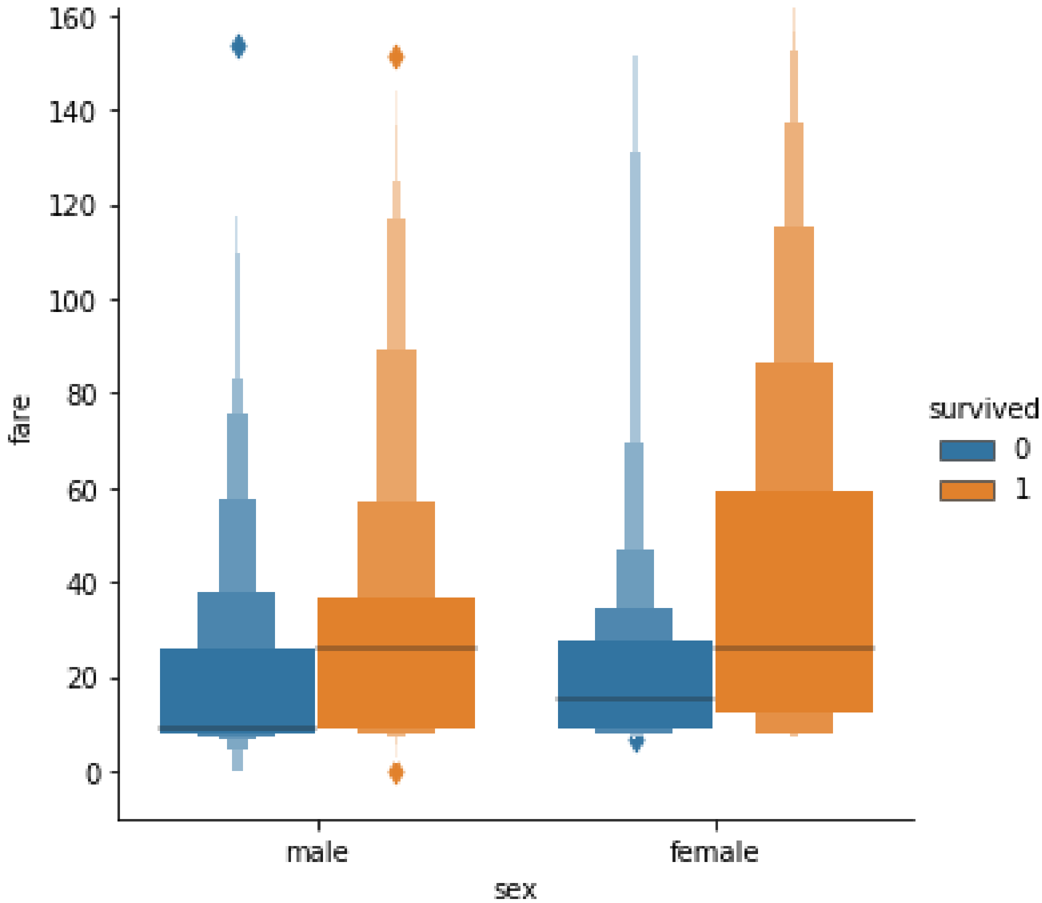


Now, let's try to look at the distribution more granularly using our boxplot variations we learned.

Generate the same plot as a boxen plot:

[11]:
```
# boxen plot of fare across sex stratified by survived for subset
sns.catplot(x = "sex", y="fare", hue = "survived", kind="boxen",␣
 ↪data=titanic_subset)
```

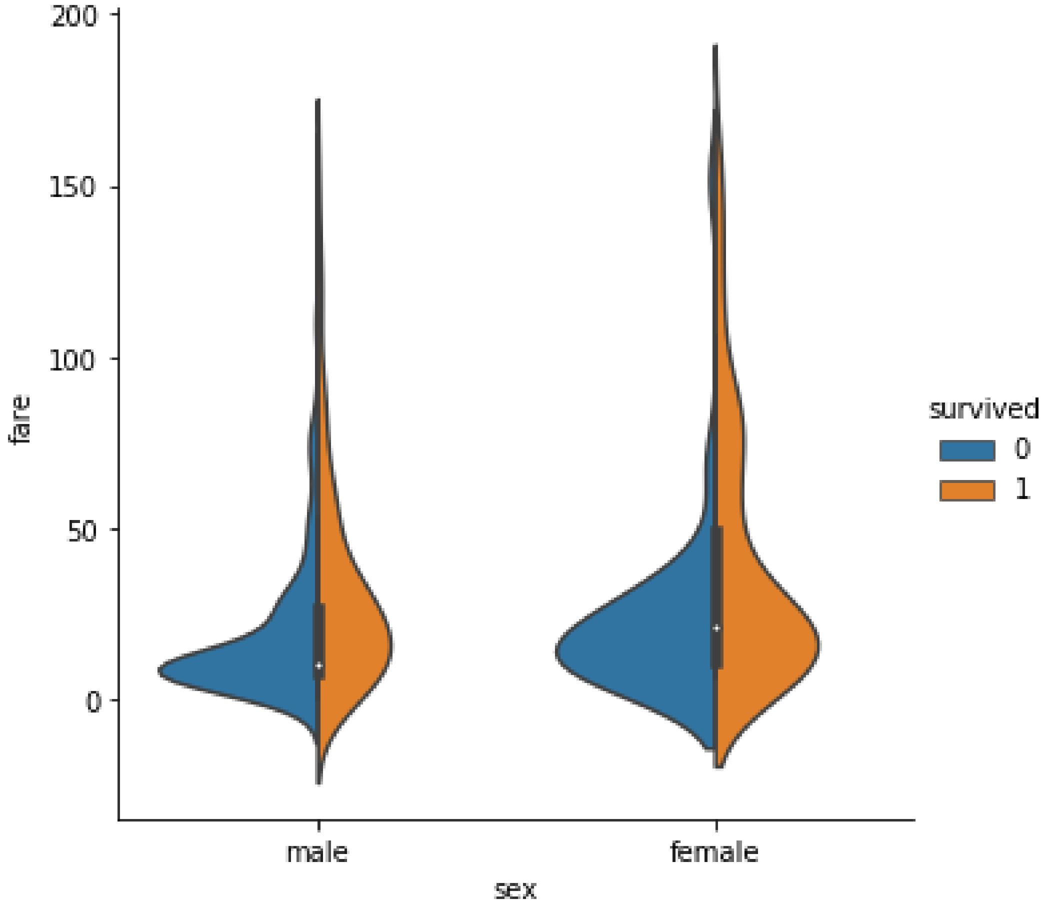
[11]:
```
<seaborn.axisgrid.FacetGrid at 0x7f4e38ef46a0>
```



Now generate the same plot as a violin plot. Use the `split = True` parameter setting to make your comparisons between the `survived` groups easier.

[12]:
```
# violin plot of fare across sex stratified by survived for subset
sns.catplot(x = "sex", y="fare", hue = "survived", kind="violin", split = True,␣
  ↪data=titanic_subset)
```

[12]:
```
<seaborn.axisgrid.FacetGrid at 0x7f4e37b89048>
```



Which plot do you think is most informative in this case: boxplot, boxen plot or split violin plot?

Based on that plot, what is your interpretation about the relationship between fare, gender and survival on the Titanic?