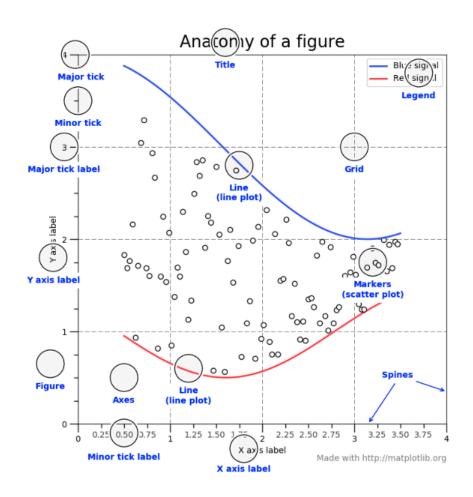


# Module 02 Lab 01 - Basic Plots





```
# Dividing the dataset into features (X) and the target variable (y)

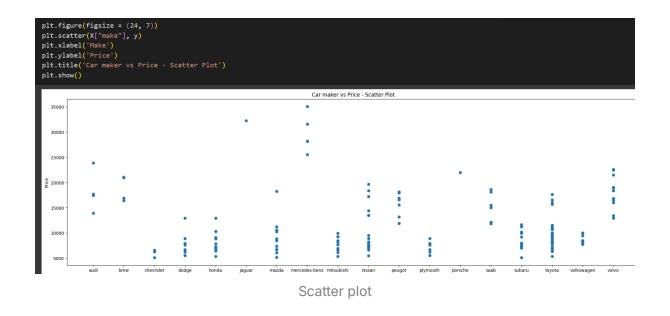
X = data.drop("price", axis = 1)
y = pd.to_numeric(data["price"])
```

- Replaces missing values: data.replace("?", np.nan, inplace = True) replaces all occurrences of the string "?" with np.nan (Not a Number), which is the standard way to represent missing values in NumPy and pandas.
   The inplace=True argument modifies the DataFrame directly.
- 2. **Removes rows with missing values**: data = data.dropna() removes all rows that contain at least one np.nan value. The resulting DataFrame, with missing values removed, is then assigned back to the data variable.

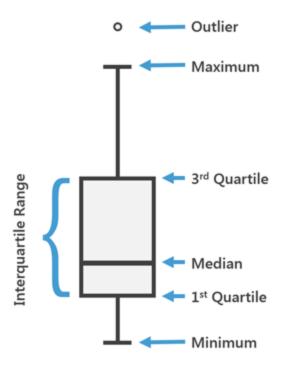
When you use x = data.drop("price", axis = 1), you are **not** dropping the "price" column from the original data DataFrame. Instead, the drop() method, by default, returns a **new** DataFrame that is a copy of the original data but without the "price" column. This new DataFrame is then assigned to the variable x.

## **SCATTER PLOT**





# **BOX PLOT**

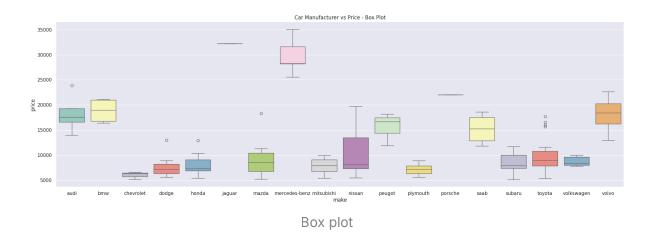


We will be creating a Box Plot. This is the type of plot that can be used to obtain more of the statistical details about the data. The straight lines at the maximum and minimum are also called as whiskers. Points outside of whiskers will be

inferred as an outliers. The box plot gives us a representation of 25th, 50th, 75th quartiles. From a box plot we can also see the Interquartile range(IQR) where maximum details of the data will be present. It also gives us a clear overview of outlier points in the data.

```
sns.set(rc={'figure.figsize':(24,7)})
sns.boxplot(x=X["make"],y=y, palette="Set3").set_title('Car Manufacturer vs P
rice - Box Plot')
```

#### **IQR**



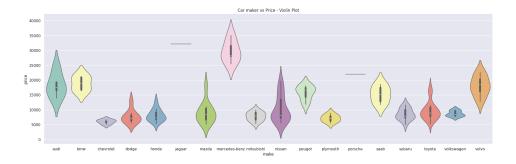
It becomes evidently clear that Mercedes-Benz, Jaguar and Porsche have the costliest cars. BMW too has costly cars but the large interquartile range suggests that the company has a broader range of cars in the market. The outliers are also important as for example, Mazda has a car listed much higher than its normal price range.

All of these conclusions could be very hard to get to using the data in a tabular format, whereas it became evidently clear straight away once we used Visualization techniques to understand the dataset.

# Violin plot

sns.violinplot(x=X["make"],y=y, palette="Set3").set\_title('Car maker vs Price -

#### Violin Plot')

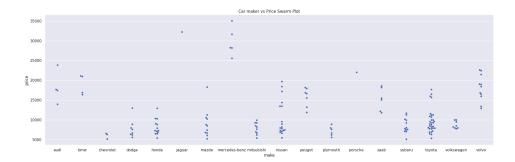


- 1. **Reveals the full distribution shape**: Unlike box plots, which only show summary statistics (quartiles, median, outliers), violin plots show the entire distribution of the data. This allows you to see if the distribution is unimodal (one peak), multimodal (multiple peaks), skewed, or symmetrical.
- 2. **Highlights data density**: The width of the violin at any given value indicates the density of the data at that point. This helps you understand where the data is most concentrated.

## **Swarm Plots.**

Another plot type are the Swarm Plots. They offer an alternate way of plotting the distribution of an attribute or the joint distribution of a couple of attributes. Unlike strip plots, swarm plots attempt to avoid obscuring points by calculating non-overlapping positions instead of adding random jitter. This sort of gives them appearance of a swarm of bees, or perhaps a honeycomb.

sns.swarmplot(x=X["make"],y=y).set\_title('Car maker vs Price Swarm Plot')



### **JOINT PLOT**

The jointplot displays a relationship between 2 variables (bivariate) as well as 1D profiles (univariate) in the margins.

I have also used the parameter "reg" which fits a regression line through the points making the correlation sign apparent. A line with positive slope would indicate a postiive correlation and vice versa. A line parallel to x-axis would indicate no correlation between the 2 variables (implying independence).

sns.jointplot(x=pd.to\_numeric(X["horsepower"]), y = y, kind="reg", color = 'gr
een')

