Data Visualisation with Seaborn

```
import seaborn as sns
import  matplotlib.pyplot as plt
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
```

matplotlib is the original visualization package in python . seaborn builds on top of that and uses custom class written internally to abstract away a lot of what you will need to manually code in matplotlib. We will use components from both packages to build our visualizations .

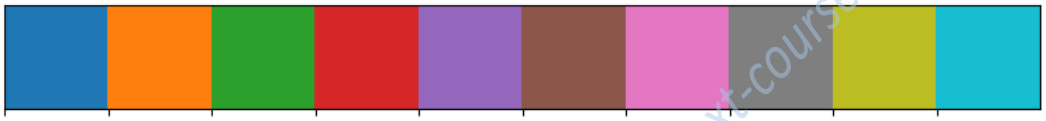
first we will look at how we can control different parts of the visual frame with matplotlib and seaborn functions and attributes and then we will get to data specific visualization . Using the control of visual frame in context of those plots is something your can practice .

Also know that there are tons of possibilities , we will focus on covering visualizing data of different kind and their combinations in our context . If you want to explore any specific kind of visual that you might have seen somewhere; it might require a ton of customization, we can explore that offline over email aside from the in-class discussion.

Color Palettes

seaborn has multiple color palettes that you can use . lets start with looking at default color palette

```
sns.palplot(sns.color_palette())
```



you can find documentation on all available palettes in seaborn here [don't get bogged down by so many available options there , you can do all of what we are going to do with default palette also]

https://www.practicalpythonfordatascience.com/ap_seaborn_palette

lets quickly discuss how to create a custom palette apart from the ones available already in seaborn . You can use hexadecimal codes for colors. You can chose as many colors as you want , if they are all exhausted in any visualization they are recycled instead of running into an error.

you can find reference for hexadecimal codes for colors here : https://htmlcolorcodes.com

```
palette = ["#F72585", "#7209B7", "#3A0CA3", "#4361EE", "#4CC9F0"]
```

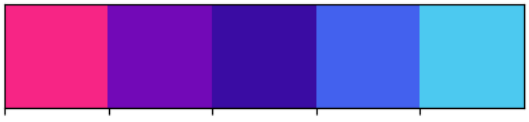
Once you have created your palette you can use sns.set_palette to make it default for the rest of your notebook also you can as many colors as you want

```
sns.set_palette(palette)
```

you can use this to set palette to other available palettes in seaborn for example : `sns.set_palette(sns.color_palette('pastel'))` will set the palette to pastel palette as you might have seen in the palette link shared earlier

```
sns.palplot(sns.color_palette())
```

These are the colors that we selected in our color palette with hexadecimal codes earlier .



Here is a good discussion on how to choose colors : https://seaborn.pydata.org/tutorial/color_palettes.html#general-principles-for-using-color-in-plots

Stlying and Customising a Visual with matplotlib.pyplot

note that we have imported matplotlib.pyplot as plt and we will be using that alias . lets read some data to visualize first

```
bd=pd.read_csv(r'./bd_train.csv')
```

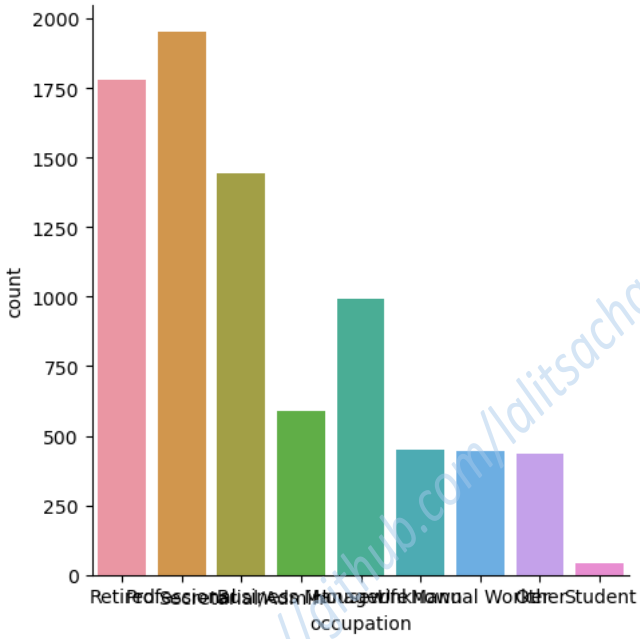
we are going to create a simple countplot for different job categories present in our data. and with that we will explore in what all ways we can do some easy customization. Lets start with default catplot.

```
bd.head()
```

	REF_NO	children	age_band	status	occupation	occupation_partner	home_status	family_income	self_emp
0	4888	Zero	55-60	Widowed	Retired	Unknown	Own Home	<10,000, >= 8,000	No
1	8525	Zero	61-65	Partner	Retired	Retired	Own Home	>=35,000	No
2	3411	3	31-35	Partner	Professional	Housewife	Own Home	<25,000, >=22,500	No
3	692	Zero	51-55	Partner	Secretarial/Admin	Other	Own Home	<20,000, >=17,500	No
4	10726	1	51-55	Partner	Retired	Retired	Own Home	>=35,000	No

5 rows × 32 columns

```
sns.catplot(x='occupation', data=bd,kind='count')
```

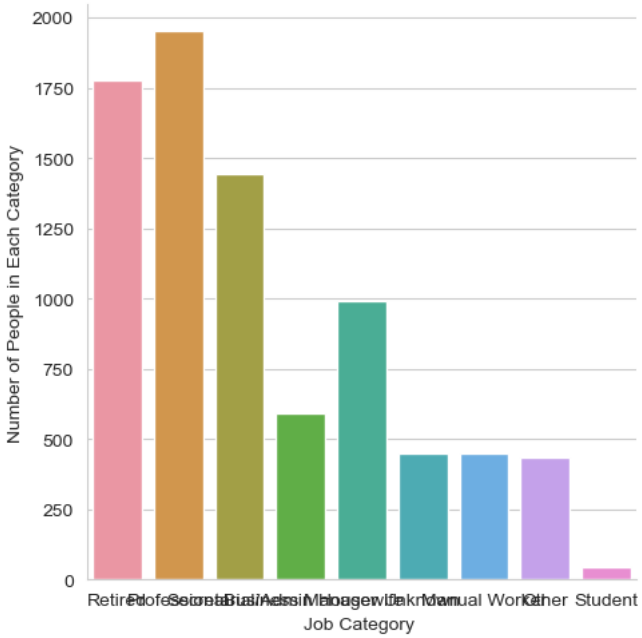


There is a lot we can do to make this look better. Lets do that and in process learn about customization options available in seaborn

There are five preset seaborn themes: `darkgrid`, `whitegrid`, `dark`, `white`, and `ticks`.They are each suited to different applications and personal preferences. Experiment with changing inputs to style and see how these themes are different visually .

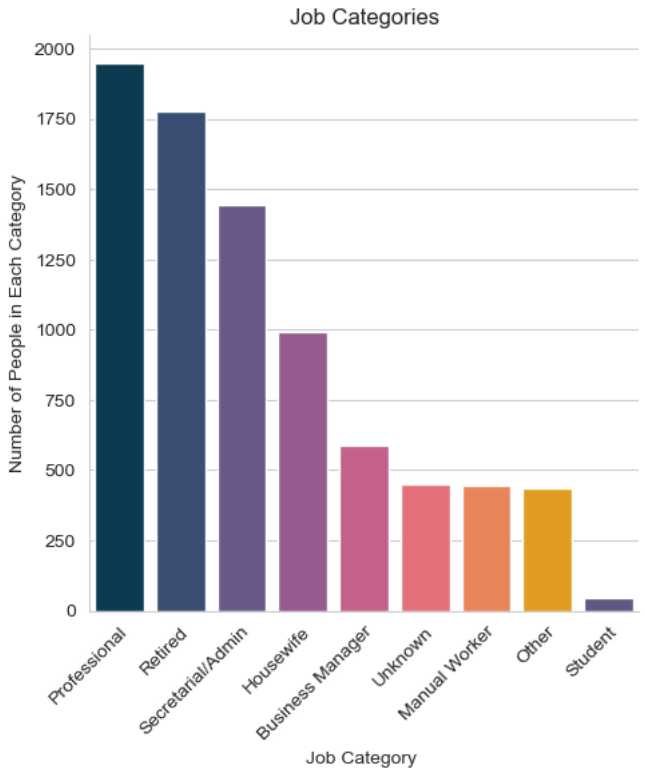
Do note that we are using `plt` here to customize some aspects of visualization around the base visual generated by seaborn. [`xlabel` and `ylabel`]

```
sns.set_style('whitegrid')
sns.catplot(x='occupation', data=bd,kind='count')

# set axes labels
plt.xlabel("Job Category ")
plt.ylabel("Number of People in Each Category")

plt.show()
```



Note that we first create the plot with seaborn and then plt object from matplotlib to modify different aspects of the visualization. We are exploring customizing multiple other elements of the plot created by seaborn here. Carefully read the comments written in between the code lines .

```
sns.set_style('whitegrid')

# Reorder the categories on x axes
# we are using here order driven by descending frequencies which we can calculate with value_counts
# but you can pass custom order also


cat_order=list(bd['occupation'].value_counts().index)

# you can also pass your own color palette , different from the set palette or default palette

my_palette=["#003f5c", "#2f4b7c", "#665191", "#a05195", "#d45087", "#f95d6a", "#ff7c43", "#ffa600", "#58508d"]


sns.catplot(x='occupation', data=bd,kind='count',order=cat_order,palette=my_palette)

# set axes labels
plt.xlabel("Job Category ")
plt.ylabel("Number of People in Each Category")

# rotate xticks to make them readable

plt.xticks(rotation=45,rotation_mode='anchor',ha='right')
# try removing each of those inputs and see what it does to your plot

# Put Title to the chart

plt.title('Job Categories')

plt.show()

```



matplotlib is a powerful low level library and plt object here comes with a ton of other options to customize things . Keep in mind that not all option will make sense in context of all kind of visualization . For example order categories will not fit with scenario of working with just numeric data.

Other notable customization options available with plt here [its not an exhaustive list]

`plt.xlim,plt.ylim` : control ranges of x and y axes in case of numeric data
`plt.legend` : add legend to chart
`plt.annotate` : to add annotation to your chart
`plt.figure` : to control different aspect of the figure like figure size , resolution etc

there is a long list of such options.

You can also explore more arguments available in the option shown earlier , for example setting font and font size in `xlabel` .

Lets now get started with what kind of visualisation we will use in context of different kind of data. Lets go!

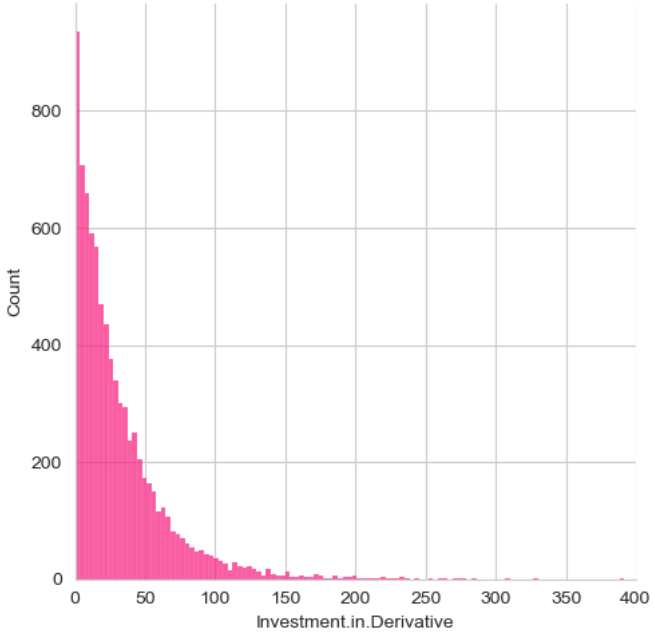
Numeric Data

For a single numeric column , visualizing individual values doesn't serve any purpose. Visualization is supposed to be a visual summary of the data. Visual summary of a numeric column gives you an idea of frequency distribution of the values . If we go about looking at frequency of individual values , that might not be very informative either because numeric columns have too many unique values. A more informative way is to first make sequential bins of the values across range of numeric column and then see how many values lie in those bins visually .

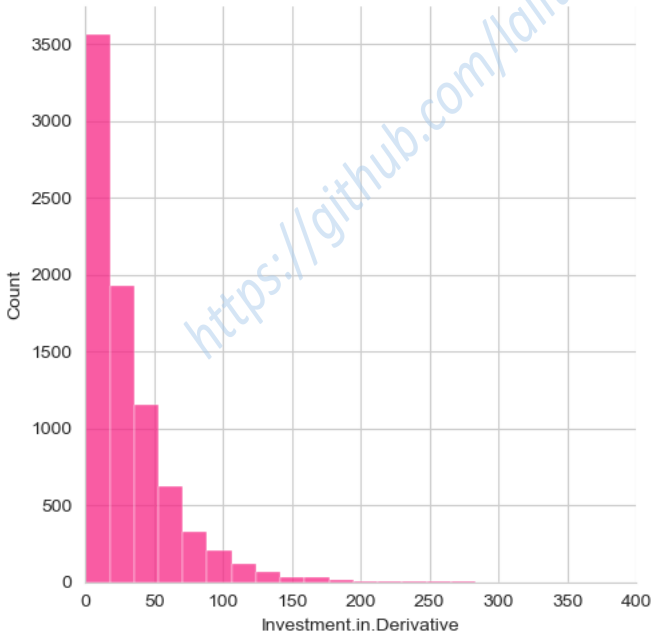
For example a numeric feature like age can broken to bins such as 0-5 , 5-10 , 10-15 and so on; seaborn does this internally for numeric features depending on the values that it see in data column.

This visual representation of frequency in sequential bins is called a `histogram` and is used for single numeric columns . we will be using function `sns.displot` . There is no default number of bins , bin width is calculated using $2 * \frac{IQR}{\sqrt[3]{n}}$ where n is number of obs in the data and IQR is `inter quartile range`. Number of bins then will be approximately range of column data divided by the bin width.

```
sns.displot(x='Investment.in.Derivative',data=bd)
plt.xlim(left=0,right=400)
plt.show()
```

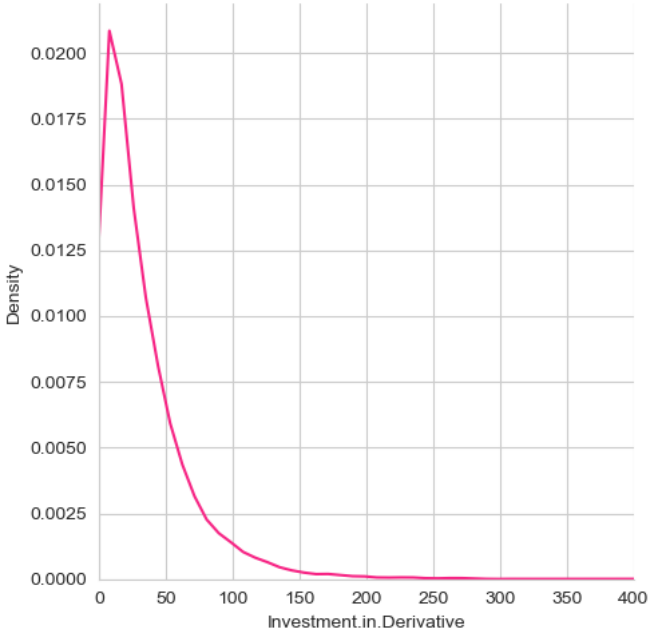



```
# you can control number of bins and thus make the bin ranges finer or coarser
# option kind='hist' generates histograms with function displot

sns.displot(x='Investment.in.Derivative',data=bd,kind='hist',bins=100)
plt.xlim(left=0,right=400)
plt.show()

# note that as you change number of bins, y-axis which is showing count will change limits
# understandably if the bin width is wider , the count will be higher too per bin because each bin will
# contain more data
```



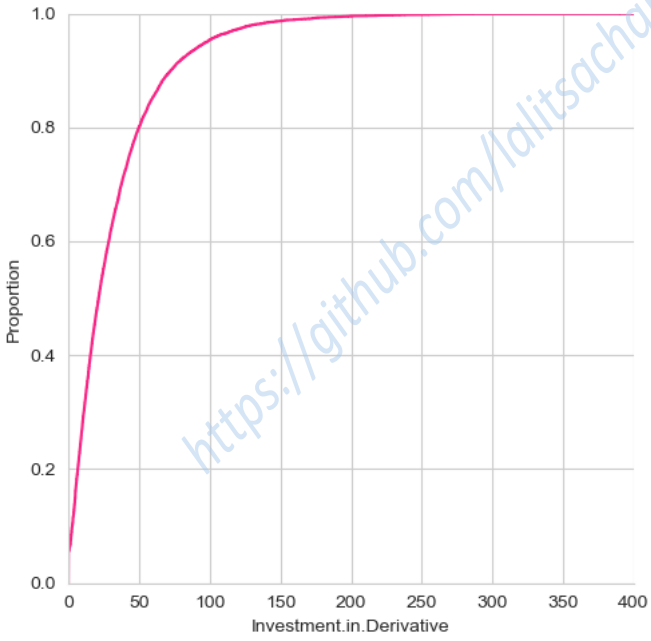
Sometimes you might want to see this as rather a density curve. At this level you can imagine density curve to be a line joining top of the bins of the histogram. Its a very simplified way to look at density curve but for now this will suffice. By default on the y-axis you will have proportion of the data instead of raw frequency. You can get density curve by setting `kind='kde'` . option `bins` isn't required with this.

```
sns.displot(x='Investment.in.Derivative',data=bd,kind='kde')
plt.xlim(left=0,right=400)
plt.show()
```



with the same function you can also get a cumulative frequency curve, where the cumulation [summation of proportions] happens in ascending manner over range of the data column. You can get that with option `kind='ecdf'`

```
sns.displot(x='Investment.in.Derivative',data=bd,kind='ecdf')
plt.xlim(left=0,right=400)
plt.show()
```



Another popular visualization for single numeric columns is `boxplot` . Boxplot has three components

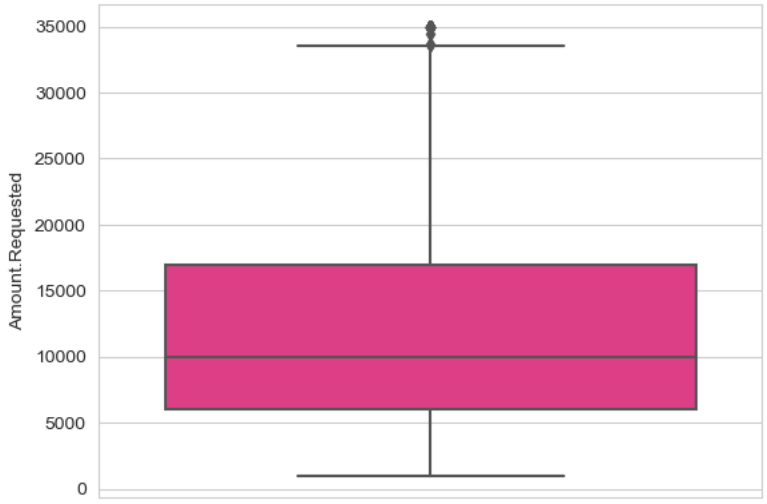
- box in the middle : has three lines along the length for Q1, Q2 [median] and Q3
- whiskers : They extend to on higher side to either Q3 + 1.5*IQR , or the max value in the data whichever is smaller. Similarly on the lower side they extend to Q3 - 1.5*IQR , or the minimum value in the data whichever comes first . This in a way tries to show default majority population range , any values which exceeds these limits is shown separately and can be considered extreme in comparison to rest of the population
- extreme values : if any value exceeds these limits [Q1-1.5*IQR , Q3+1.5*IQR] it is displayed individually

Note that an extreme value or an outlier is not necessarily useless. It is an important piece of information especially for long tailed processes where these values occur naturally just not as often and hence get termed as extreme

```
ld=pd.read_csv(r'./loan_data_train.csv')
```

```
ld['Amount.Requested']=pd.to_numeric(ld['Amount.Requested'],errors='coerce')
```

```
sns.boxplot(y='Amount.Requested',data=ld)
```



Note that boxplots for columns where the distribution of values is very skewed to one side will look peculiar with very thin box and long whisker and a large number of values will show as extreme.

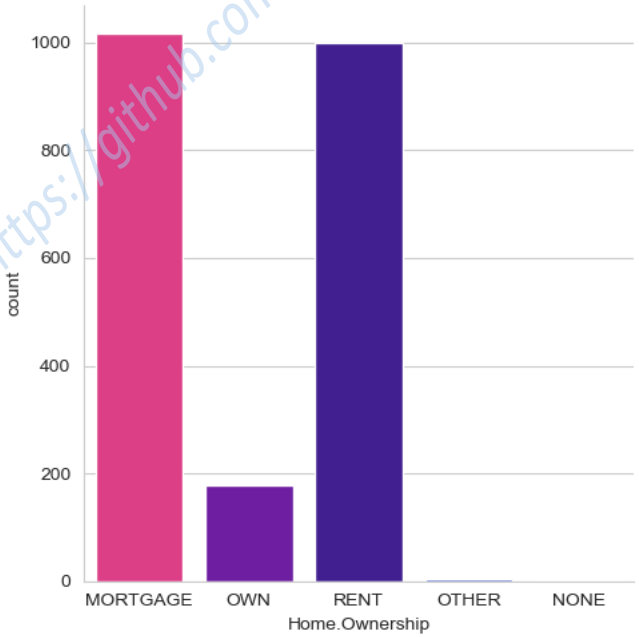
There are some variations of boxplot which you can explore : `striplot` , `swarmplot` , `violin plot` etc

Remember that visualizations are used to tell your story in an appealing manner. Your choices will not only be driven by what you prefer but also by what makes sense to your intended audience. While we are learning this, its ok to look at many possibilities. But in your work, use visualization as a communication tool , don't make visualizations for the sake of it, consider how they fit in your data story .

Categorical Data

The default go to option here is the count plot that we saw earlier when learning about customization of different aspect of your chart . Lets do that [without the customization] for another data column .

```
sns.catplot(x='Home.Ownership',data=ld,kind='count')

# experiment with customising this as we did earlier
```

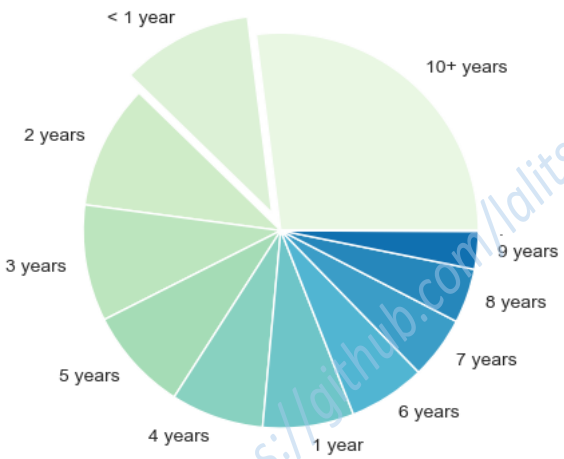


there is no direct function for pie charts in seaborn , however we can use `plt` for that to use pie chart functionality from matplotlib

```
ld['Employment.Length'].value_counts()
```

```
10+ years    575
< 1 year     229
2 years      217
3 years      203
5 years      181
4 years      162
1 year       159
6 years      134
7 years      109
8 years       95
9 years       66
.              1
Name: Employment.Length, dtype: int64
```

```
sns.set_palette(sns.color_palette('GnBu',12))

# by default each palette has 10 distinct colors , which you can increase as per your data
k=ld['Employment.Length'].value_counts()
count=k.values
categories=k.index

# to move some of the categories pieces of pie to move out we can make use of explode option, its not mandatory
though
explode=[0]*12 # there are 12 categories , we are setting same values [0] of explode for all
explode[1]=0.1 # we want to make 2nd position count to stand out by providing non-zero value of explode
# for it

plt.pie(count,labels=categories,labeldistance=1.1,explode=explode)

plt.show()
```



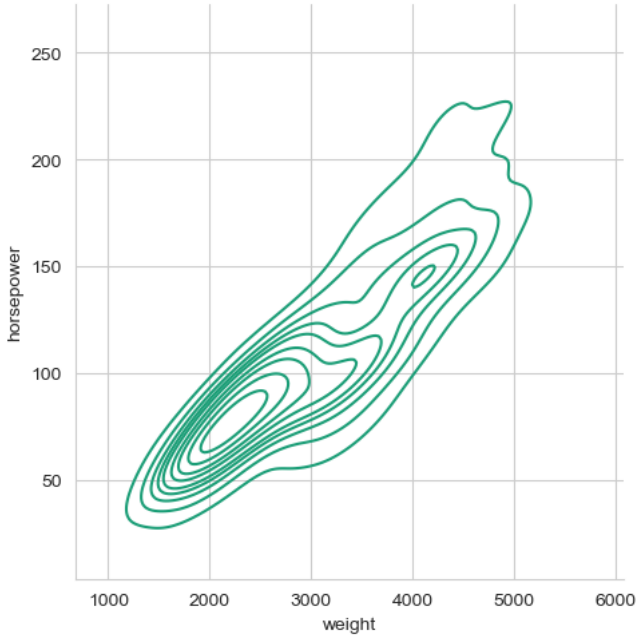
Combinations of Data

when you are looking at a combination of numeric numeric column, we make scatter plot or joint density plot where x and y axes represent two numeric features

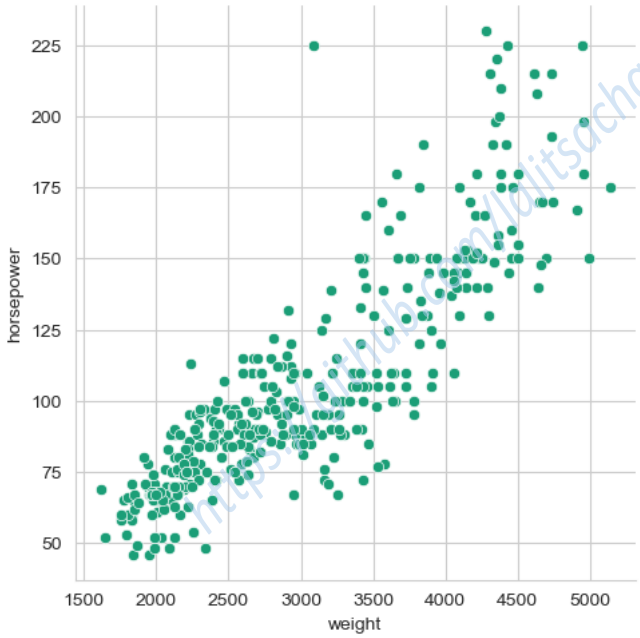
```
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/auto-mpg/auto-mpg.data"

# Column names for the dataset
column_names = ['mpg', 'cylinders', 'displacement', 'horsepower', 'weight', 'acceleration', 'model year', 'origin',
'car name']

# Load the dataset
cars = pd.read_csv(url, names=column_names, delim_whitespace=True, na_values='?')

```

you can use `displot` to create that however `relplot` is more versatile. lets look at `displot` first

```
sns.set_palette(sns.color_palette('Dark2'))
sns.displot(x='weight',y='horsepower',data=cars,kind='kde')
```




```
sns.relplot(x='weight',y='horsepower',data=cars,kind='scatter')
```



you can bring in other factors in this from the data using color, size etc. Lets see

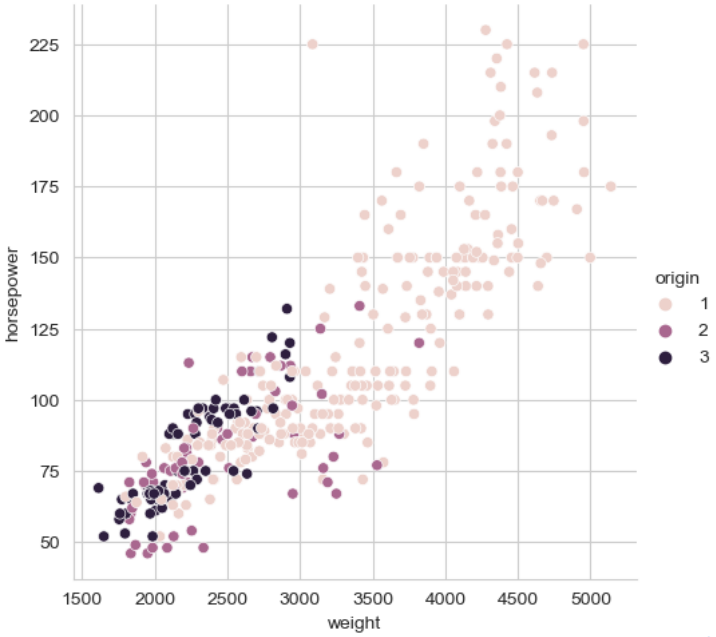
```
cars.head()
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	model year	origin	car name
0	18.0	8	307.0	130.0	3504.0	12.0	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	165.0	3693.0	11.5	70	1	buick skylark 320
2	18.0	8	318.0	150.0	3436.0	11.0	70	1	plymouth satellite
3	16.0	8	304.0	150.0	3433.0	12.0	70	1	amc rebel sst
4	17.0	8	302.0	140.0	3449.0	10.5	70	1	ford torino

We can use other properties of the points to visualise more data points. for instance , in our next example we are using , color or `hue` of the points to represent column `origin` from the data.

While we are creating these , also try to analyze what these visuals tell you about the data.

```
sns.relplot(x='weight',y='horsepower',data=cars,kind='scatter',hue='origin')
# see if relplot allows you to experiment with other properties like size and shape of the points also
# to represent more data columns in the same plot
```



you create facets , row and columns of plot where data gets subsetted on categories of specified columns in row and col argument

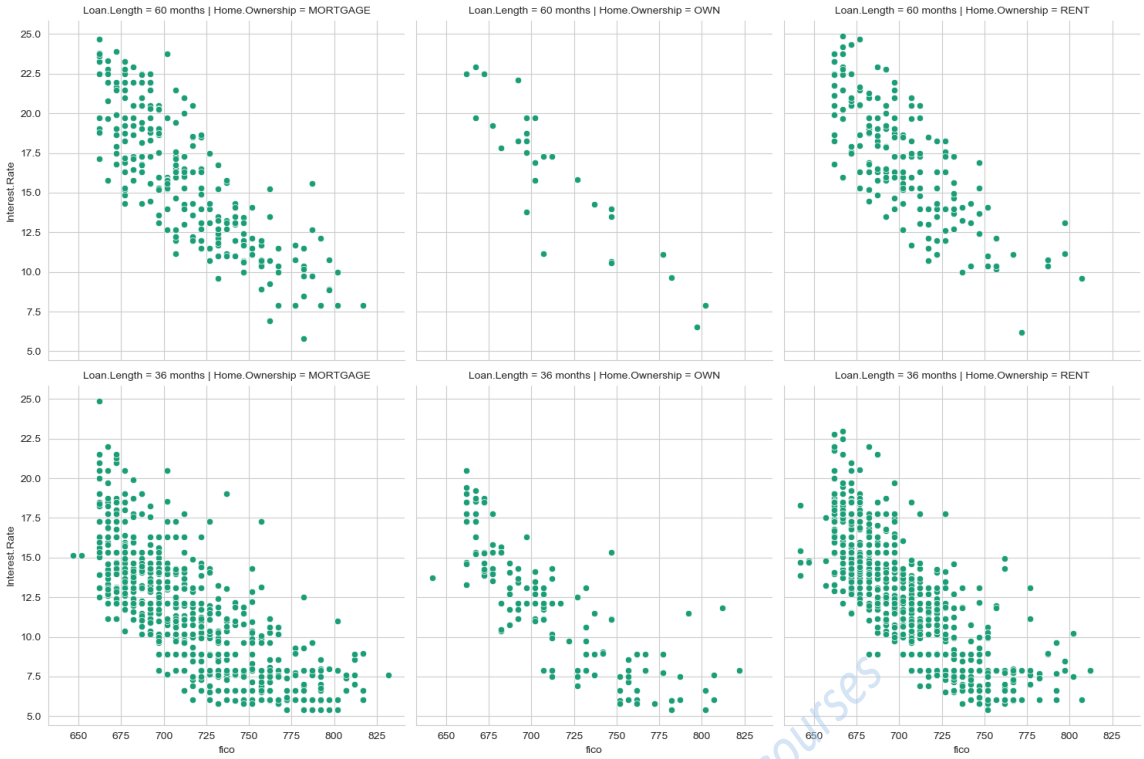
```
ld.head()
```

	ID	Amount.Requested	Amount.Funded.By.Investors	Interest.Rate	Loan.Length	Loan.Purpose	Debt.To.Income
0	79542.0	25000.0	25000	18.49%	60 months	debt_consolidation	27.56%
1	75473.0	19750.0	19750	17.27%	60 months	debt_consolidation	13.39%
2	67265.0	2100.0	2100	14.33%	36 months	major_purchase	3.50%
3	80167.0	28000.0	28000	16.29%	36 months	credit_card	19.62%
4	17240.0	24250.0	17431.82	12.23%	60 months	credit_card	23.79%


```
ld['fico']=ld['FICO.Range'].str.split('-',expand=True).astype(int).mean(axis=1)
ld['Interest.Rate']=pd.to_numeric(ld['Interest.Rate'].str.replace('%',''),errors='coerce')
```

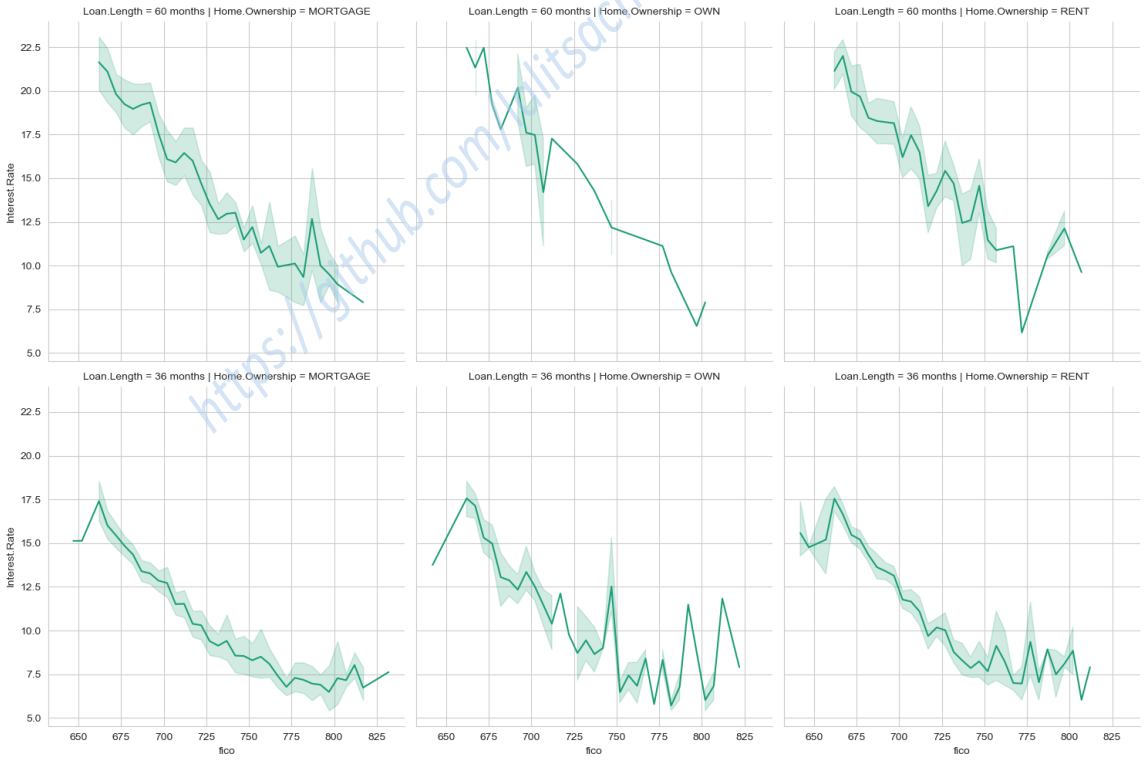
```
ld_sub=ld[ld['Loan.Length'].isin(['60 months', '36 months']) &
ld['Home.Ownership'].isin(['MORTGAGE','OWN','RENT'])]
```

```
sns.relplot(x='fico',y='Interest.Rate',data=ld_sub,kind='scatter',row='Loan.Length',col='Home.Ownership')
```



if you want to visualize relationship , you can use `kind='line'`

```
sns.relplot(x='fico',y='Interest.Rate',data=ld_sub,kind='line',row='Loan.Length',col='Home.Ownership')
```



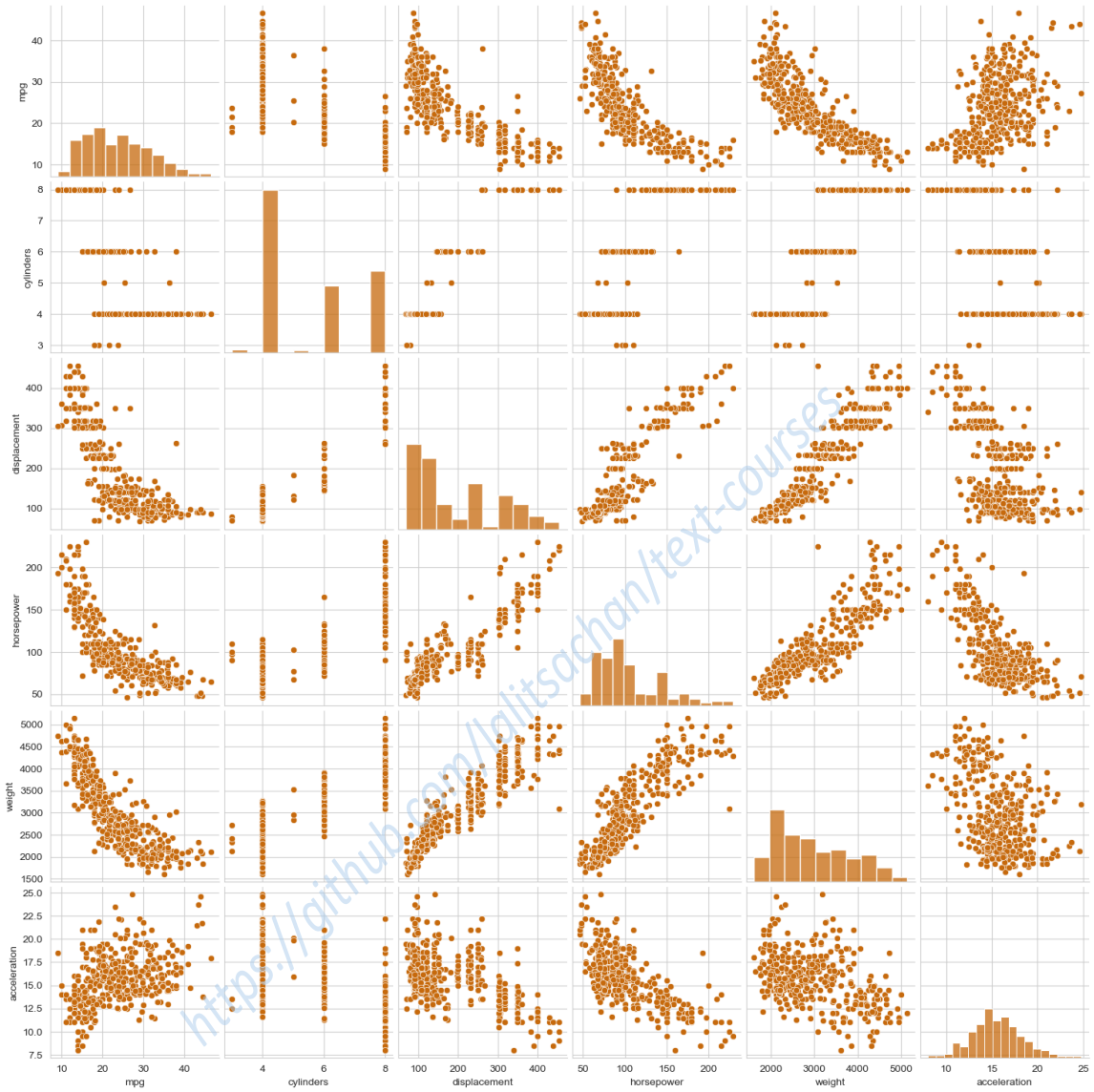
You can visualise multiple columns with function `pairplot`

```
cars.columns
```

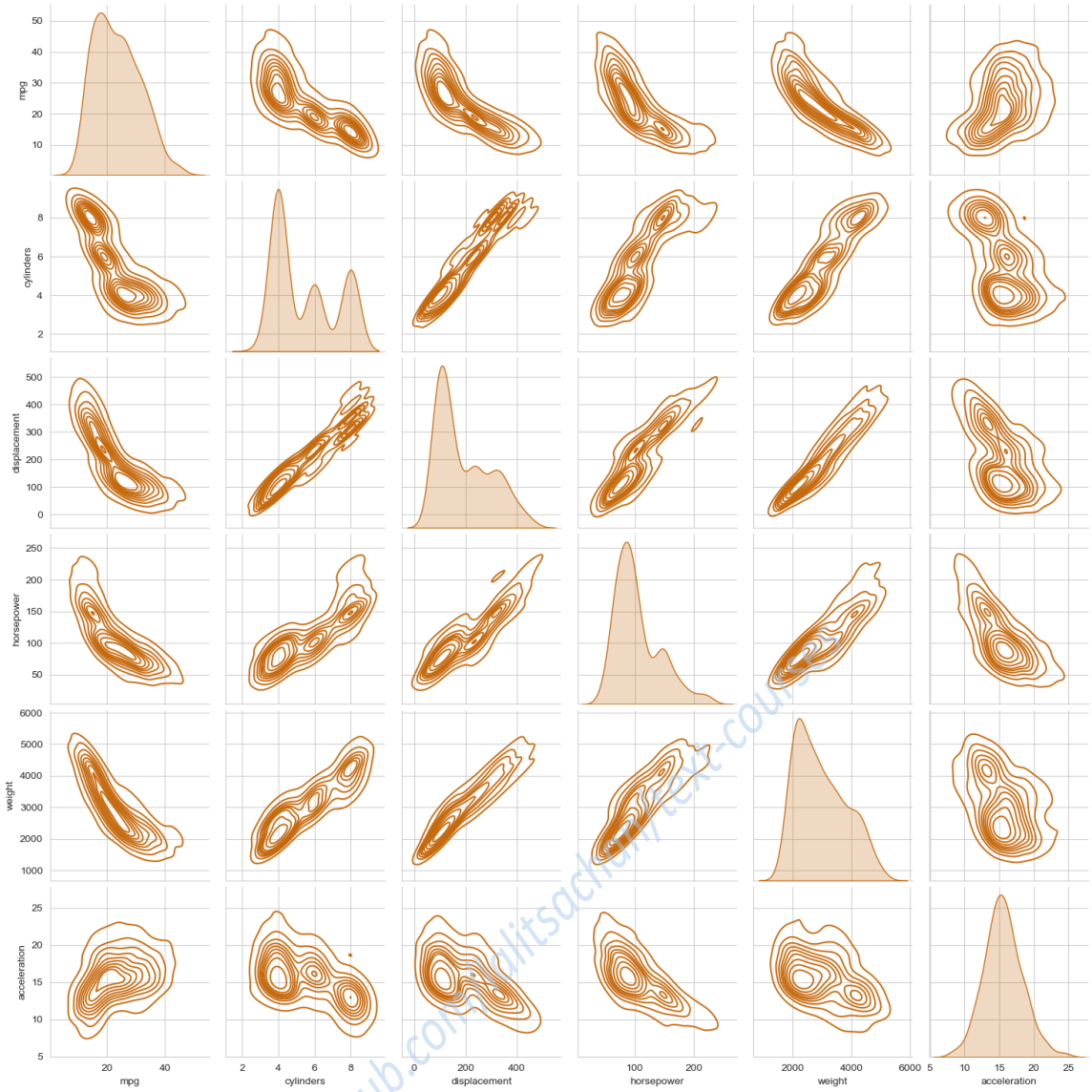
```
Index(['mpg', 'cylinders', 'displacement', 'horsepower', 'weight',
       'acceleration', 'model year', 'origin', 'car name'],
      dtype='object')
```

```
cars_sub=cars[['mpg', 'cylinders', 'displacement', 'horsepower', 'weight',
       'acceleration']]
```

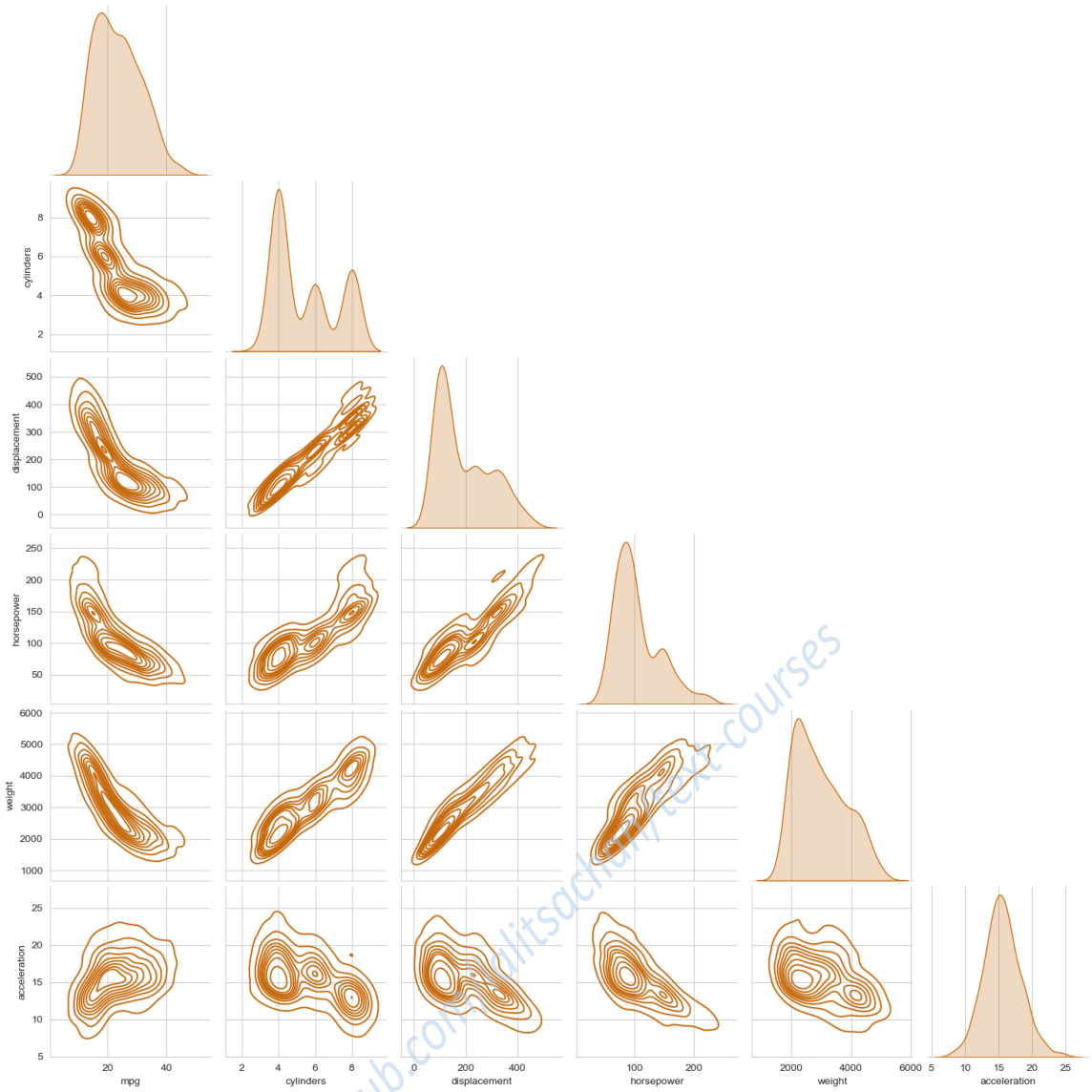
```
sns.set_palette('PuOr')

sns.pairplot(cars_sub)
```




```
sns.pairplot(cars_sub,kind='kde')
```



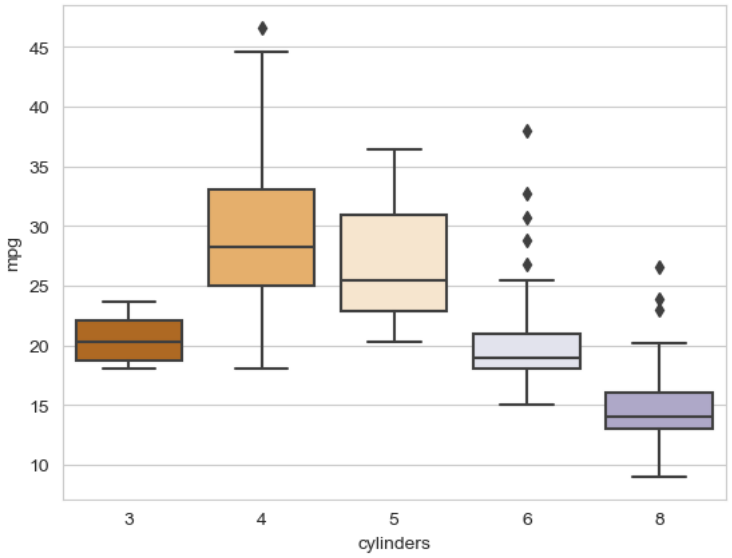

```
sns.pairplot(cars_sub,kind='kde',corner=True)
```



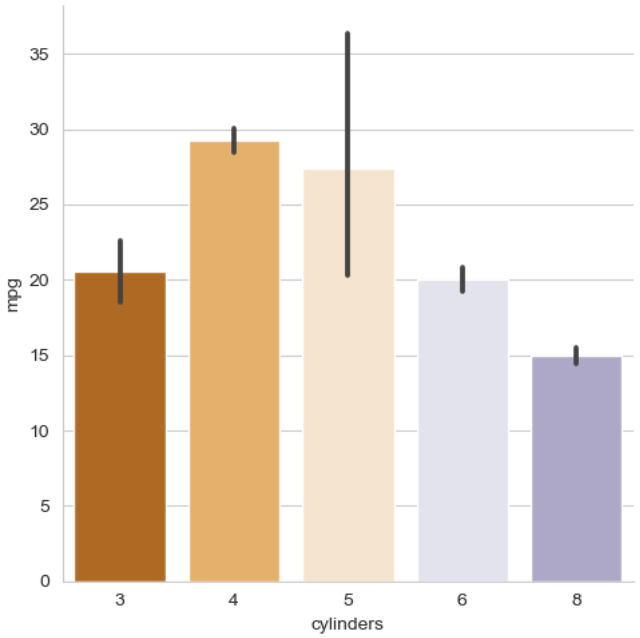
here also you can use argument `hue` to show additional categorical factor subsetting in the data

for visualizing effect of a categorical column on single numeric column, we can create single column numeric visualizations across the categories

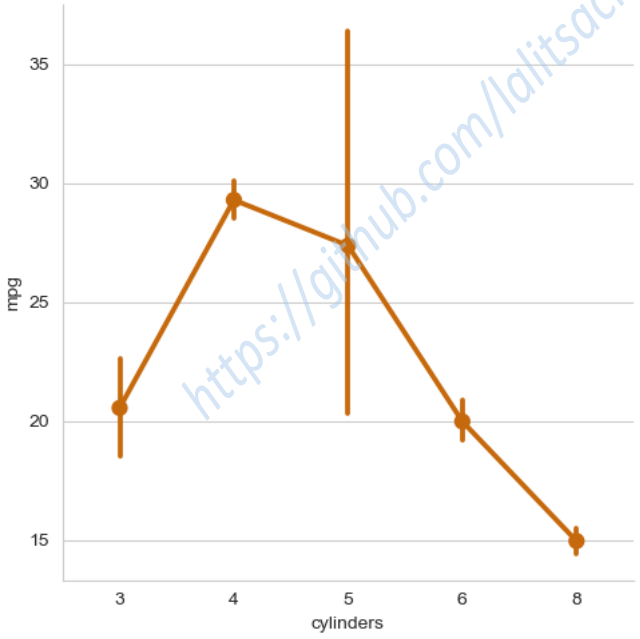
```
1 sns.boxplot(x='cylinders',y='mpg',data=cars)
```



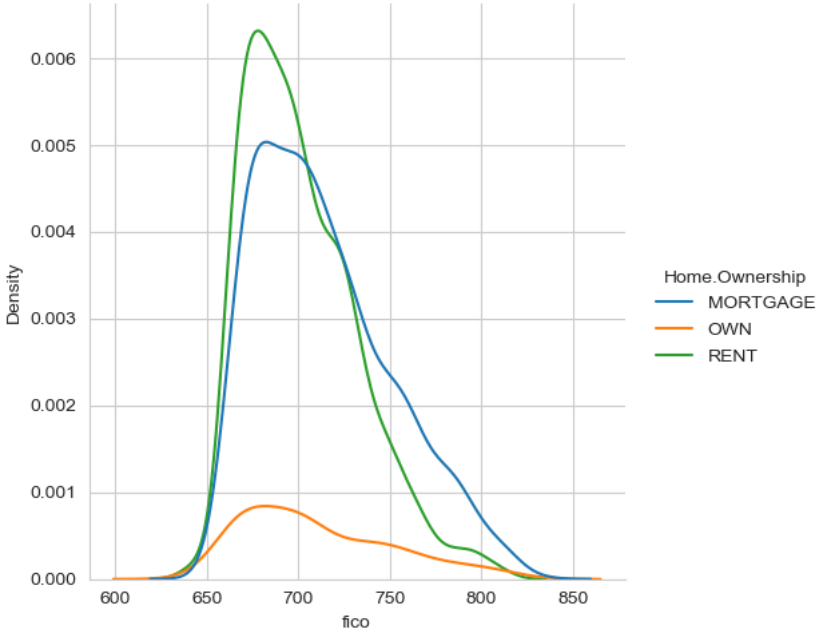
```
sns.catplot(x='cylinders',y='mpg',data=cars,kind='bar')
```




```
sns.catplot(x='cylinders',y='mpg',data=cars,kind='point')
```




```
sns.set_palette('tab10')
sns.displot(hue='Home.Ownership',x='fico',data=ld_sub,kind='kde')
```



We will conclude for now , there are many context specific visualization that we will come across later in the course , for example : time series data , text data.

those who are interested in geospatial data, this seems like a good place to start : https://sustainability-gis.readthedocs.io/en/latest/lessons/L1/intro-to-python-geostack.html