

# Data Analysis - Pandas

June 28, 2024

## Abstract

This paper explores data analysis using the Pandas library in Python. We discuss various techniques and functions provided by Pandas to manipulate, analyze, and visualize data effectively.

Credits - zero-to-mastery-ml - <https://github.com/mrdbourke/zero-to-mastery-ml/tree/master/data>

<https://www.udemy.com/course/complete-machine-learning-and-data-science-zero-to-mastery>

```
[334]: from IPython.display import display, Image  
  
display(Image(filename="./Resources/Images/Pandas Image.png"))
```



This statement imports the Pandas library and allows you to use it in your script with the alias `pd`, which is a common convention in the Python community. <https://pandas.pydata.org/>

```
[291]: import pandas as pd
```

`pd.Series` is a data structure in the Pandas library, which is a powerful data manipulation and analysis library for Python. A Series is a one-dimensional array-like object that can hold data of any type (integer, float, string, Python objects, etc.). It is similar to a column in a spreadsheet or a SQL table. Each element in a Series has an associated label, known as the index.

```
[292]: # Series = 1 - dimensional

series = pd.Series(["BMW","Toyota","Honda"])
colours = pd.Series(["White","Yellow","Blue"])
series,colours
```

```
[292]: (0      BMW
1     Toyota
2      Honda
dtype: object,
0     White
1     Yellow
2      Blue
dtype: object)
```

A **DataFrame** is another core data structure in the Pandas library. It is a two-dimensional, size-mutable, and potentially heterogeneous tabular data structure with labeled axes (rows and columns). Think of it as a table or a spreadsheet in Python, where each column can hold different types of data.

```
[293]: # Dataframe = 2 - dimensional

car_data = pd.DataFrame({"Car make": series,"Colours": colours})
car_data
```

```
[293]:   Car make Colours
0      BMW   White
1  Toyota  Yellow
2   Honda   Blue
```

```
[294]: # Importing the data

car_sales =pd.read_csv("./Resources/car-sales.csv")
car_sales
```

```
[294]:   Make Colour  Odometer (KM)  Doors    Price
0  Toyota  White      150043      4  $4,000.00
1   Honda   Red       87899      4  $5,000.00
2  Toyota  Blue      32549      3  $7,000.00
3    BMW  Black       11179      5 $22,000.00
4  Nissan  White     213095      4  $3,500.00
5  Toyota  Green      99213      4  $4,500.00
6   Honda  Blue      45698      4  $7,500.00
7   Honda  Blue      54738      4  $7,000.00
8  Toyota  White      60000      4  $6,250.00
9  Nissan  White      31600      4  $9,700.00
```

Anatomy of a Pandas DataFrame - Credits [https://www.ibmmainframer.com/python-tutorial/pandas\\_viewing\\_data/](https://www.ibmmainframer.com/python-tutorial/pandas_viewing_data/)

```
[295]: from IPython.display import display, Image

display(Image(filename="./Resources/Images/pandas-dataframe-anatomy.png"))
```

The diagram illustrates the anatomy of a Pandas DataFrame. It shows a table with 5 rows and 5 columns. The columns are labeled 'Make', 'Colour', 'Odometer', 'Doors', and 'Price'. The rows are indexed from 0 to 4. The 'Odometer' column has values 150043, 87899, 32549, 11179, and 213095. The 'Doors' column has values 4, 4, 3, 5, and 4. The 'Price' column has values \$4,000, \$5,000, \$7,000, \$22,000, and \$3,500. The diagram also shows the 'Index number (starts at 0 by default)' on the left and 'Column name' on the right. A 'Data' label points to the values in the 'Odometer' and 'Doors' columns.

	Column (axis = 1)	Make	Colour	Odometer	Doors	Price	Column name
Index number (starts at 0 by default)	0	Toyota	White	150043	4	\$4,000	
	1	Honda	Red	87899	4	\$5,000	
	2	Toyota	Blue	32549	3	\$7,000	
Row (axis = 0)	3	BMW	Black	11179	5	\$22,000	
	4	Nissan	White	213095	4	\$3,500	

```
[296]: # Exporting the DataFrame to see how does it work
## Note index=False removes additional indexing column

car_sales.to_csv("Resources/exported-car-sales.csv", index=False)
exported_car_sales = pd.read_csv("Resources/exported-car-sales.csv")
exported_car_sales
```

```
[296]:
```

	Make	Colour	Odometer (KM)	Doors	Price
0	Toyota	White	150043	4	\$4,000.00
1	Honda	Red	87899	4	\$5,000.00
2	Toyota	Blue	32549	3	\$7,000.00
3	BMW	Black	11179	5	\$22,000.00
4	Nissan	White	213095	4	\$3,500.00
5	Toyota	Green	99213	4	\$4,500.00
6	Honda	Blue	45698	4	\$7,500.00
7	Honda	Blue	54738	4	\$7,000.00
8	Toyota	White	60000	4	\$6,250.00
9	Nissan	White	31600	4	\$9,700.00

### 0.0.1 Describing the data using Attributes and functions.

```
[297]: #information about the dataset
car_sales.dtypes
```

```
[297]: Make                object
       Colour            object
       Odometer (KM)      int64
       Doors             int64
       Price             object
       dtype: object
```

```
[298]: # How to return list of column names
car_sales_columns = car_sales.columns
car_sales_columns
```

```
[298]: Index(['Make', 'Colour', 'Odometer (KM)', 'Doors', 'Price'], dtype='object')
```

```
[299]: # Index data
car_sales.index
```

```
[299]: RangeIndex(start=0, stop=10, step=1)
```

```
[300]: # Describing the data set, Statistically. Works only on Numeric Columns.
car_sales.describe()
#if we notice only the int64 dtypes gets populated.
```

```
[300]:
```

	Odometer (KM)	Doors
count	10.000000	10.000000
mean	78601.400000	4.000000
std	61983.471735	0.471405
min	11179.000000	3.000000
25%	35836.250000	4.000000
50%	57369.000000	4.000000
75%	96384.500000	4.000000
max	213095.000000	5.000000

```
[301]: #This method provides useful information about the DataFrame, such as the
       ↪number of non-null entries,
       #data type of each column, memory usage, and more.
car_sales.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 5 columns):
#   Column          Non-Null Count  Dtype
---  -
0   Make            10 non-null    object
1   Colour          10 non-null    object
```

```

2   Odometer (KM)   10 non-null   int64
3   Doors           10 non-null   int64
4   Price           10 non-null   object
dtypes: int64(2), object(3)
memory usage: 528.0+ bytes

```

```

[302]: # Lets find the mean for numeric values.
car_sales.mean(numeric_only=True)

```

```

[302]: Odometer (KM)    78601.4
Doors                4.0
dtype: float64

```

```

[303]: # Lets find the sum
car_sales.sum(numeric_only=True)

```

```

[303]: Odometer (KM)    786014
Doors                40
dtype: int64

```

```

[304]: #Number of rows
len(car_sales)

```

```

[304]: 10

```

## 0.0.2 Viewing and selecting data

```

[305]: #Look first few rows - By default head() returns five if not specified else
↳ goes by head(7)
car_sales.head()

```

```

[305]:
   Make Colour  Odometer (KM)  Doors  Price
0  Toyota  White         150043     4  $4,000.00
1   Honda   Red          87899     4  $5,000.00
2  Toyota  Blue         32549     3  $7,000.00
3    BMW   Black         11179     5 $22,000.00
4  Nissan  White         213095     4  $3,500.00

```

```

[306]: #Look bottom few rows - By default tail() returns five if not specified else
↳ goes by tail(7)
car_sales.tail(2)

```

```

[306]:
   Make Colour  Odometer (KM)  Doors  Price
8  Toyota  White         60000     4  $6,250.00
9  Nissan  White         31600     4  $9,700.00

```

```

[307]: # .loc and .iloc
animals = pd.Series(["Panda", "Snake", "cat", "Dog"], index=[0,3,9,3])

```

```
animals
```

```
[307]: 0    Panda
      3    Snake
      9     cat
      3     Dog
      dtype: object
```

loc method is used for label-based indexing. It allows you to access a group of rows and columns by labels or a boolean array.

iloc method is used for integer-location based indexing. It allows you to access a group of rows and columns by integer positions (similar to indexing in NumPy).

```
[308]: animals.loc[3],animals.iloc[3]
```

```
[308]: (3    Snake
      3     Dog
      dtype: object,
      'Dog')
```

```
[309]: # upto position 3 that is 0 ,1 and 2 Index.
      animals.iloc[:3]
```

```
[309]: 0    Panda
      3    Snake
      9     cat
      dtype: object
```

```
[310]: # various ways to read a particular column
      car_sales.Make
```

```
[310]: 0    Toyota
      1     Honda
      2    Toyota
      3     BMW
      4     Nissan
      5    Toyota
      6     Honda
      7     Honda
      8    Toyota
      9     Nissan
      Name: Make, dtype: object
```

```
[311]: # various ways to read a particular column
      car_sales["Make"]
```

```
[311]: 0    Toyota
      1    Honda
      2    Toyota
      3     BMW
      4    Nissan
      5    Toyota
      6    Honda
      7    Honda
      8    Toyota
      9    Nissan
      Name: Make, dtype: object
```

```
[312]: # Applying filters
      car_sales[car_sales["Make"]=="Toyota"]
```

```
[312]:      Make Colour  Odometer (KM)  Doors      Price
0  Toyota  White      150043         4  $4,000.00
2  Toyota  Blue       32549         3  $7,000.00
5  Toyota  Green       99213         4  $4,500.00
8  Toyota  White       60000         4  $6,250.00
```

```
[313]: # Crosstab It is used to summarize the relationship between two variables.
      # The function returns a DataFrame that contains the frequency of each
      ↪ combination of the factors.
      pd.crosstab(car_sales["Make"], car_sales["Doors"])
```

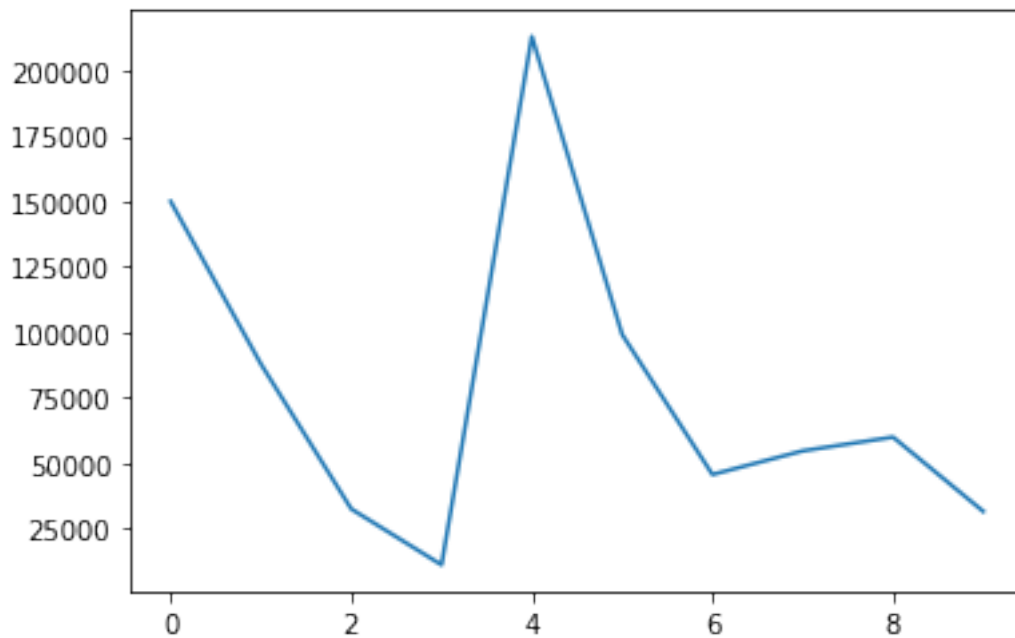
```
[313]: Doors    3    4    5
      Make
      BMW      0    0    1
      Honda    0    3    0
      Nissan   0    2    0
      Toyota   1    3    0
```

```
[314]: #Group By function
      car_sales.groupby(["Make"]).mean()
```

```
[314]:      Odometer (KM)  Doors
      Make
      BMW      11179.000000    5.00
      Honda    62778.333333    4.00
      Nissan   122347.500000    4.00
      Toyota   85451.250000    3.75
```

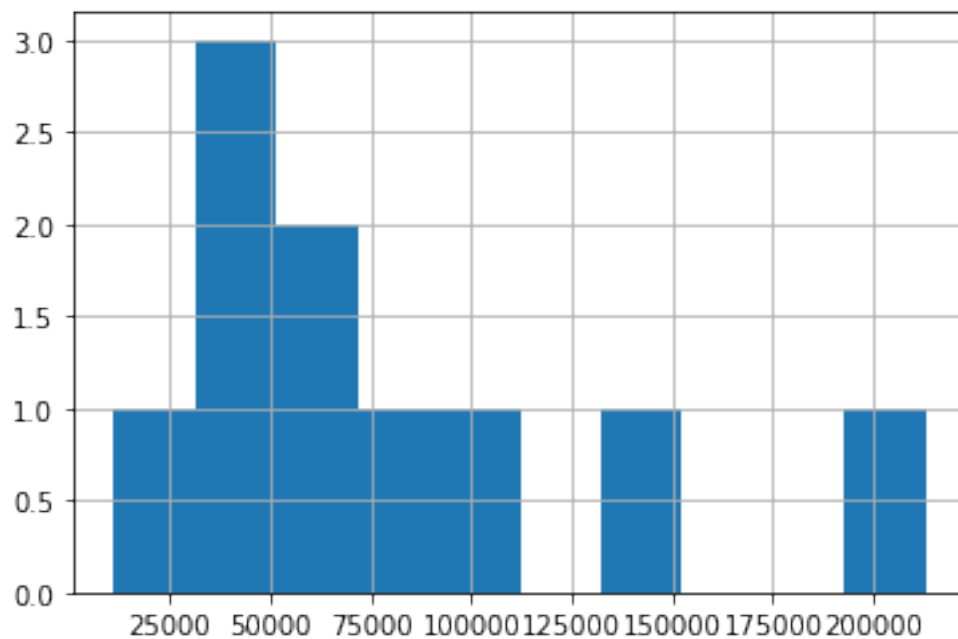
```
[315]: # just few charts from Matplotlib
      car_sales["Odometer (KM)"].plot()
```

```
[315]: <AxesSubplot:>
```



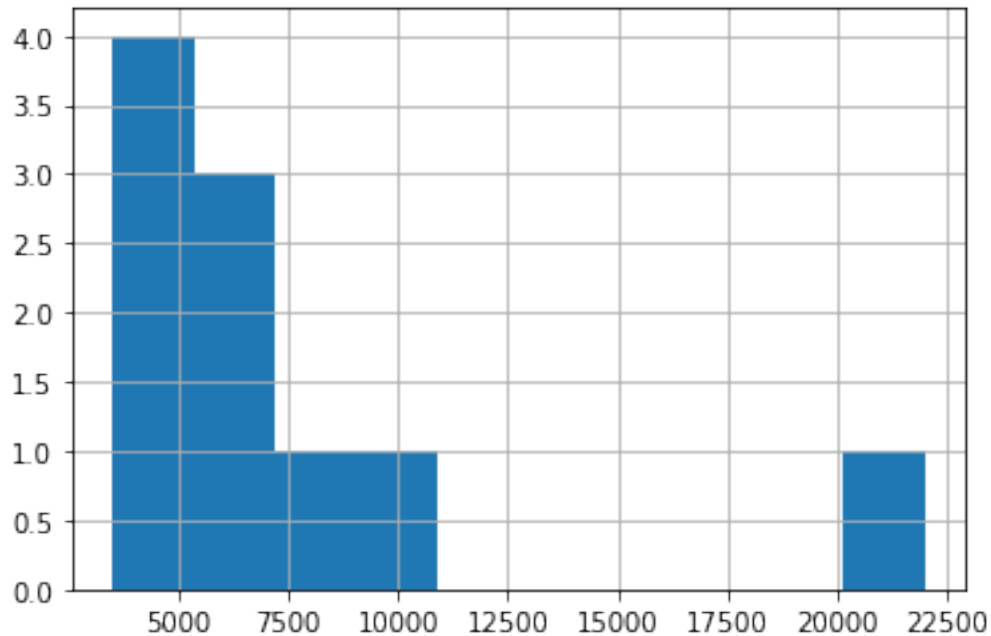
```
[316]: # just few charts from Matplotlib
car_sales["Odometer (KM)"].hist()
```

[316]: <AxesSubplot:>









### 0.0.3 Manipulating Data

```
[320]: #Exploring one of the column using upper case function
car_sales["Make"]=car_sales["Make"].str.upper()
car_sales
```

```
[320]:
```

	Make	Colour	Odometer (KM)	Doors	Price
0	TOYOTA	White	150043	4	4000
1	HONDA	Red	87899	4	5000
2	TOYOTA	Blue	32549	3	7000
3	BMW	Black	11179	5	22000
4	NISSAN	White	213095	4	3500
5	TOYOTA	Green	99213	4	4500
6	HONDA	Blue	45698	4	7500
7	HONDA	Blue	54738	4	7000
8	TOYOTA	White	60000	4	6250
9	NISSAN	White	31600	4	9700

```
[321]: #Importing another csv files where we can find some missing values and play_
↪around with it
car_sales_missing = pd.read_csv("Resources/car-sales-missing-data.csv")
car_sales_missing
```

```
[321]:
```

	Make	Colour	Odometer	Doors	Price
0	Toyota	White	150043.0	4.0	\$4,000

1	Honda	Red	87899.0	4.0	\$5,000
2	Toyota	Blue	NaN	3.0	\$7,000
3	BMW	Black	11179.0	5.0	\$22,000
4	Nissan	White	213095.0	4.0	\$3,500
5	Toyota	Green	NaN	4.0	\$4,500
6	Honda	NaN	NaN	4.0	\$7,500
7	Honda	Blue	NaN	4.0	NaN
8	Toyota	White	60000.0	NaN	NaN
9	NaN	White	31600.0	4.0	\$9,700

```
[322]: #filling missing values using mean function.
car_sales_missing["Odometer"]=car_sales_missing["Odometer"].
    ↪fillna(car_sales_missing["Odometer"].mean())
car_sales_missing["Odometer"]=car_sales_missing["Odometer"].astype(int)
car_sales_missing
```

```
[322]:
```

	Make	Colour	Odometer	Doors	Price
0	Toyota	White	150043	4.0	\$4,000
1	Honda	Red	87899	4.0	\$5,000
2	Toyota	Blue	92302	3.0	\$7,000
3	BMW	Black	11179	5.0	\$22,000
4	Nissan	White	213095	4.0	\$3,500
5	Toyota	Green	92302	4.0	\$4,500
6	Honda	NaN	92302	4.0	\$7,500
7	Honda	Blue	92302	4.0	NaN
8	Toyota	White	60000	NaN	NaN
9	NaN	White	31600	4.0	\$9,700

```
[323]: # we can drop the missing values using the function.
car_sales_missing_dropped=car_sales_missing.dropna()
car_sales_missing_dropped
```

```
[323]:
```

	Make	Colour	Odometer	Doors	Price
0	Toyota	White	150043	4.0	\$4,000
1	Honda	Red	87899	4.0	\$5,000
2	Toyota	Blue	92302	3.0	\$7,000
3	BMW	Black	11179	5.0	\$22,000
4	Nissan	White	213095	4.0	\$3,500
5	Toyota	Green	92302	4.0	\$4,500

```
[324]: #Lets create few more series and add them to the dataframe.

seats_column = pd.Series([5,5,5,5,6])

#New column called seats
car_sales["Seats"]=seats_column
car_sales
```

```
[324]:
```

	Make	Colour	Odometer (KM)	Doors	Price	Seats
0	TOYOTA	White	150043	4	4000	5.0
1	HONDA	Red	87899	4	5000	5.0
2	TOYOTA	Blue	32549	3	7000	5.0
3	BMW	Black	11179	5	22000	5.0
4	NISSAN	White	213095	4	3500	6.0
5	TOYOTA	Green	99213	4	4500	NaN
6	HONDA	Blue	45698	4	7500	NaN
7	HONDA	Blue	54738	4	7000	NaN
8	TOYOTA	White	60000	4	6250	NaN
9	NISSAN	White	31600	4	9700	NaN

```
[244]: car_sales["Seats"]=car_sales["Seats"].fillna(car_sales["Seats"].min())
car_sales
```

```
[244]:
```

	Make	Colour	Odometer (KM)	Doors	Price	Seats
0	TOYOTA	White	150043	4	\$4,000.00	5.0
1	HONDA	Red	87899	4	\$5,000.00	5.0
2	TOYOTA	Blue	32549	3	\$7,000.00	5.0
3	BMW	Black	11179	5	\$22,000.00	5.0
4	NISSAN	White	213095	4	\$3,500.00	6.0
5	TOYOTA	Green	99213	4	\$4,500.00	5.0
6	HONDA	Blue	45698	4	\$7,500.00	5.0
7	HONDA	Blue	54738	4	\$7,000.00	5.0
8	TOYOTA	White	60000	4	\$6,250.00	5.0
9	NISSAN	White	31600	4	\$9,700.00	5.0

```
[325]: # Adding column - fuel economy with few arithmetic operations to gain some
↳ experience.
fuel_economy =[7.5,9.2,5.0,9.6,8.7,8.3,8.1,9.1,9.6,8.7]
car_sales["Fuel per 100KM"]=fuel_economy
car_sales
```

```
[325]:
```

	Make	Colour	Odometer (KM)	Doors	Price	Seats	Fuel per 100KM
0	TOYOTA	White	150043	4	4000	5.0	7.5
1	HONDA	Red	87899	4	5000	5.0	9.2
2	TOYOTA	Blue	32549	3	7000	5.0	5.0
3	BMW	Black	11179	5	22000	5.0	9.6
4	NISSAN	White	213095	4	3500	6.0	8.7
5	TOYOTA	Green	99213	4	4500	NaN	8.3
6	HONDA	Blue	45698	4	7500	NaN	8.1
7	HONDA	Blue	54738	4	7000	NaN	9.1
8	TOYOTA	White	60000	4	6250	NaN	9.6
9	NISSAN	White	31600	4	9700	NaN	8.7

```
[326]: car_sales["Total Fuel Used"]=car_sales["Odometer (KM)"]/100*car_sales["Fuel per
↳ 100KM"].astype(int)
```

```
car_sales
```

```
[326]:      Make Colour  Odometer (KM)  Doors  Price  Seats  Fuel per 100KM  \
0  TOYOTA  White      150043      4   4000    5.0          7.5
1   HONDA   Red       87899      4   5000    5.0          9.2
2  TOYOTA  Blue      32549      3   7000    5.0          5.0
3    BMW  Black       11179      5  22000    5.0          9.6
4  NISSAN  White     213095      4   3500    6.0          8.7
5  TOYOTA  Green      99213      4   4500   NaN          8.3
6   HONDA  Blue      45698      4   7500   NaN          8.1
7   HONDA  Blue      54738      4   7000   NaN          9.1
8  TOYOTA  White     60000      4   6250   NaN          9.6
9  NISSAN  White      31600      4   9700   NaN          8.7
```

```
      Total Fuel Used
0          10503.01
1           7910.91
2          1627.45
3          1006.11
4         17047.60
5          7937.04
6          3655.84
7          4926.42
8          5400.00
9          2528.00
```

```
[327]: car_sales["Number of Wheels"]=4
car_sales["Number of Wheel"]=4
car_sales["Safety Test Passed"]=True
car_sales
```

```
[327]:      Make Colour  Odometer (KM)  Doors  Price  Seats  Fuel per 100KM  \
0  TOYOTA  White      150043      4   4000    5.0          7.5
1   HONDA   Red       87899      4   5000    5.0          9.2
2  TOYOTA  Blue      32549      3   7000    5.0          5.0
3    BMW  Black       11179      5  22000    5.0          9.6
4  NISSAN  White     213095      4   3500    6.0          8.7
5  TOYOTA  Green      99213      4   4500   NaN          8.3
6   HONDA  Blue      45698      4   7500   NaN          8.1
7   HONDA  Blue      54738      4   7000   NaN          9.1
8  TOYOTA  White     60000      4   6250   NaN          9.6
9  NISSAN  White      31600      4   9700   NaN          8.7

      Total Fuel Used  Number of Wheels  Number of Wheel  Safety Test Passed
0          10503.01              4              4              True
1           7910.91              4              4              True
2          1627.45              4              4              True
```

3	1006.11	4	4	True
4	17047.60	4	4	True
5	7937.04	4	4	True
6	3655.84	4	4	True
7	4926.42	4	4	True
8	5400.00	4	4	True
9	2528.00	4	4	True

```
[328]: # How to remove one of the column
car_sales.drop("Number of Wheel",axis=1,inplace=True)
car_sales
```

```
[328]:      Make Colour  Odometer (KM)  Doors  Price  Seats  Fuel per 100KM  \
0  TOYOTA  White      150043      4    4000    5.0          7.5
1   HONDA   Red       87899      4    5000    5.0          9.2
2  TOYOTA  Blue       32549      3    7000    5.0          5.0
3    BMW   Black       11179      5   22000    5.0          9.6
4  NISSAN  White      213095      4    3500    6.0          8.7
5  TOYOTA  Green       99213      4    4500   NaN          8.3
6   HONDA  Blue       45698      4    7500   NaN          8.1
7   HONDA  Blue       54738      4    7000   NaN          9.1
8  TOYOTA  White      60000      4    6250   NaN          9.6
9  NISSAN  White       31600      4    9700   NaN          8.7
```

	Total Fuel Used	Number of Wheels	Safety Test Passed
0	10503.01	4	True
1	7910.91	4	True
2	1627.45	4	True
3	1006.11	4	True
4	17047.60	4	True
5	7937.04	4	True
6	3655.84	4	True
7	4926.42	4	True
8	5400.00	4	True
9	2528.00	4	True

```
[331]: #How to shuffle the rows in the dataframe and return. Fraction 0.5 is 50 percent
car_sales=car_sales.sample(frac=1)
car_sales
```

```
[331]:      Make Colour  Odometer (KM)  Doors  Price  Seats  Fuel per 100KM  \
5  TOYOTA  Green       99213      4    4500   NaN          8.3
0  TOYOTA  White      150043      4    4000    5.0          7.5
3    BMW   Black       11179      5   22000    5.0          9.6
4  NISSAN  White      213095      4    3500    6.0          8.7
7   HONDA  Blue       54738      4    7000   NaN          9.1
1   HONDA   Red       87899      4    5000    5.0          9.2
```

9	NISSAN	White	31600	4	9700	NaN	8.7
6	HONDA	Blue	45698	4	7500	NaN	8.1
8	TOYOTA	White	60000	4	6250	NaN	9.6
2	TOYOTA	Blue	32549	3	7000	5.0	5.0

	Total Fuel Used	Number of Wheels	Safety Test Passed
5	7937.04	4	True
0	10503.01	4	True
3	1006.11	4	True
4	17047.60	4	True
7	4926.42	4	True
1	7910.91	4	True
9	2528.00	4	True
6	3655.84	4	True
8	5400.00	4	True
2	1627.45	4	True

```
[332]: #How to reset the shuffled dataset to back in order
car_sales.reset_index(drop=True, inplace=True)
car_sales
```

```
[332]:
```

	Make	Colour	Odometer (KM)	Doors	Price	Seats	Fuel per 100KM \
0	TOYOTA	Green	99213	4	4500	NaN	8.3
1	TOYOTA	White	150043	4	4000	5.0	7.5
2	BMW	Black	11179	5	22000	5.0	9.6
3	NISSAN	White	213095	4	3500	6.0	8.7
4	HONDA	Blue	54738	4	7000	NaN	9.1
5	HONDA	Red	87899	4	5000	5.0	9.2
6	NISSAN	White	31600	4	9700	NaN	8.7
7	HONDA	Blue	45698	4	7500	NaN	8.1
8	TOYOTA	White	60000	4	6250	NaN	9.6
9	TOYOTA	Blue	32549	3	7000	5.0	5.0

	Total Fuel Used	Number of Wheels	Safety Test Passed
0	7937.04	4	True
1	10503.01	4	True
2	1006.11	4	True
3	17047.60	4	True
4	4926.42	4	True
5	7910.91	4	True
6	2528.00	4	True
7	3655.84	4	True
8	5400.00	4	True
9	1627.45	4	True

A lambda function in Python is a small anonymous function defined using the lambda keyword. It allows you to create a function without a proper name (anonymous) and

is typically used for short, simple operations where defining a full function using def would be overkill.

```
[333]: #Applying Lambda function
car_sales["Odometer (KM)"]=car_sales["Odometer (KM)"].apply(lambda x: x/1.6)
car_sales
```

```
[333]:      Make Colour  Odometer (KM)  Doors  Price  Seats  Fuel per 100KM  \
0  TOYOTA  Green      62008.125      4   4500    NaN          8.3
1  TOYOTA  White      93776.875      4   4000    5.0          7.5
2    BMW  Black       6986.875      5  22000    5.0          9.6
3  NISSAN  White     133184.375      4   3500    6.0          8.7
4  HONDA   Blue      34211.250      4   7000    NaN          9.1
5  HONDA   Red       54936.875      4   5000    5.0          9.2
6  NISSAN  White     19750.000      4   9700    NaN          8.7
7  HONDA   Blue      28561.250      4   7500    NaN          8.1
8  TOYOTA  White      37500.000      4   6250    NaN          9.6
9  TOYOTA   Blue      20343.125      3   7000    5.0          5.0
```

	Total Fuel Used	Number of Wheels	Safety Test Passed
0	7937.04	4	True
1	10503.01	4	True
2	1006.11	4	True
3	17047.60	4	True
4	4926.42	4	True
5	7910.91	4	True
6	2528.00	4	True
7	3655.84	4	True
8	5400.00	4	True
9	1627.45	4	True

```
[ ]:
```