Code.Hub

Data Visualization (part 2)

Seaborn

> Seaborn is a visualization library based on matplotlib. It provides a higher-level interface for drawing statistical graphs. It also supports data structures from numpy and pandas and statistical routines from scipy.

As we saw, matplotlib does has a lot of options, but it can be rather hard to make its figures aesthetically pleasing. Seaborn's goal is to fill that gap and produce figures much easier than with matplotlib.

Similar to matplotlib's styles, in seaborn we can also set all the aesthetic parameters in one step. This is done by the `seaborn.set(...)` .

Visualizing the distribution of a variable

This can be achieved through a **distribution plot**

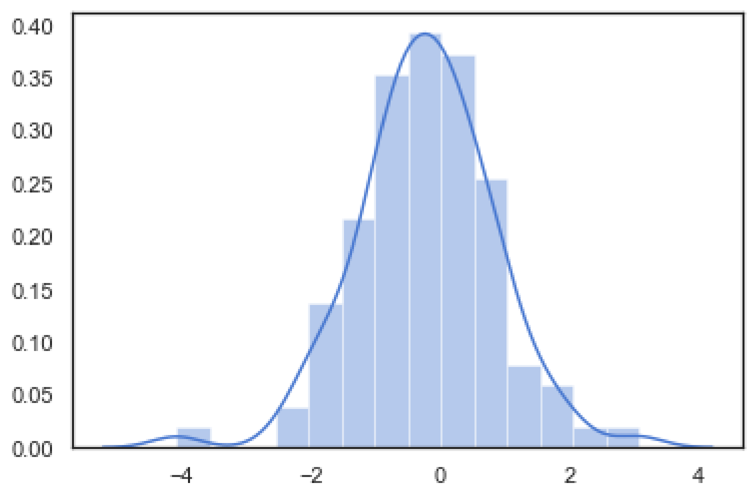
These plots can be useful for visualizing the distribution of a continuous variable.

```
sns.distplot(x)
```

where `x` is a sequence of samples of a continuous-valued variable. If `x` is a pandas Series with a `name` attribute, then the name will be used to label the axis. `sns.distplot` (https://seaborn.pydata.org/generated/seaborn.distplot.html) can internally calculate the optimal size of the bins with the Freedman–Diaconis rule (https://en.wikipedia.org/wiki/Freedman%E2%80%93Diaconis_rule). Obviously, we can select our own bins through the `bins` argument.

In [1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline

sns.set(style="white", palette="muted", color_codes=True)  # sets aesthetic param

d = np.random.normal(size=100)  # random normal

sns.distplot(d)  # plot the distribution of d
```

Out[1]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x20119f19a20>
```



Notice how we produced a rather complex graph in just one line! In order to produce the same through matplotlib we would need to first bin the data, draw a barplot, customize it so that the bars are closer and have the same color and finally calculate and draw the thick line on top. But what is this line?

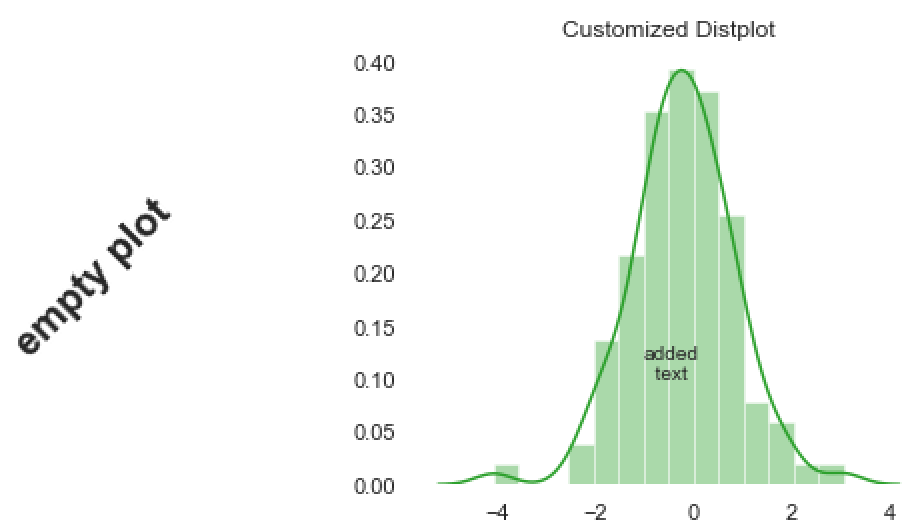
By default `sns.distplot()` will draw a histogram and fit a [Kernel Density Estimation (KDE) (https://en.wikipedia.org/wiki/Kernel_density_estimation)](https://en.wikipedia.org/wiki/Kernel_density_estimation). This is a non-parametric way to predict the probability density function of a random variable. The KDE can be removed by setting the parameter `kde=False` .

Seaborn has a [great tutorial (https://seaborn.pydata.org/tutorial/distributions.html)](https://seaborn.pydata.org/tutorial/distributions.html) exploring the different options when visualizing variable distributions.

Because seaborn is built on top of matplotlib, we can further customize the plot in any way we want. It can accept an *axes* object (parameter `ax`) and draw the plot on that object. This is useful for placing it in a subplot, wherever we want. It returns the same *axes* object with drawn plot. If no *axes* is passed, like before, it will produce one on its own.

In [2]:
```
# We want to create two subplots and place it on the right one
f = plt.figure(figsize=(10, 4))
ax1 = plt.subplot(121)
ax2 = plt.subplot(122)

# Write something on the left subplot
ax1.text(0.4, 0.6, 'empty plot', rotation=45, size=20, weight='bold')
ax1.axis('off')

# Draw the distplot and retrieve its 'axes' object
ax2 = sns.distplot(d, color='#2ca02c', ax=ax2)

# Customize the 'axes' object any way we want
ax2.set_title('Customized Distplot')
ax2.set_xlabel('$x$')
ax2.set_xlabel('')
ax2.spines['right'].set_visible(False)
ax2.spines['left'].set_visible(False)
ax2.spines['top'].set_visible(False)
ax2.spines['bottom'].set_visible(False)

# Add more elements to the distplot
ax2.text(-1, 0.1, 'added\n  text')
```

Out[2]:
```
Text(-1,0.1,'added\n  text')
```



Visualizing the relationship among two continuous variables

The easiest way to do this is through a **regression plot**.

This type of plot scatters the data points and **fits a linear regression** model to it.

```
sns.regplot(x, y, data=None)
```

There are two ways to draw a regplot:

1. The regular way of using `x` and `y`, two sequences containing the x and y coordinates of the data points.
2. By using a pandas DataFrame. In this case the DataFrame should be passed as the `data` argument and should contain two columns with the x and y coordinates of the data points. The names of these two columns are passed as strings to the `x` and `y`.

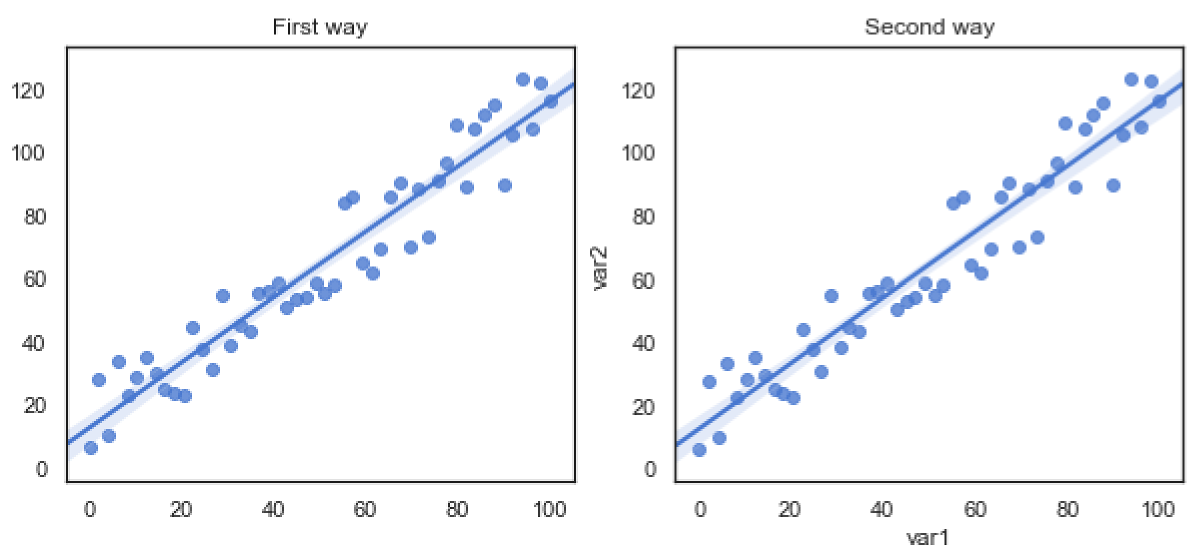
Seaborn **synergizes** well with DataFrames, so the second way is recommended.

Most of the other parameters regulate the functionality of the estimator performing the fit. An important parameter is `ax`, which works like we saw in the previous plot. A list of all available parameters can be found [here (https://seaborn.pydata.org/generated/seaborn.regplot.html)](https://seaborn.pydata.org/generated/seaborn.regplot.html).

We'll create two regplots, one with the first way and one with the second.

In [3]:
```
# Create new x and y data
np.random.seed(5)
x = np.linspace(0, 100, 50)
y = x + np.random.random(50) * 30

# Store these two in a DataFrame
df = pd.DataFrame({'var1': x, 'var2': y})

plt.figure(figsize=(10, 4))

# Draw first figure
ax = plt.subplot(121)
ax = sns.regplot(x, y, ax=ax)
ax.set_title('First way')

# Draw second figure
ax = plt.subplot(122)
ax = sns.regplot(x='var1', y='var2', data=df, ax=ax)
ax.set_title('Second way')
```

Out[3]:
```
Text(0.5,1,'Second way')
```



These two ways produced identical plots, with the only difference that the second took the liberty of naming the axes with the column names from the DataFrame.

In the figures above the blue dots are the **data points** contained in the two variables. The blue line is the **linear regression** line, while the shaded light blue area is the **confidence interval**, currently at 95%.

A nice tutorial on visualizing linear relationships in seaborn can be found [here (https://seaborn.pydata.org/tutorial/regression.html#regression-tutorial)](https://seaborn.pydata.org/tutorial/regression.html#regression-tutorial).

Visualizing the relationship between a continuous (dependent) and a discrete (independent) variable

Another way of visualizing relationships between discrete and continuous variables is through barplots. Barplots can be used with both **ordinal** and **categorical** discrete variables. Seaborn has its own way of creating barplots, through [`sns.barplot` (https://seaborn.pydata.org/generated/seaborn.barplot.html)](https://seaborn.pydata.org/generated/seaborn.barplot.html).

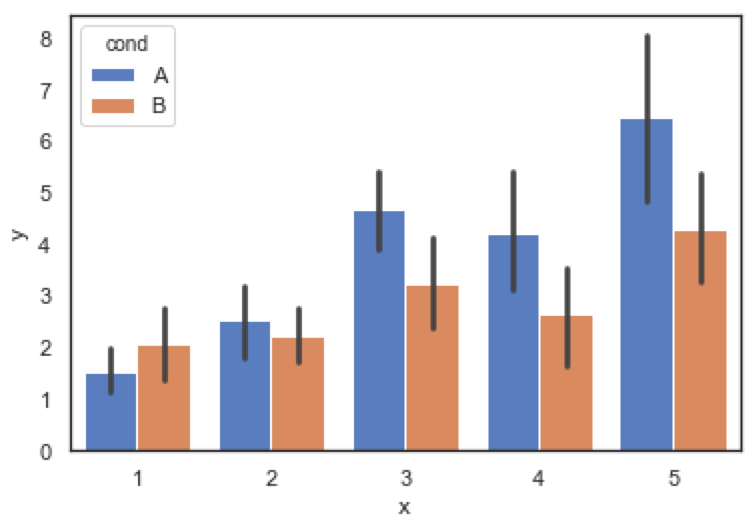
```
ax = sns.barplot(x, y, data=None)
```

Like we saw in the previous seaborn functions, there are two ways to draw barplots. Either `x` and `y` sequences containing the relevant data or they are the names of the columns in a DataFrame containing the same; the second way is recommended.

Seaborn barplots can subset the data like we saw with the `sns.lmplot` before. However, seaborn barplots **can** accept and return matplotlib *axes* objects.

In [13]:
```
df3 = pd.DataFrame({'x': [1] * 15 + [2] * 15 + [3] * 15 + [4] * 15 + [5] * 15 +
                         [1] * 15 + [2] * 15 + [3] * 15 + [4] * 15 + [5] * 15,
                    'y': np.r_[np.random.random(15) * 3, np.random.random(15) * 5
                               np.random.random(15) * 7, np.random.random(15) * 9
                               np.random.random(15) * 11,
                               np.random.random(15) * 4, np.random.random(15) * 5
                               np.random.random(15) * 6, np.random.random(15) * 7
                               np.random.random(15) * 8],
                    'cond': ['A'] * 75 + ['B'] * 75})

sns.barplot(x='x', y='y', hue='cond', data=df3)
```

Out[13]: `<matplotlib.axes._subplots.AxesSubplot at 0x2011d8ed940>`

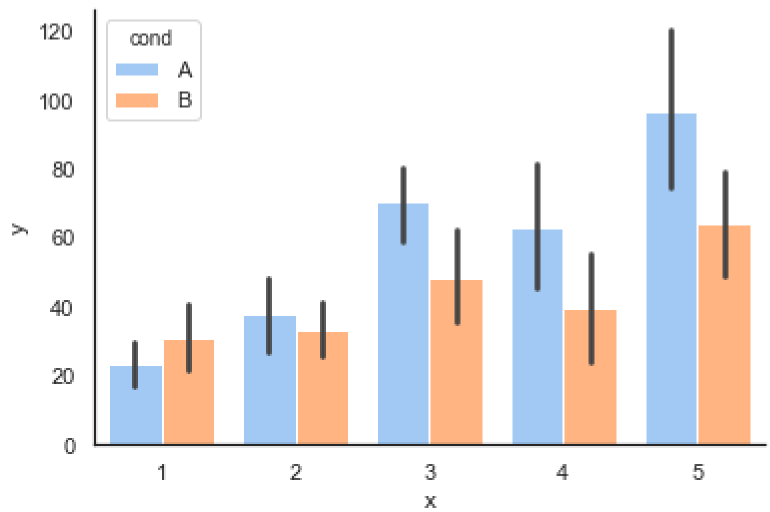


The above barplot shows the *mean* y for each category in x, partitioned by `cond`. The black lines represent the **confidence interval** of each category, currently set to 95% of the observations.

We can change the **estimator** (i.e. the function that maps the values of each bin to a single value; currently `np.mean`) if we want. We are going to make it so that the y axis represents the *sum* of all values in a bin, instead of the *mean*.

We'll also change the colors of the bars by changing the [color palette (https://seaborn.pydata.org/tutorial/color_palettes.html)](https://seaborn.pydata.org/tutorial/color_palettes.html) and **saturation** of the colors.

In [14]:
```
ax = sns.barplot(x='x', y='y', hue='cond', palette='pastel', saturation=1, estima
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
```



There are two more plots we can use to visualize the same information: **boxplots** and **violinplots**. Besides the relationship visible through the barplot, both boxplots and violinplots also convey information about the **distribution** of data in each category.

```
sns.boxplot(x, y, data=None)
```

```
sns.violinplot(x, y, data=None)
```

A more extensive tutorial on plotting categorical data with seaborn can be found [here (https://seaborn.pydata.org/tutorial/categorical.html#categorical-tutorial)](https://seaborn.pydata.org/tutorial/categorical.html#categorical-tutorial)

Visualizing the relationship between two discrete variables

One way of visualizing the relationship between two discrete variables, is through a **heatmap**. A heatmap is essentially a color-coded 2-dimensional matrix. Heatmaps can be done with categorical data, but work best with ordinal variables, as it provides spatial information.

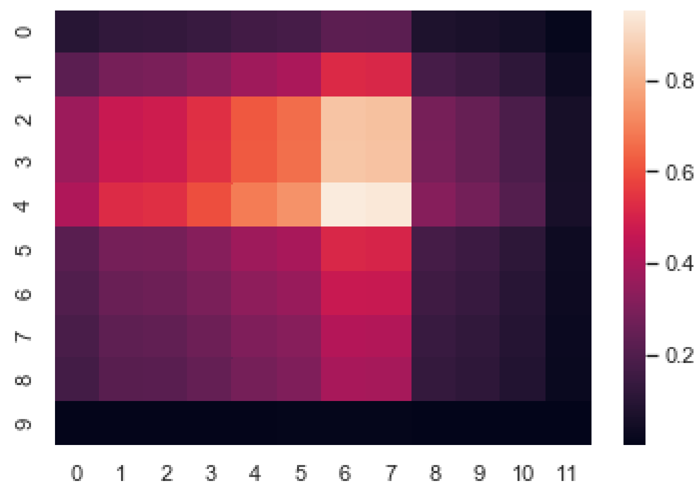
This is done with `sns.heatmap` (https://seaborn.pydata.org/generated/seaborn.heatmap.html).

```
sns.heatmap(data)
```

Heatmaps are different than the other seaborn functions we've seen up till now in that they require the 2D array to be passed as an argument in order to work.

In [17]:
```
# Create heatmap data. We want the highest values to be near the center and the l
np.random.seed(8)
# Create 10 columns the first 5 with random ascending values the last 5 with desc
cols = np.r_[np.sort(np.random.random(5)).reshape(-1, 1), np.sort(np.random.rando
# Create 12 rows in the same fashion
rows = np.r_[np.sort(np.random.random(6)), np.sort(np.random.random(6))[::-1]]
# Let numpy's broadcasting do the trick to populate the 2D array.
data = cols * rows

sns.heatmap(cols * rows)
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x2011ed722e8>



Obviously, this way isn't very helpful, as we must construct the full 2D array ourselves. Pandas' [pivot (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.pivot.html)](https://pandas.pydata.org/pandas-docs/stable/generated/pandas.DataFrame.pivot.html) can make our life easier.

In [18]:
```
# Create a DataFrame containing monthly revenues during a 10-year span
np.random.seed(9)
month_trend = np.r_[np.sort(np.random.random(6)).reshape(-1, 1), np.sort(np.randc
months = ['January', 'Febuary', 'March', 'April', 'May', 'June', 'July',
          'August', 'September', 'October', 'November', 'December']
year_trend = np.sort(np.random.random(20))
years = range(1999, 2019)

revenue = month_trend * year_trend * 10000
month_col = np.repeat(months, len(years))
year_col = np.tile(years, len(months))

df4 = pd.DataFrame({'Month': month_col, 'Year': year_col, 'Revenue': revenue.rave

print(df4.shape)
df4.sample(5)
```

```
(240, 3)
```

Out[18]:

	Month	Revenue	Year
190	October	1734	2009
201	November	282	2000
196	October	2333	2015
104	June	2615	2003
166	September	1978	2005

We can easily turn this into a 2D array through the `pd.DataFrame.pivot()` method.

In [19]:

```
df4.pivot('Month', 'Year', 'Revenue')
```

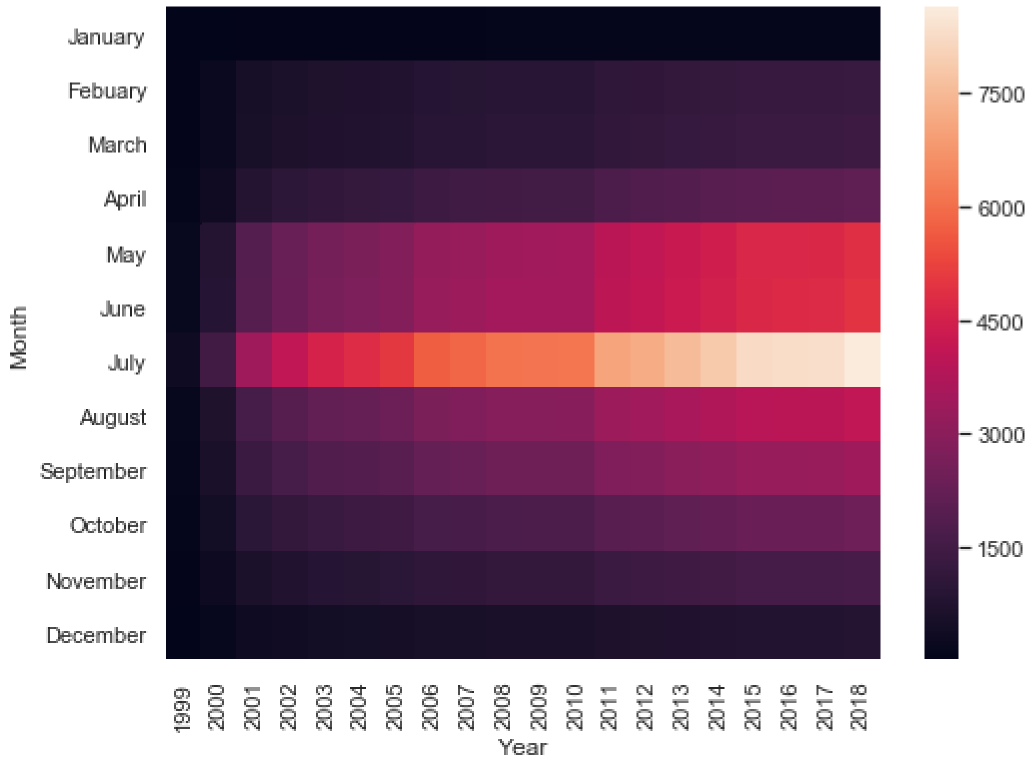
Out[19]:

Year	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Month														
April	84	370	844	1017	1138	1197	1251	1419	1457	1517	1527	1535	1756	1802
August	162	709	1617	1948	2180	2292	2397	2718	2791	2906	2925	2939	3363	3452
December	32	142	324	391	438	460	481	546	560	583	587	590	675	693
Febuary	51	227	517	623	697	733	766	869	892	929	935	940	1075	1103
January	4	17	40	48	54	56	59	67	69	72	72	72	83	85
July	340	1490	3395	4091	4578	4813	5032	5706	5859	6101	6142	6171	7061	7246
June	194	851	1939	2337	2615	2749	2874	3259	3346	3485	3508	3525	4033	4139
March	55	241	549	661	740	778	813	923	947	986	993	998	1142	1172
May	192	841	1916	2308	2583	2716	2839	3220	3306	3442	3465	3482	3984	4089
November	64	282	644	776	869	913	955	1083	1112	1158	1165	1171	1340	1375
October	96	420	958	1155	1292	1359	1421	1611	1654	1722	1734	1742	1994	2046
September	133	586	1335	1608	1800	1892	1978	2244	2304	2399	2415	2426	2776	2849

This pivot is almost what we need; the only problem is that the months are not sorted. However, in order to benefit from the ordinal nature of the `Month` variable and consequently from the spatial nature of the heatmap, we should order the months properly.

In [20]:
```
plt.figure(figsize=(8, 6))
sns.heatmap(df4.pivot('Month', 'Year', 'Revenue').reindex(months, axis=0))
```

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x2011eca0668>



Heatmaps are useful for these situations, because its spatial nature can convey a lot of information. For instance, from the heatmap above we can deduce that almost all revenue comes from summer months and the revenue raises steadily from year to year.

Another common use of heatmaps is to visualize the correlations between variables. We'll see an example later.

Final remarks

Seaborn introduces a nice way of creating nice plots with relative ease. The fact that it is built on top of matplotlib, gives us a lot of freedom in customizing any of the plots, however we want.

Of course, the types of plots we covered are only few of the many seaborn functions. An easy way of discovering the capabilities of this library is through seaborn's [example gallery (https://seaborn.pydata.org/examples/index.html)](https://seaborn.pydata.org/examples/index.html).

Another, very useful resource covering both matplotlib and seaborn examples is the [Python graph gallery (https://python-graph-gallery.com/)](https://python-graph-gallery.com/). From this site you can find examples of any plot you can imagine, along with tips on using them.

Now that we've gone showcasing several of matplotlib and seaborn's capabilities, it's time we use them in practice.

Exploratory Data Analysis

In a previous tutorial we saw how we can perform EDA with the pandas library. However, EDA isn't complete unless we can visualize our data. First, let's see an example of **why** data visualization in necessary in EDA. The data we are going to use are called the [Anscombe's quartet (https://en.wikipedia.org/wiki/Anscombe%27s_quartet)](https://en.wikipedia.org/wiki/Anscombe%27s_quartet).

> Anscombe's quartet comprises four datasets that have nearly identical simple descriptive statistics, yet appear very different when graphed. Each dataset consists of eleven (x,y) points. They were constructed in 1973 by the statistician Francis Anscombe to demonstrate both the importance of graphing data before analyzing it and the effect of outliers on statistical properties.

In [21]:
```
quartet = sns.load_dataset('anscombe')

# create new columns for statistical descriptions
for num in quartet.dataset.unique():
    quartet[str(num) + 'x'] = quartet[quartet.dataset == str(num)].x
    quartet[str(num) + 'y'] = quartet[quartet.dataset == str(num)].y
```

Let's try to describe these four different datasets, using **just** their statistical characteristics:

In [22]:
```
quartet.loc[:, ['Ix', 'IIx', 'IIIx', 'IVx']].describe()
```

Out[22]:

	Ix	IIx	IIIx	IVx
count	11.000000	11.000000	11.000000	11.000000
mean	9.000000	9.000000	9.000000	9.000000
std	3.316625	3.316625	3.316625	3.316625
min	4.000000	4.000000	4.000000	8.000000
25%	6.500000	6.500000	6.500000	8.000000
50%	9.000000	9.000000	9.000000	8.000000
75%	11.500000	11.500000	11.500000	8.000000
max	14.000000	14.000000	14.000000	19.000000

In [23]:
```
quartet.loc[:, ['Iy', 'IIy', 'IIIy', 'IVy']].describe()
```

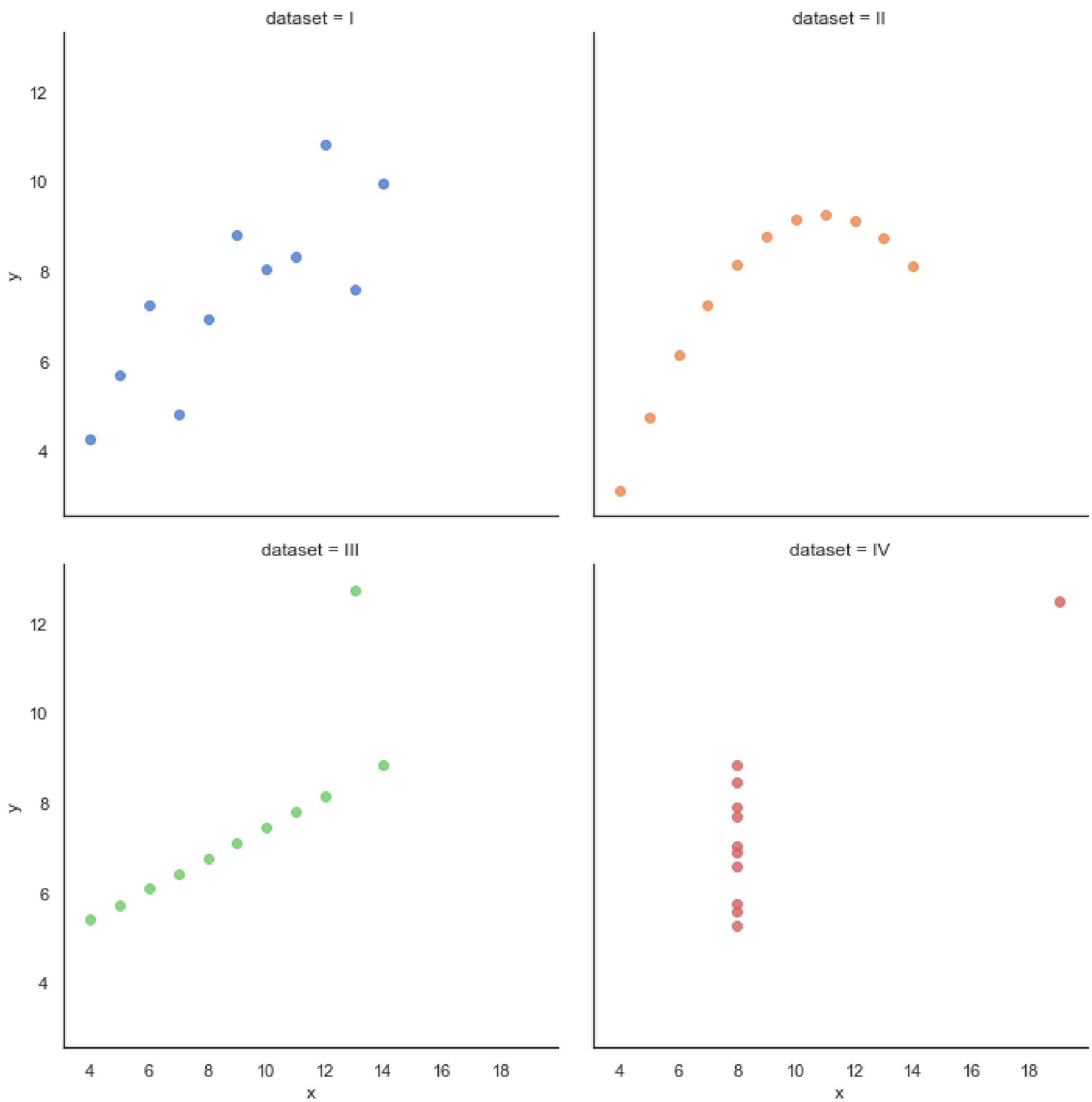
Out[23]:

	Iy	IIy	IIIy	IVy
count	11.000000	11.000000	11.000000	11.000000
mean	7.500909	7.500909	7.500000	7.500909
std	2.031568	2.031657	2.030424	2.030579
min	4.260000	3.100000	5.390000	5.250000
25%	6.315000	6.695000	6.250000	6.170000
50%	7.580000	8.140000	7.110000	7.040000
75%	8.570000	8.950000	7.980000	8.190000
max	10.840000	9.260000	12.740000	12.500000

These four datasets share virtually the same basic statistical characteristics, but if we plot them, we'll see that they are indeed very different.

In [24]:
```
sns.lmplot(x='x', y='y', col='dataset', hue='dataset', data=quartet, col_wrap=2,
```

Out[24]: <seaborn.axisgrid.FacetGrid at 0x2011eef3550>



This is an extreme example, but it shows that we can't rely solely on descriptive statistics when performing an EDA, as it can sometimes mislead us. We can gain a lot of insight by visualizing our data!

Let's continue to our main EDA example. While we won't perform an extensive EDA covering every variable, we'll instead view a few distributions and associations to see how they can be visualized in practice. First, we'll import a [dataset (http://archive.ics.uci.edu/ml/machine-learning-databases/autos/imports-85.names)](http://archive.ics.uci.edu/ml/machine-learning-databases/autos/imports-85.names) describing automobile sales.

In [25]:
```
df = pd.read_csv('http://archive.ics.uci.edu/ml/machine-learning-databases/autos/

df.columns = ['symboling', 'normalized-losses', 'make', 'fuel-type', 'aspiration'
              'body-style', 'drive-wheels', 'engine-location', 'wheel-base', 'ler
              'curb-weight', 'engine-type', 'num-of-cylinders', 'engine-size', 'f
              'stroke', 'compression-ratio', 'horsepower', 'peak-rpm', 'city-mpg'

# Remove NaN values:
df = df.applymap(lambda x: x if '?' not in str(x) else np.nan)
df = df.dropna()

print(df.shape)
df.head()
```

(159, 26)

Out[25]:

	symboling	normalized-losses	make	fuel-type	aspiration	num-of-doors	body-style	drive-wheels	engine-location	wheel-base	...	e
3	2	164	audi	gas	std	four	sedan	fwd	front	99.8	...	
4	2	164	audi	gas	std	four	sedan	4wd	front	99.4	...	
6	1	158	audi	gas	std	four	sedan	fwd	front	105.8	...	
8	1	158	audi	gas	turbo	four	sedan	fwd	front	105.8	...	
10	2	192	bmw	gas	std	two	sedan	rwd	front	101.2	...	

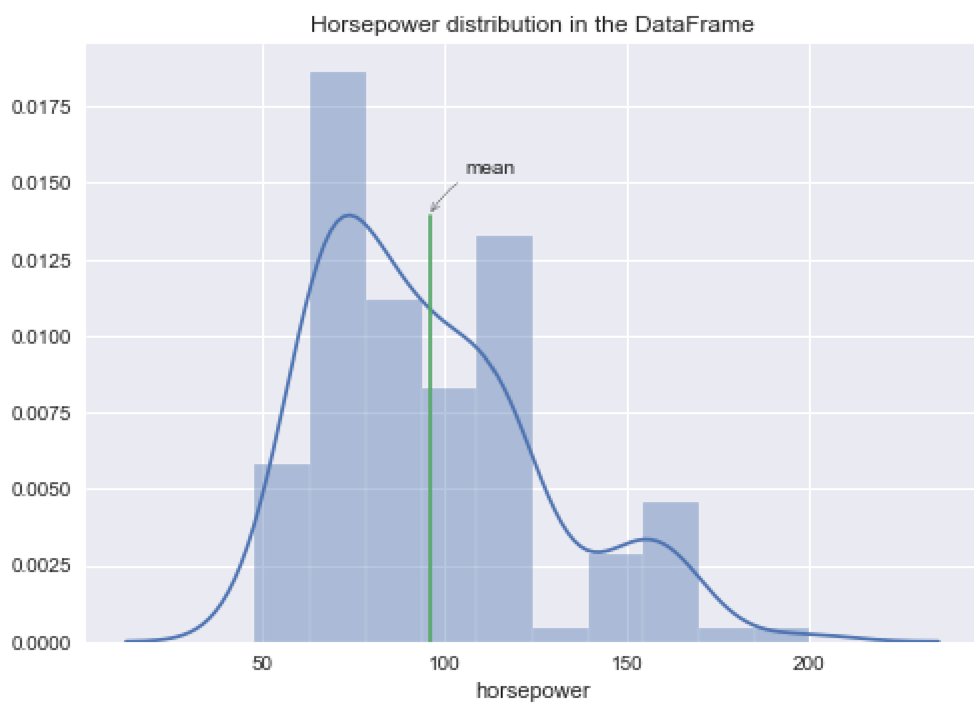
5 rows × 26 columns

When dealing with **continuous** (numerical) variables, a good practice is to visualize their distribution.

In [26]:
```
plt.style.use('seaborn')  # use different plot style
# Reminder: we can view available styles by: print(plt.style.available)

df.horsepower = df.horsepower.astype(int)  # cast column as integer

# Statistical information:
print('Average age: {:.2f}%'.format(df.horsepower.mean()*100))
print('Standard deviation: {:.2f}%'.format(df.horsepower.std()*100))
print('Skewness: {:.2f}%'.format(df.horsepower.skew()*100))
print('Kurtosis: {:.2f}%'.format(df.horsepower.kurtosis()*100))

# Distplot:
ax = sns.distplot(df.horsepower)

# Auxiliary information:
mn = df.horsepower.mean()
mx = ax.lines[0].get_ydata().max()

# Plot median line:
ax.plot([mn]*2, [0, mx])

# Title:
ax.set_title('Horsepower distribution in the DataFrame')

# Annotation:
plt.annotate('mean', [mn, mx],  xytext=[mn*1.1, mx*1.1], fontsize=10,
             arrowprops=dict(arrowstyle='->', connectionstyle='arc3, rad=.2', col
```

```
Average age: 9583.65%
Standard deviation: 3071.86%
Skewness: 91.67%
Kurtosis: 29.89%
```

Out[26]:
```
Text(105.42,0.0153337,'mean')
```

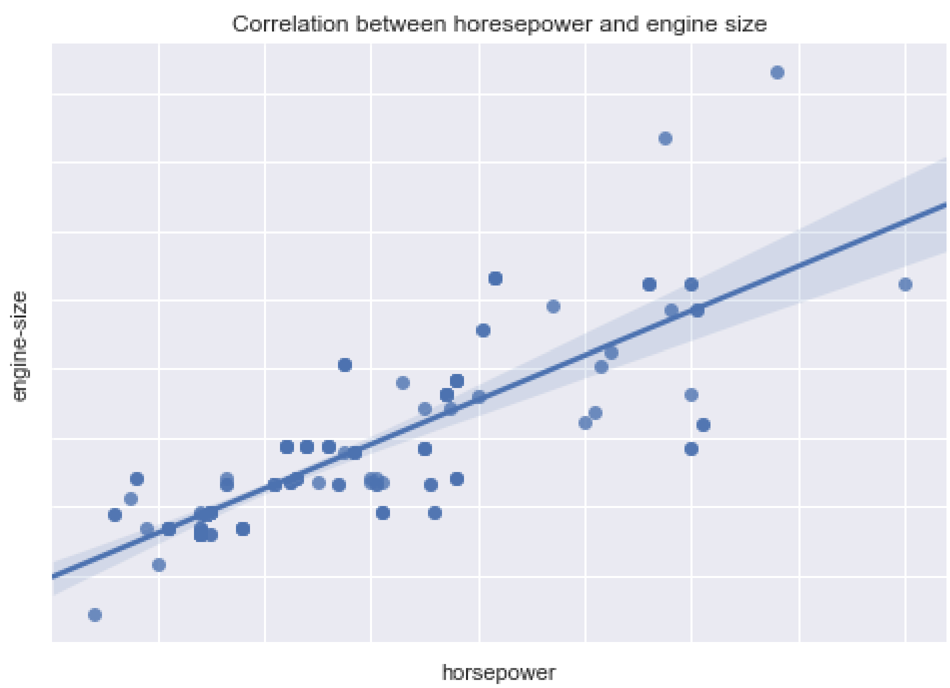


From the above plot we can easily see several of the properties of a specific variable, such as the positive skewness, the high number of samples between the 75-125 range, the low representation of the 130hp range, etc.

We can also view the association between two continuous variables through a regplot.

In [27]:
```
df['engine-size'] = df['engine-size'].astype(int)

# Plot:
ax = sns.regplot(x='horsepower', y='engine-size', data=df)
ax.set_xticklabels(['']*df.shape[0])  # remove axis labels
ax.set_yticklabels(['']*df.shape[0])
ax.set_title('Correlation between horesepower and engine size')

# Calculate correlation:
print('Correlation:', df.corr()['horsepower']['engine-size'])
```

```
Correlation: 0.8120726263087286
```



The positive correlation between the two variables is apparent through this plot.

Bonus:

To view if the correlation is statistically significant we must run our own linear regression on these two variables.

In [28]:
```
import scipy

slope, intercept, r_value, p_value, std_err = scipy.stats.linregress(df.horsepowe

print('r:', r_value)
print('p:', p_value)
```

```
r: 0.8120726263087285
p: 1.4699668393890564e-38
```

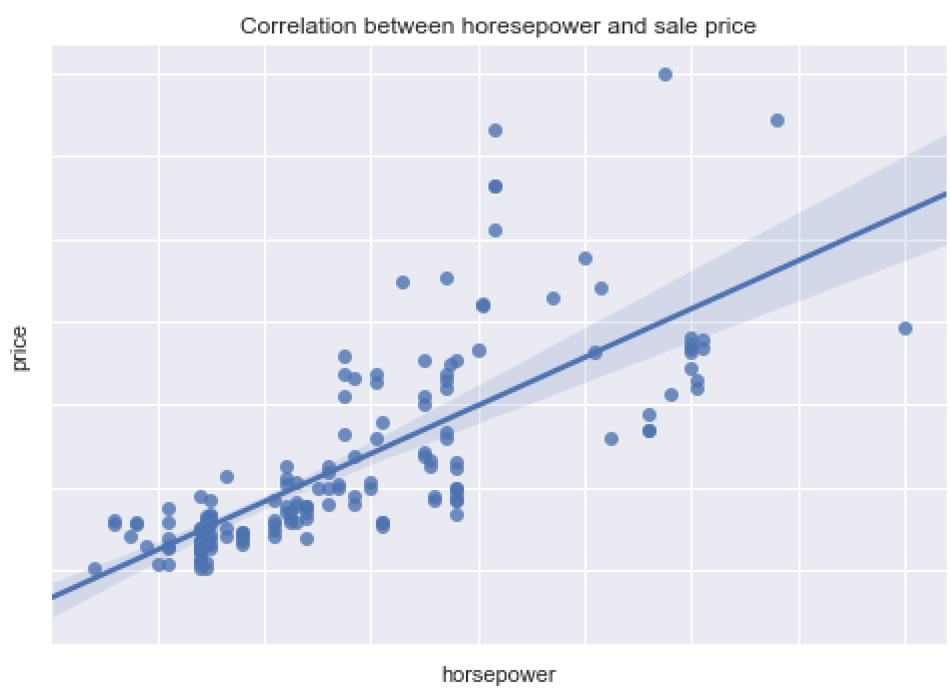
Exercise 1:

Do the same thing as above for the pair `horsepower - price` . Determine if they are correlated.

Solution:

In [29]:
```
df.price = df.price.astype(int)  # we need to cast this as an int as well

ax = sns.regplot(x='horsepower', y='price', data=df)
ax.set_xticklabels(['']*df.shape[0])
ax.set_yticklabels(['']*df.shape[0])
ax.set_title('Correlation between horesepower and sale price')

print('Correlation:', df.corr()['horsepower']['price'])
```

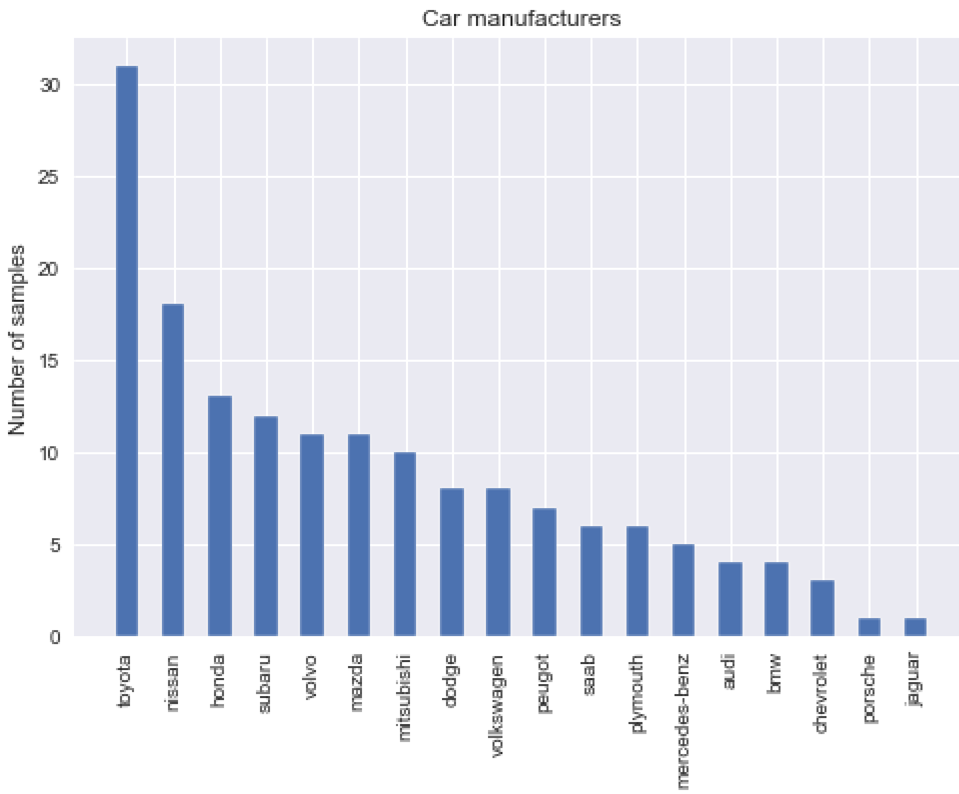
```
Correlation: 0.7598739453801002
```



When dealing with **categorical** variables. The first thing we want to do is to draw a bar plot, to view their distribution. This can be done either with matplotlib or seaborn.

In [30]:
```
plt.bar(x=pd.value_counts(df.make).keys(), height=pd.value_counts(df.make), widtł
plt.xticks(rotation='vertical')
plt.title('Car manufacturers')
plt.ylabel('Number of samples')
```

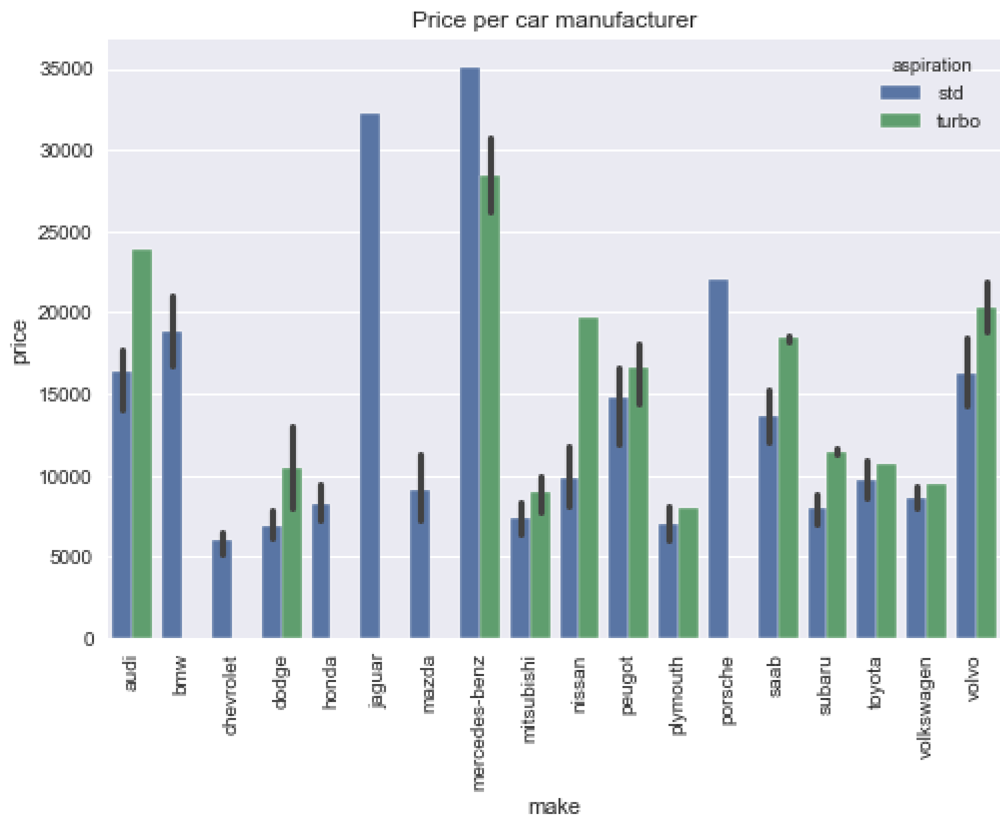
Out[30]: Text(0,0.5,'Number of samples')



We can also see the association between a categorical and a continuous variable this way.

In [31]:
```
sns.barplot(x='make', y='price', hue='aspiration', data=df)
plt.xticks(rotation='vertical')
plt.title('Price per car manufacturer')
```

Out[31]: Text(0.5,1,'Price per car manufacturer')

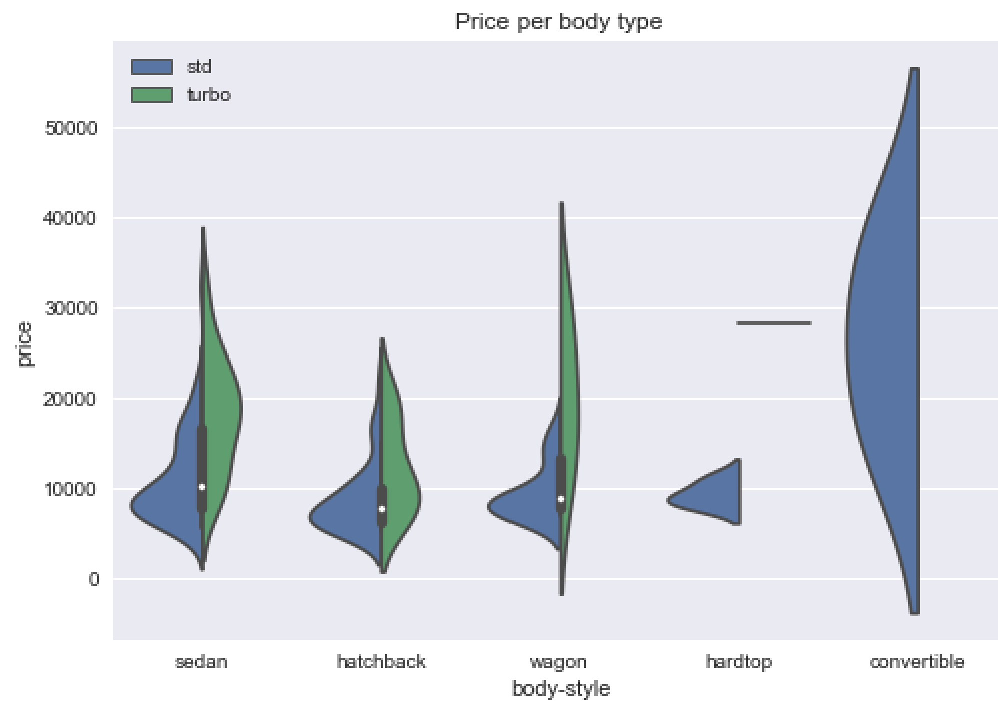


Through this plot the association of `make` and `price` becomes apparent. For example, we can easily see that Mercedes Benz and Jaguars are more expensive than Honda an Nissan cars, or that (besides Mercedes Benz, `turbo` are more expensive than standard aspired engines - `std`).

Another excellent chart carrying a lot of information is the violinplot.

In [32]:
```
sns.violinplot(x='body-style', y='price', hue='aspiration', data=df, split=True)
plt.legend(loc='upper left')
plt.title('Price per body type')
```

Out[32]: Text(0.5,1,'Price per body type')

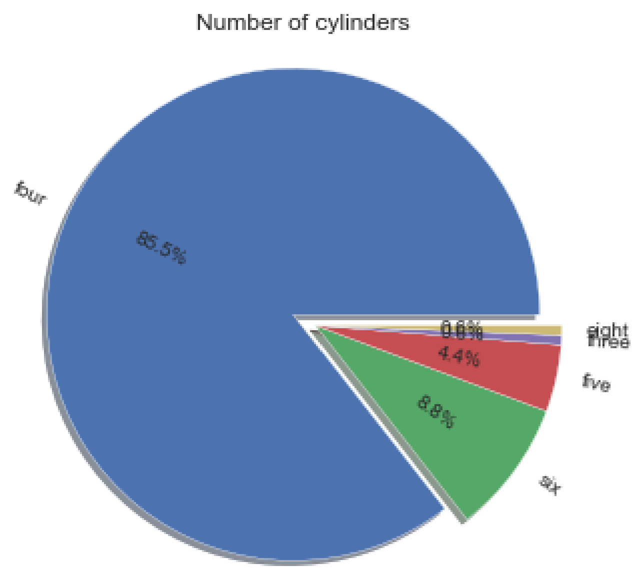


Besides the information presented through the barplot, the violinplot also depicts the distribution of each variable. The two variables on the right are half, because we only have 1 and 0 samples for those categories.

Another very popular way to visualize a variable is the pie chart. This is typically used when wanting to visualize a comparison between each category and a total (e.g. the proportion of the number of samples each category has with the total number of samples). When wanting to compare variables with each other it's best to use a bar plot.

In [33]:
```
labels = pd.value_counts(df['num-of-cylinders']).keys()
sizes = pd.value_counts(df['num-of-cylinders'])

# Explode the most frequent category:
explode = [0] * len(sizes)
explode[np.argmax(list(sizes))] = 0.1

plt.figure(figsize=(5, 5))

# Draw pie chart
properties = plt.pie(sizes, labels=labels, explode=explode, shadow=True, startang

# Rotate labels:
# [0] = wedges, [1] = labels, [2] = fractions
for i in range(len(properties[0])):
    angle = (properties[0][i].theta2 + properties[0][i].theta1) / 2  # find angle
    if angle < 180:  # rotate upside down labels
        angle = angle - 180
    properties[1][i].set_rotation(angle)  # set label rotation
    properties[2][i].set_rotation(angle)  # set fraction rotation

plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
plt.title('Number of cylinders')
```

Out[33]: Text(0.5,1,'Number of cylinders')



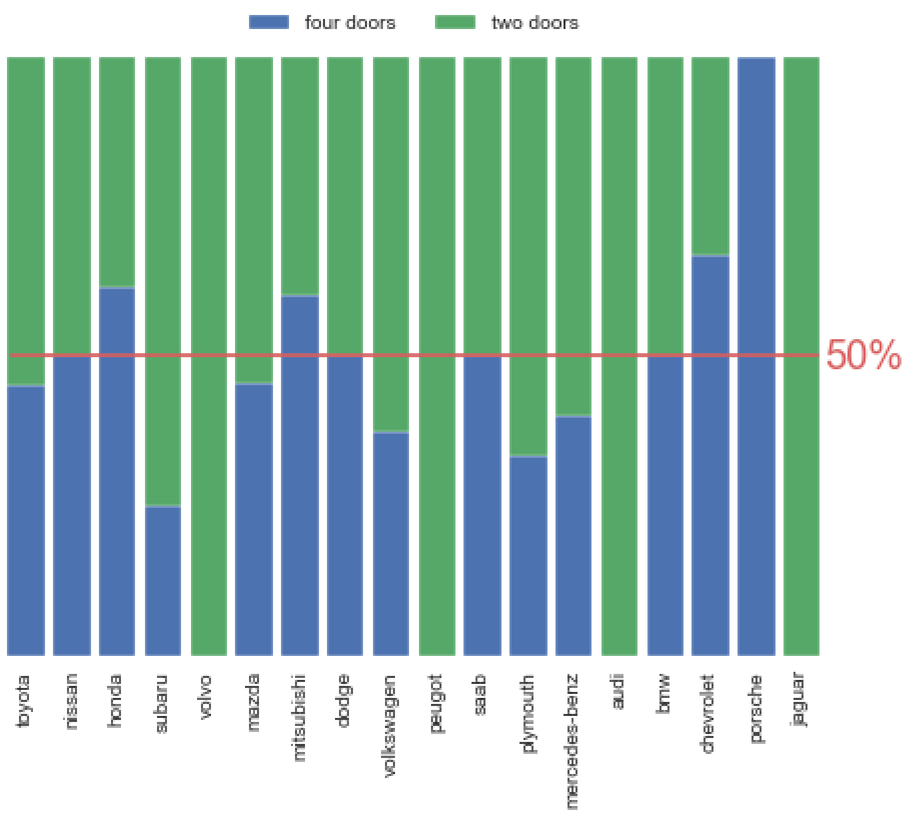
The clear dominance of four cylinders is visible through the pie chart.

We can also compare two **discrete variables**.

Say we want to visualize the proportion of cars with two doors to those with four, for each car manufacturer.

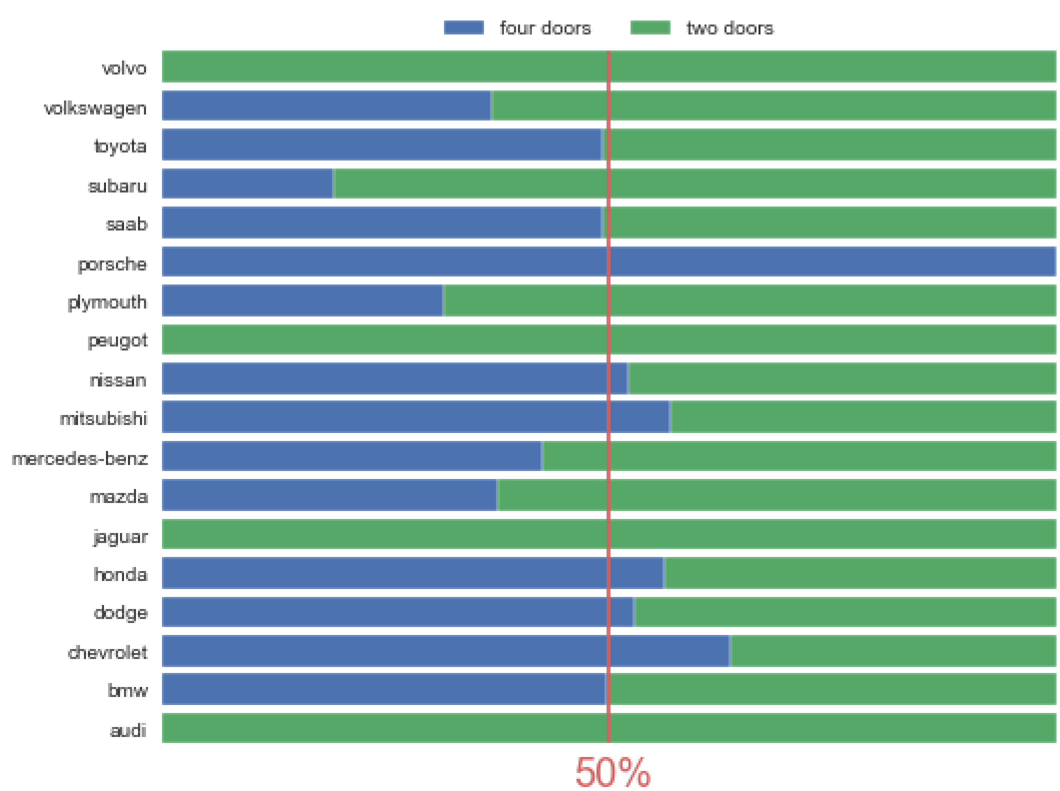
We'll use a different kind of plot to visualize this. Rather than a standard bar plot, we'll create a stacked bar plot where each bar reaches a total height of 1. The relative size between the lower and upper bars will show us the relationship we described.

In [34]:
```
d = pd.value_counts(df.make)  # count the total number of samples each car manufa
d2 = pd.value_counts(df[df['num-of-doors'] == 'two'].make)  # count the number of
d2 /= d  # normalize to [0, 1]
d2 = d2[d.keys()].fillna(0)  # get all categories and fill missing ones with 0
d4 = pd.value_counts(df[df['num-of-doors'] == 'four'].make)  # count the number o
d4 /= d
d4 = d4[d.keys()].fillna(0)

plt.bar(d2.keys(), d2, label='four doors')
plt.bar(d4.keys(), d4, bottom=d2, label='two doors')  # stack the second bar plot

plt.plot([-0.35, 17.35], [0.5, 0.5], c='r') # add horizontal line right in the mi
plt.text(17.5, 0.48, '50%', color='r', fontsize=20) # add text

plt.legend(loc='upper center', bbox_to_anchor=(0.5, 1.1), ncol=2)  # place the le
plt.xticks(rotation='vertical')

ax = plt.gca()
ax.set_facecolor('white')  # make the background white
ax.get_yaxis().set_visible(False)  # remove y axis
```



We can also visualize the relative price of two and four doored cars, for each manufacturer. This time we'll make the bars horizontal. We'll do this one a bit more conventionally.

In [35]:
```
# Define figure
plt.figure(figsize=(8, 7))

# Create a pivot table with the car manufacturer as its rows, the number of doors
# total price of the cars in each sub-category as its values. Categories with no
dd = pd.pivot_table(df, values='price', index='make', columns='num-of-doors', agg

# Normalize each of the manufacturer categories to [0, 1]
d2 = dd['two'] / dd.sum(axis=1)
d4 = dd['four'] / dd.sum(axis=1)

# Create a subplot
ax = plt.subplot(111)

# Draw the two barplots, stacked next to each other
ax.barh(d2.keys(), d2, label='four doors')
ax.barh(d4.keys(), d4, left=d2, label='two doors')

# Draw a vertical line at the middle and text
plt.plot([0.5, 0.5], [-0.35, 17.35], c='r')
plt.text(0.46, -1.5, '50%', color='r', fontsize=20)

# Create a legend outside of the plot
ax.legend(loc='upper center', bbox_to_anchor=(0.5, 1.02), ncol=2)

# Change background to white
ax.set_facecolor('white')

# Remove x-axis completely
ax.get_xaxis().set_visible(False)
```



Another way to visualize the same thing is through a heatmap.

In [36]:
```
# Do the same thing as before without normalization.

# Unfortunately we can't do it the easy way: df.pivot('make', 'num-of-doors', 'pr
# because df.pivot() doesn't support data aggregation

# Use pd.pivot_table() with mean aggrigation
dd = pd.pivot_table(df, values='price', index='make', columns='num-of-doors', agg

sns.heatmap(dd)
```

Out[36]: <matplotlib.axes._subplots.AxesSubplot at 0x2011eee8b38>