Introduction

Based on NumPy, Pandas is one of the most popular and robust data analysis libraries in Python. Data analysts, data scientists, and machine learning engineers utilize it essentially every day for projects involving data wrangling, data manipulation and data visualization. In this tutorial, we'll be using an actual dataset to perform data analysis so you can get started with Pandas and utilize it in your own projects.

Getting started

Installation

Pandas must be installed first before you can use it in your system:

```
pip install pandas
conda install pandas
```

Once installed, it is now ready to be imported in the kernel or notebook:

```
import pandas as pd
```

Importing libraries

It is useful to import a few required libraries before working with Pandas, such as NumPy for data processing, and matplotlib and seaborn for data visualization.

To perform mathematical array operations:

```
import numpy as np
```

To create interactive, fully-functional visualizations:

```
import matplotlib.pyplot as plt
import seaborn as sns
```

Working with Data

Pandas offers primarily two types of data structures: series and dataframes. These are designed in a way to make data fast and easier to analyze.

Series

Pandas series is a one dimensional array object of key-value pairs of integers, strings, floats, and other data types. Each element (value) of a series is assigned a unique label, often known as an index or key. Series are often used in data manipulation tasks.

To create a series in pandas, we use *pandas.Series():*

```
import pandas as pd

# initialize the series object
num = pd.Series([12, 3, 2, 8])
print(num)
```

```
0    12
1     3
2     2
3     8
dtype: int64
```

DataFrame

However, dataframes have a two-dimensional structure that is similar to a spreadsheet or table with rows and columns. A dataframes is basically an arrangement of two or more series, with distinct data types, such as name (*string*), age (*int*), and date_of_birth (*datetime*), in each column.

To create a dataframe in pandas, we use *pandas.DataFrame():*

```
import pandas as pd

customers = {‘name’: [‘Zeke’, ‘Alex’, ‘Keith’, ‘Elen’],
                    ‘age’: [65, 40, 30, 28],
                    ‘year’: [1958, 1983, 1993, 1995]}
df = pd.DataFrame(customers)
```

```
  age   name  year
0   65   Zeke  1958
1   40   Alex  1983
2   30  Keith  1993
3   28   Elen  1995
```

Loading and Saving Data

Pandas allows us to import and store data in different formats such as CSV and Excel files and connect to databases like SQLite as well.

```
# load the data
df = pd.read_csv(‘file.csv’)
df = pd.read_excel(‘file.xlsx’, sheet_name=‘data’)

# save the data
df.to_csv(‘output.csv’)
df.to_excel(‘output.xlsx’)
```

Using SQLite:

```
# connect to databases
import sqlite3
conn = sqlite3.connect(‘data.db’)
query = “SELECT * FROM table_name”
df = pd.read_sql_query(query, conn)

# save the databases
df.to_sql(‘data’, conn, if_exists=‘replace’, index=False)
df.to_sql(‘data’, conn, if_exists=‘replace’, index=False)

# close the connection
conn.close()
```

Data Analysis with Pandas

Now that we understand the fundamentals, let’s proceed to utilize pandas for exploratory data analysis (EDA) processes. EDA involves several data analysis techniques, such as :

- Data collection: This includes collecting a significant amount of data from various sources like csv, xlsx files, SQL databases or APIs for analysis.
- Data exploration: It provides a brief overview of the dataset to comprehend its size, distribution, datatype of variables and key metrics.
- Data cleaning: Identifying and handling missing and duplicate data, eliminating irrelevant columns, and making the data consistent for better results.
- Data manipulation: Applying techniques like normalization and standardization to transform data in accordance with the requirements of our project. This is a typical approach for machine learning projects, you can learn more about it here.

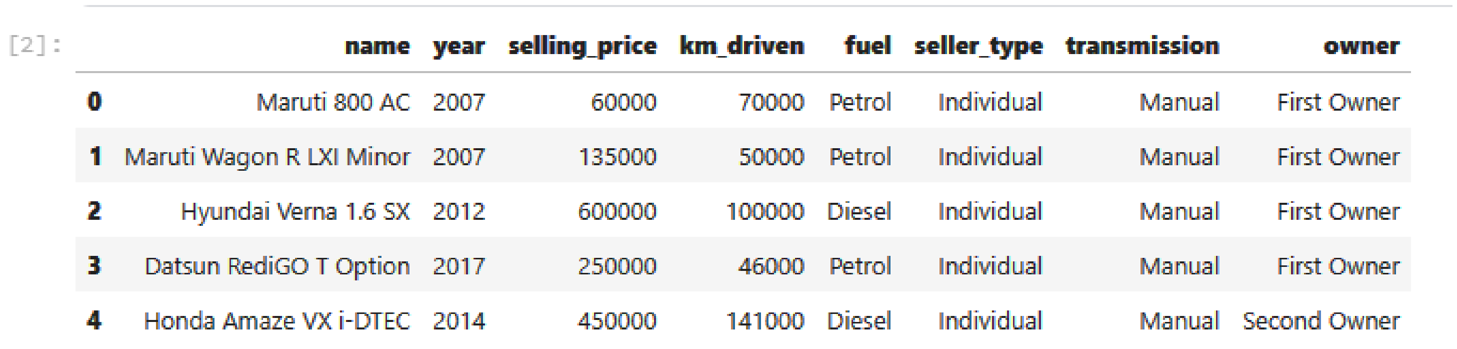
Data Exploration

We are going to use this dataset from Kaggle. The CSV file can be downloaded and used locally in your Jupyter notebook, or it can be used directly via Kaggle notebooks, choose the one you prefer and load the dataset:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

df = pd.read_csv('data.csv')
```

.head() allows us to peek into the first 5 rows of the dataset:

```
df.head()
```



[2]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner
0	Maruti 800 AC	2007	60000	70000	Petrol	Individual	Manual	First Owner
1	Maruti Wagon R LXI Minor	2007	135000	50000	Petrol	Individual	Manual	First Owner
2	Hyundai Verna 1.6 SX	2012	600000	100000	Diesel	Individual	Manual	First Owner
3	Datsun RediGO T Option	2017	250000	46000	Petrol	Individual	Manual	First Owner
4	Honda Amaze VX i-DTEC	2014	450000	141000	Diesel	Individual	Manual	Second Owner

.shape() returns a tuple of two elements, total number of rows and columns, respectively. This helps to understand the dataset size:

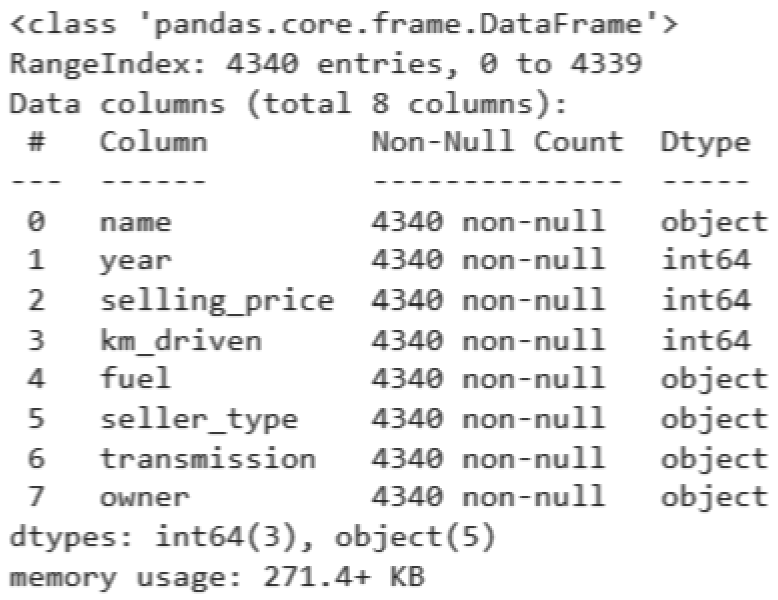
```
df.shape()
```

```
>> (4340, 8)
```

There are 4340 rows and 8 columns in the dataset.

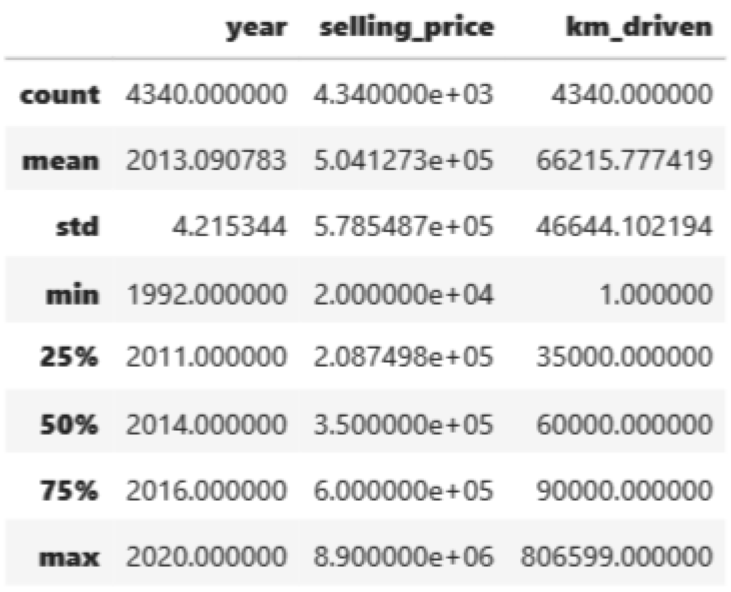
The .info() and .describe() method provide a summary of numerical data and helps with data types and distribution of data, respectively:

```
df.info()
```



```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4340 entries, 0 to 4339
Data columns (total 8 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   name           4340 non-null   object
 1   year           4340 non-null   int64
 2   selling_price  4340 non-null   int64
 3   km_driven      4340 non-null   int64
 4   fuel           4340 non-null   object
 5   seller_type    4340 non-null   object
 6   transmission   4340 non-null   object
 7   owner          4340 non-null   object
dtypes: int64(3), object(5)
memory usage: 271.4+ KB
```

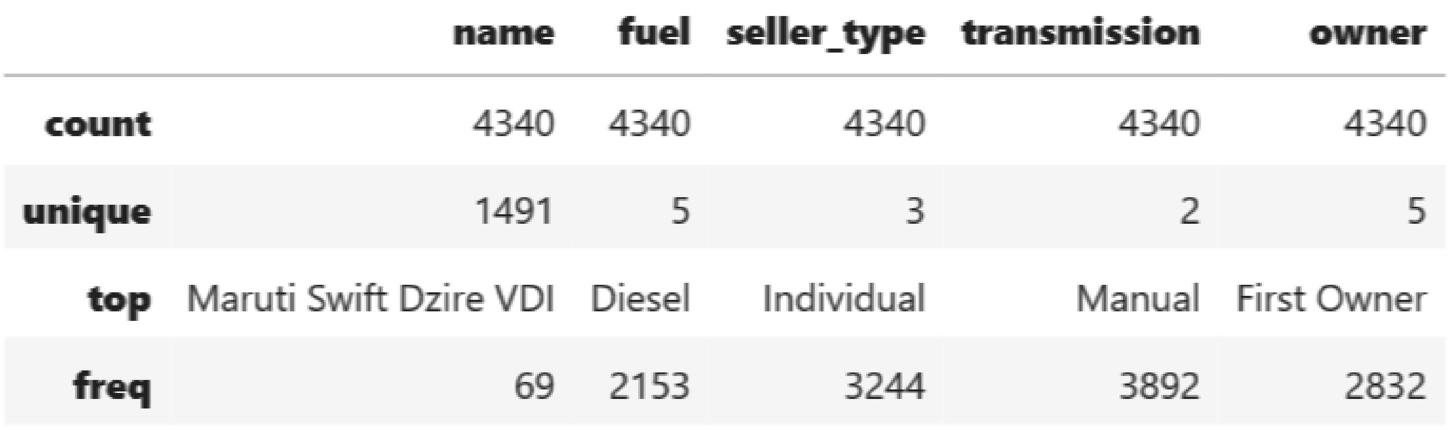
```
df.describe()
```



	year	selling_price	km_driven
count	4340.000000	4.340000e+03	4340.000000
mean	2013.090783	5.041273e+05	66215.777419
std	4.215344	5.785487e+05	46644.102194
min	1992.000000	2.000000e+04	1.000000
25%	2011.000000	2.087498e+05	35000.000000
50%	2014.000000	3.500000e+05	60000.000000
75%	2016.000000	6.000000e+05	90000.000000
max	2020.000000	8.900000e+06	806599.000000

By default, the .describe() method only returns numerical variables. To look for ‘object’ columns:

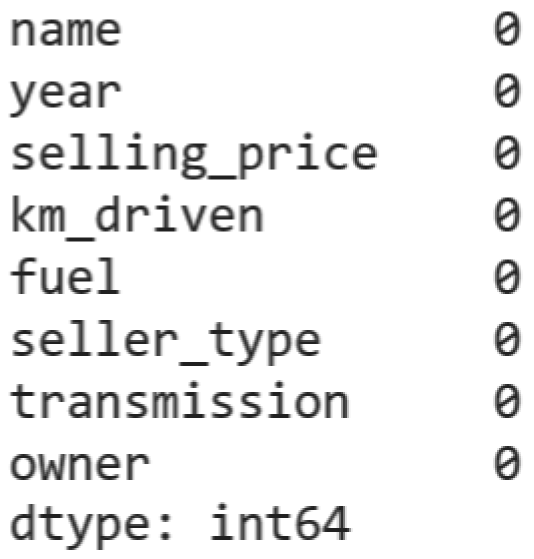
```
df.describe(include=‘object’)
```



	name	fuel	seller_type	transmission	owner
count	4340	4340	4340	4340	4340
unique	1491	5	3	2	5
top	Maruti Swift Dzire VDI	Diesel	Individual	Manual	First Owner
freq	69	2153	3244	3892	2832

To check for missing values, we use *.isnull()* method:

```
# sum of missing values in each column

df.isnull().sum()
```



```
name             0
year             0
selling_price    0
km_driven        0
fuel             0
seller_type      0
transmission     0
owner            0
dtype: int64
```

This dataset has no null values. Awesome!

To check for duplicate data, we use .duplicated():

```
# sum of duplicate rows
df.duplicated().sum()
```

```
>> 763
```

There are 763 duplicate rows in this dataset.

In the following section we will learn how to deal with duplicates and missing data in our dataset, as these values can significantly affect our analysis.

Data Cleaning

Handling missing data

Too much missing data in the dataset can influence the findings of our analysis. In order to address such circumstances, mean or median value of the respective column can be used to fill in the missing data points.

The choice of whether the mean or median value should be chosen depends on the data to be processed. Suppose that our data is highly skewed, the mean value is not a reliable indicator of central tendency in this case. Therefore we will use the median value to fill the missing data.

```
median_col = df['col'].median()

# filling missing values
df['col'].fillna(median_col, inplace=True)
```

Handling duplicate data

For duplicate rows, we can simply use the drop_duplicates() method, which eliminates all the repetitive rows except the first occurrence:

```
df_clean = df.drop_duplicates()
df_clean.shape
```

```
>>(3577, 8)
```

```
# to modify the original dataframe, set inplace to 'True'
df.drop_duplicates(inplace=True)
```

In this step, a good practice is to create a copy of the dataset to protect the original dataset from any unintended data losses.

Removing irrelevant columns

When performing data analysis, columns like customer reviews or product descriptions are not necessary. We can drop such columns to keep the data clean and easier to explore.

```
df = df.drop([‘customer_reviews’], axis=1)
```

Data Manipulation

Data manipulation and transformation include tasks that prepare our data for analysis, such as aggregating, filtering and sorting data, as well as creating new columns from pre-existing ones.

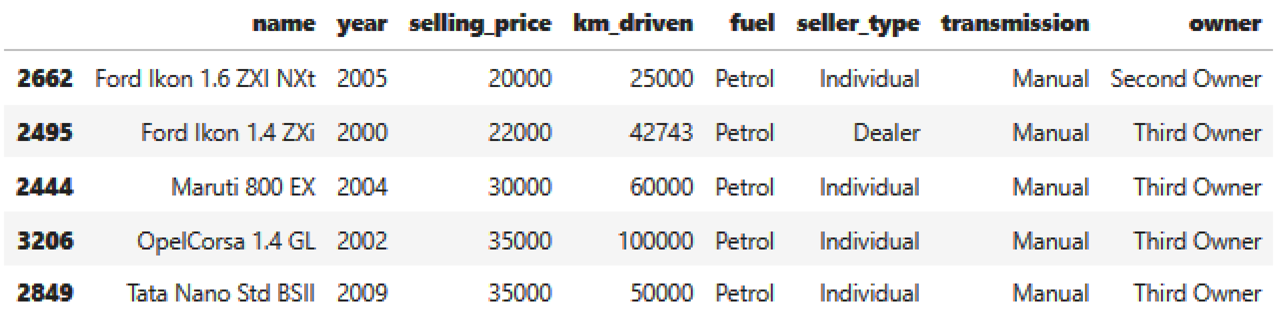
Aggregate functions

```
# total selling price:
total_selling_price = df[‘selling_price’].sum()

# average distance covered:
average_km_driven = df[‘km_driven’].mean()

# number of cars for each fuel type:
fuel_counts = df[‘fuel’].value_counts()
```

Sorting a DataFrame

Sorting is useful when we are trying to understand trends and patterns among different variables:

```
df.sort_values(by=‘selling_price’, ascending=True, inplace=True)
```



	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner
2662	Ford Ikon 1.6 ZXI NXt	2005	20000	25000	Petrol	Individual	Manual	Second Owner
2495	Ford Ikon 1.4 ZXi	2000	22000	42743	Petrol	Dealer	Manual	Third Owner
2444	Maruti 800 EX	2004	30000	60000	Petrol	Individual	Manual	Third Owner
3206	OpelCorsa 1.4 GL	2002	35000	100000	Petrol	Individual	Manual	Third Owner
2849	Tata Nano Std BSII	2009	35000	50000	Petrol	Individual	Manual	Third Owner

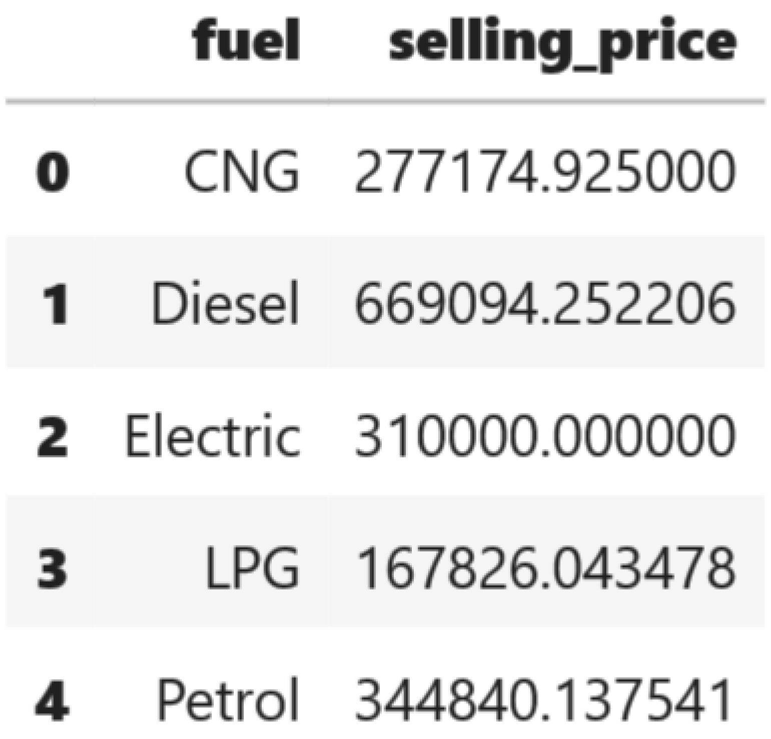
Filtering a DataFrame

```
year_below_2000 = df[df['year'] < 2000]
len(year_below_2000)

>> 29
```

29 data values are available for vehicles registered before the year 2000.

Grouping a DataFrame

```
by_price = df.groupby('fuel')['selling_price'].mean().reset_index()
by_price
```



	fuel	selling_price
0	CNG	277174.925000
1	Diesel	669094.252206
2	Electric	310000.000000
3	LPG	167826.043478
4	Petrol	344840.137541

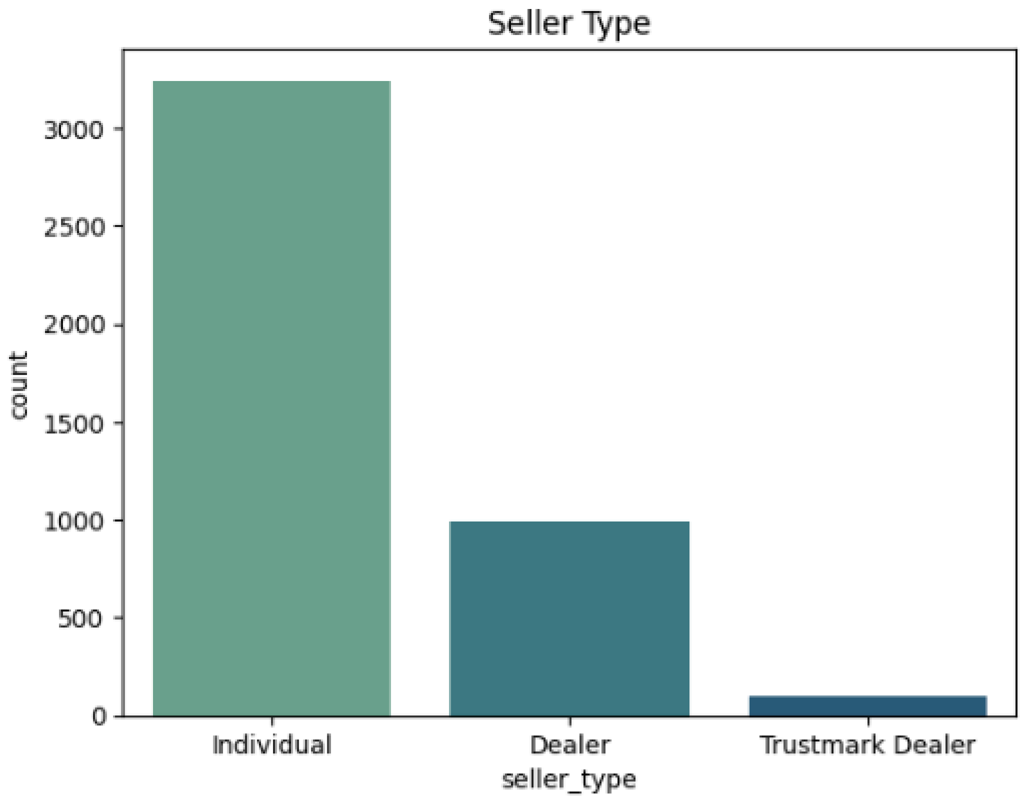
On average, diesel cars have a higher selling price compared to petrol cars, considering the factors like market demand and efficiency of fuel.

Data Visualization

Data visualization libraries like Matplotlib, Seaborn and Plotly offer various plots, graphs and visuals that can be employed with pandas.

Here are a few examples:

```
sns.countplot(data=df,x="seller_type",palette="crest")
plt.title("Seller Type")
plt.show()
```



```
sns.lineplot(data=df,x='year',y='selling_price',hue='fuel')
```

Predictive Analytics

In machine learning, data analysis takes a step further to carry out feature engineering using different techniques like:

- Standardization and normalization to keep variables on the same scale.
- Principal Component Analysis (PCA) to reduce data complexity by dimensionality reduction in huge datasets.
- NLP methods like TF-IDF and bag of words to transform textual data into numerical data.
- Time series analysis for forecasting datetime variables, and more.