Descriptive Analytics

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Learning Objectives

- Working with DataFrames and perform basic exploratory Analysis
- Data Preparation Activities: Filtering, grouping, ordering, joining etc.
- Dealing with Missing Values
- Prepare plots such as bar plot, histogram, distribution plot, box plot, scatter plot, pair plot and heat maps to find insights.

Working with Dataframes

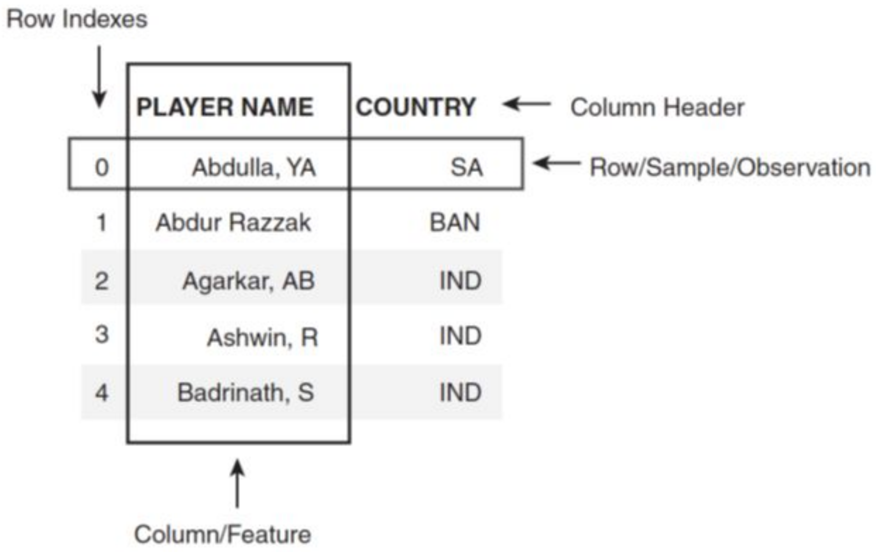


FIGURE 2.1 Structure of a DataFrame.

Example: IPL data set

TABLE 2.1 IPL auction price data description

Data Code	Data Type	Description
AGE	Categorical	Age of the player at the time of auction classified into 3 categories. Category 1 (L25) means the player is less than 25 years old, 2 means that age is between 25 and 35 years (B25–35) and category 3 means that the age is more than 35 (A35).
RUNS-S	Continuous	Number of runs scored by a player
RUNS-C	Continuous	Number of runs conceded by a player
HS	Continuous	Highest score by the batsman in IPL
AVE-B	Continuous	Average runs scored by the batsman in IPL
AVE-BL	Continuous	Bowling average (Number of runs conceded / number of wickets taken) in IPL
SR-B	Continuous	Batting strike rate (ratio of the number of runs scored to the number of balls faced) in IPL
SR-BL	Continuous	Bowling strike rate (ratio of the number of balls bowled to the number of wickets taken) in IPL
SIXERS	Continuous	Number of six runs scored by a player in IPL
WKTS	Continuous	Number of wickets taken by a player in IPL
ECON	Continuous	Economy rate of a bowler (number of runs conceded by the bowler per over) in IPL
CAPTAINCY EXP	Categorical	Captained either a T20 team or a national team
ODI-SR-B	Continuous	Batting strike rate in One-Day Internationals
ODI-SR-BL	Continuous	Bowling strike rate in One-Day Internationals
ODI-RUNS-S	Continuous	Runs scored in One-Day Internationals
ODI-WKTS	Continuous	Wickets taken in One-Day Internationals
T-RUNS-S	Continuous	Runs scored in Test maches
T-WKTS	Continuous	Wickets taken in Test maches
PLAYER-SKILL	Categorical	Player's primary skill (batsman, bowler, or all-rounder)
COUNTRY	Categorical	Country of origin of the player (AUS: Australia; IND: India; PAK: Pakistan; SA: South Africa; SL: Sri Lanka; NZ: New Zealand; WI: West Indies; OTH: Other countries)
YEAR-A	Categorical	Year of Auction in IPL
IPL TEAM	Categorical	Team(s) for which the player had played in the IPL (CSK: Chennai Super Kings, DC: Deccan Chargers, DD: Delhi Daredevils, KXI: Kings XI Punjab, KKR: Kolkata Knight Riders; MI: Mumbai Indians; PWI: Pune Warriors India; RR: Rajasthan Royals; RCB: Royal Challengers Bangalore). A + sign was used to indicate that the player had played for more than one team. For example, CSK+ would mean that the player had played tor CSK as well as for one or more other teams.

Loading Dataset into DataFrame

```
import pandas as pd
ipl_auction_df = pd.read_csv('IPL IMB381IPL2013.csv')
```

```
ipl_auction_df.head(5)
```

	Sl. NO.	Player Name	Age	...	Auction Year	Base Price	Sold Price
0	1	Abdulla, YA	2	...	2009	50000	50000
1	2	Abdur Razzak	2	...	2008	50000	50000
2	3	Agarkar, AB	2	...	2008	200000	350000
3	4	Ashwin, R	1	...	2011	100000	850000
4	5	Badrinath, S	2	...	2011	100000	800000

Finding summary of the DataFrame

```
ipl_auction_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 130 entries, 0 to 129
Data columns (total 26 columns):
Sl.NO.           130   non-null   int64
PLAYER NAME      130   non-null   object
AGE              130   non-null   int64
COUNTRY          130   non-null   Object
TEAM             130   non-null   Object
PLAYING ROLE     130   non-null   Object
T-RUNS           130   non-null   int64
T-WKTS           130   non-null   int64
ODI-RUNS-S       130   non-null   int64
ODI-SR-B         130   non-null   float64
ODI-WKTS         130   non-null   int64
ODI-SR-BL        130   non-null   float64
CAPTAINCY EXP    130   non-null   int64
RUNS-S           130   non-null   int64
HS               130   non-null   int64
AVE              130   non-null   float64
SR-B             130   non-null   float64
SIXERS           130   non-null   int64
RUNS-C           130   non-null   int64
WKTS             130   non-null   int64
AVE-BL           130   non-null   float64
ECON             130   non-null   float64
SR-BL            130   non-null   float64
AUCTION YEAR     130   non-null   int64
BASE PRICE       130   non-null   int64
SOLD PRICE       130   non-null   int64
dtypes: float64(7), int64(15), object(4)
memory usage: 26.5+ KB
```

Slicing and Indexing of the DataFrame by ROWS

```
ipl_auction_df[0:5]
```

	Sl. NO.	Player Name	Age	...	Auction Year	Base Price	Sold Price
0	1	Abdulla, YA	2	...	2009	50000	50000
1	2	Abdur Razzak	2	...	2008	50000	50000
2	3	Agarkar, AB	2	...	2008	200000	350000
3	4	Ashwin, R	1	...	2011	100000	850000
4	5	Badrinath, S	2	...	2011	100000	800000

BY Rows: First five entries

```
ipl_auction_df[-5:]
```

	Sl. NO.	Player Name	Age	...	Auction Year	Base Price	Sold Price
125	126	Yadav, AS	2	...	2010	50000	750000
126	127	Younis Khan	2	...	2008	225000	225000
127	128	Yuvraj Singh	2	...	2011	400000	1800000
128	129	Zaheer Khan	2	...	2008	200000	450000
129	130	Zoysa, DNT	2	...	2008	100000	110000

BY Rows: Last five entries

Slicing and Indexing of the DataFrame by Columns

```
ipl_auction_df['PLAYER NAME'][0:5]
```

```
0      Abdulla, YA
1    Abdur Razzak
2      Agarkar, AB
3        Ashwin, R
4    Badrinath, S
Name: PLAYER NAME, dtype: object
```

```
ipl_auction_df[['PLAYER NAME', 'COUNTRY']][0:5]
```

	PLAYER NAME	COUNTRY
0	Abdulla, YA	SA
1	Abdur Razzak	BAN
2	Agarkar, AB	IND
3	Ashwin, R	IND

Sorting DataFrame by Column Values

```
ipl_auction_df[['PLAYER NAME', 'SOLD PRICE']].sort_values
('SOLD PRICE')[0:5]
```

	Player Name	Sold Price
73	Noffke, AA	20000
46	Kamran Khan	24000
0	Abdulla, YA	50000
1	Abdur Razzak	50000
118	Van der Merwe	50000

```
ipl_auction_df[['PLAYER NAME', 'SOLD PRICE']].sort_values('SOLD
PRICE', ascending = False)[0:5]
```

	Player Name	Sold Price
93	Sehwag, V	1800000
127	Yuvraj Singh	1800000
50	Kohli, V	1800000
111	Tendulkar, SR	1800000
113	Tiwary, SS	1600000

To sort the records in descending order, pass *False* to *ascending* parameter.

Creating New Columns

```
ipl_auction_df['premium'] = ipl_auction_df['SOLD PRICE'] -
                            ipl_auction_df['BASE PRICE']
```

```
ipl_auction_df[['PLAYER NAME', 'BASE PRICE', 'SOLD PRICE',
'premium']][0:5]
```

	Player Name	Base Price	Sold Price	Premium
0	Abdulla, YA	50000	50000	0
1	Abdur Razzak	50000	50000	0
2	Agarkar, AB	200000	350000	150000
3	Ashwin, R	100000	850000	750000
4	Badrinath, S	100000	800000	700000

Grouping and Aggregating

- To find average *SOLD PRICE* for each age category, group all records by *AGE* and then apply *mean()* on *SOLD PRICE* column.

```
soldprice_by_age = ipl_auction_df.groupby('AGE')['SOLD PRICE'].
                       mean().reset_index()
print(soldprice_by_age)
```

	Age	Sold Price
0	1	720250.000000
1	2	484534.883721
2	3	520178.571429

Handling Missing Values

- **Autos-mpg dataset**: It contains information about different cars and their characteristics
  1. mpg – miles per gallon
  2. cylinders – Number of cylinders (values between 4 and 8)
  3. displacement – Engine displacement (cu. inches)
  4. horsepower – Engine horsepower
  5. weight – Vehicle weight (lbs.)
  6. acceleration – Time to accelerate from 0 to 60 mph (sec.)
  7. year – Model year (modulo 100)
  8. origin – Origin of car (1. American, 2. European, 3. Japanese)
  9. name – Vehicle name

Assigning Names to the Columns(As file is header less)

```
autos.columns = ['mpg','cylinders', 'displacement',
                 'horsepower', 'weight', 'acceleration',
                 'year', 'origin', 'name']
autos.head(5)
```

	mpg	cylinders	displacement	...	year	origin	name
0	18.0	8	307.0	...	70	1	chevrolet chevelle malibu
1	15.0	8	350.0	...	70	1	buick skylark 320
2	18.0	8	318.0	...	70	1	plymouth satellite
3	16.0	8	304.0	...	70	1	amc rebel sst
4	17.0	8	302.0	...	70	1	ford torino

5 rows × 9 columns

Summary of Autos-mpg data(Observer horsepower)

```
autos.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
mpg              398  non-null  float64
cylinders        398  non-null  int64
displacement     398  non-null  float64
horsepower       398  non-null  object
weight           398  non-null  float64
acceleration     398  non-null  float64
year             398  non-null  int64
origin           398  non-null  int64
name             398  non-null  object
dtypes: float64(4), int64(3), object(2)
memory usage: 28.1+ KB
```

Here the column ***horsepower*** has been inferred as ***object***, whereas it should have been inferred as *float64*. This may be **because some of the rows contain non-numeric** values in the *horsepower* column.

Handling Missing Values...(Observer horsepower)

```
autos["horsepower"] = pd.to_numeric(autos["horsepower"],
errors = 'corece') autos.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 398 entries, 0 to 397
Data columns (total 9 columns):
mpg              398  non-null  float64
cylinders        398  non-null  int64
displacement     398  non-null  float64
horsepower       392  non-null  float64
weight           398  non-null  float64
acceleration     398  non-null  float64
year             398  non-null  int64
origin           398  non-null  int64
name             398  non-null  object
dtypes: float64(5), int64(3), object(1)
memory usage: 28.1+ KB
```

Handling Missing Values…Now check for null values in horsepower

```
memory usage: 28.1+ KB
```

```
#Now check null in horsepower
autos[autos.horsepower.isnull()]
```

	mpg	cylinders	displacement	horsepower	weight	acceleration	year	origin	name
32	25.0	4	98.0	NaN	2046.0	19.0	71	1	ford pinto
126	21.0	6	200.0	NaN	2875.0	17.0	74	1	ford maverick
330	40.9	4	85.0	NaN	1835.0	17.3	80	2	renault lecar deluxe
336	23.6	4	140.0	NaN	2905.0	14.3	80	1	ford mustang cobra
354	34.5	4	100.0	NaN	2320.0	15.8	81	2	renault 18i
374	23.0	4	151.0	NaN	3035.0	20.5	82	1	amc concord dl

Handling Missing Values...Remove the nulls

```
autos = autos.dropna(subset = ['horsepower']
```

```
autos[autos.horsepower.isnull()]
```

mpg	cylinders	displacement	...	year	origin	name

0 rows × 9 columns

Exploration of Data Using Visualization

- Data Visualization is useful
  - To gain insights in data
  - To understand what happened in the past in a given context
  - For feature engineering
- Drawing Plots

```
import matplotlib.pyplot as plt
import seaborn as sn
%matplotlib inline
```

Bar Chart

- A frequency chart for qualitative variables (or categorical variables)
- Used to assess the most-occurring and least-occurring categories within a dataset

```
sn.barplot(x = 'AGE', y = 'SOLD PRICE', data = soldprice_by_age);
```

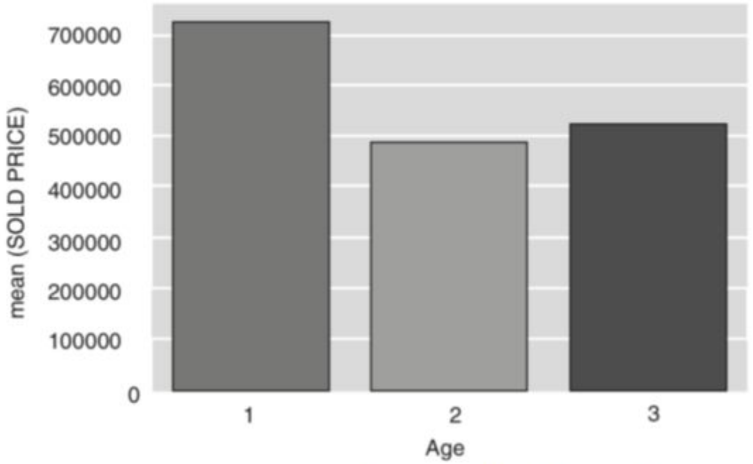


FIGURE 2.3 Bar plot for average sold price versus age.

Histogram

- A plot that shows the frequency distribution of a set of continuous variable.
- Gives an insight into the underlying distribution of the variable, outliers, etc.

```
plt.hist( ipl_auction_df['SOLD PRICE'], bins = 20 );
```

Note: By default, *plt.hist()* function creates 10 bins in the histogram. To create more bins, the bins parameter can be set in the *hist()* method accordingly.

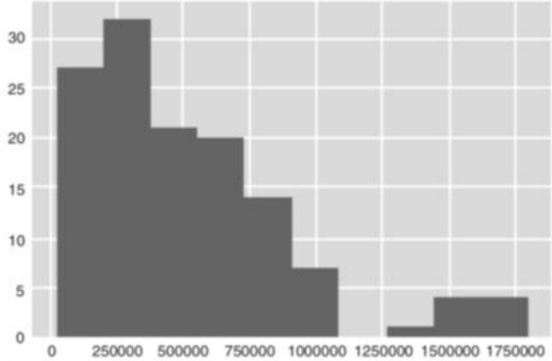


FIGURE 2.5 Histogram for SOLD PRICE.

Box Plot

- Box plot is designed by identifying the following descriptive statistics:

1. Lower quartile (1st quartile), median and upper quartile (3rd quartile).

2. Lowest and highest values.

3. Inter-quartile range (IQR).

```
box = sn.boxplot(ipl_auction_df['SOLD PRICE']);
```

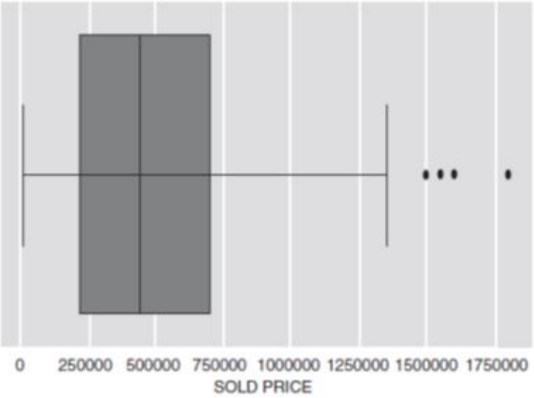


FIGURE 2.8 Box plot for SOLD PRICE.

Box Plot..

IQR:

- IQR is the distance (difference) between the 3rd quartile and 1st quartile.
- The length of the box is equivalent to IQR.
- The whisker of the box plot extends till Q1 – 1.5IQR and Q3 + 1.5IQR
- Observations beyond these two limits are potential outliers.

- The *caps* key in box variable returns the **min and max** values of the distribution

```
[item.get_ydata()[0] for item in box['caps']]
```

```
[20000.0, 1350000.0]
```

Box Plot..

IQR:

- The *whiskers* key in box variable returns the values of the distribution at 25 and 75 quantiles.

```
[item.get_ydata()[0] for item in box['whiskers']]
```

```
[225000.0, 700000.0]
```

So, inter-quartile range (IQR) is 700,000 − 225,000 = 475,000.

- The *medians* key in box variable returns the median value of the distribution.

```
[item.get_ydata()[0] for item in box['medians']]
```

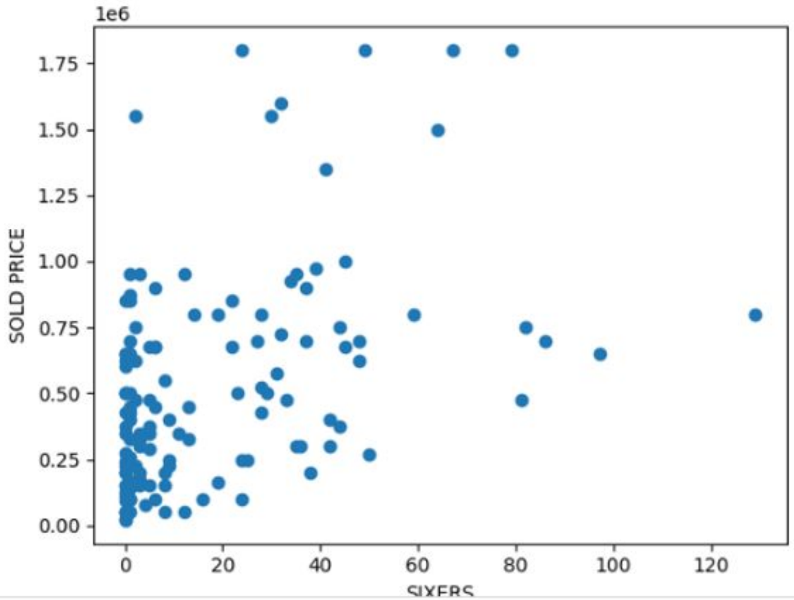
```
[437500.0]
```

Scatter plot

- Two variables are plotted along two axes
- Can reveal correlation present between two variables, if any
- Useful for assessing the strength of the relationship and to find the outliers in the data
- Mostly used during regression model building to decide on the initial model

```
plt.scatter(x=ipl_auction_df['SIXERS'],y=ipl_auction_df['SOLD PRICE'])
plt.xlabel('SIXERS')
plt.ylabel('SOLD PRICE')
plt.title('Scatter plot between players sixers and sold price')
```

```
Text(0, 0.5, 'SOLD PRICE')
```



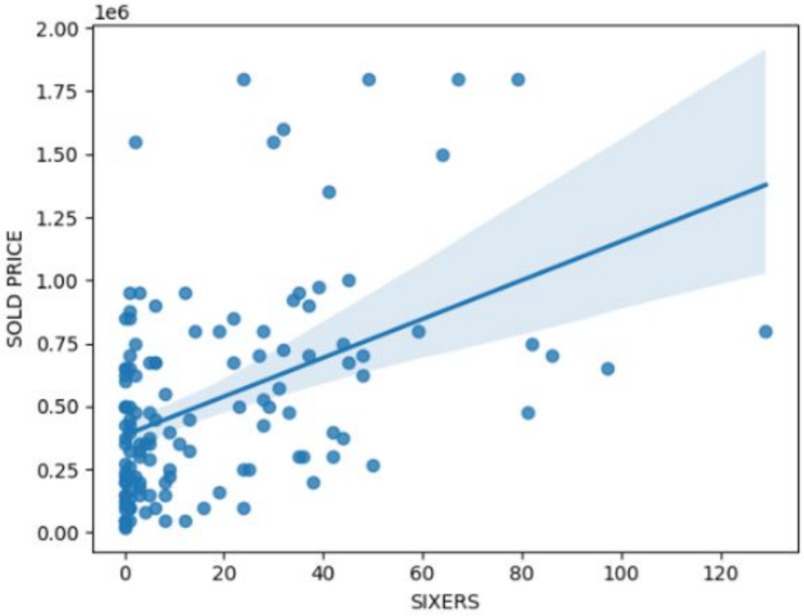
✓ Connected to Python 3 Googl

Scatter plot..

- To draw the direction of relationship between the variables, *regplot() of seaborn can be used*

```
sn.regplot(x=ipl_auction_df['SIXERS'],y=ipl_auction_df['SOLD PRICE'])
```

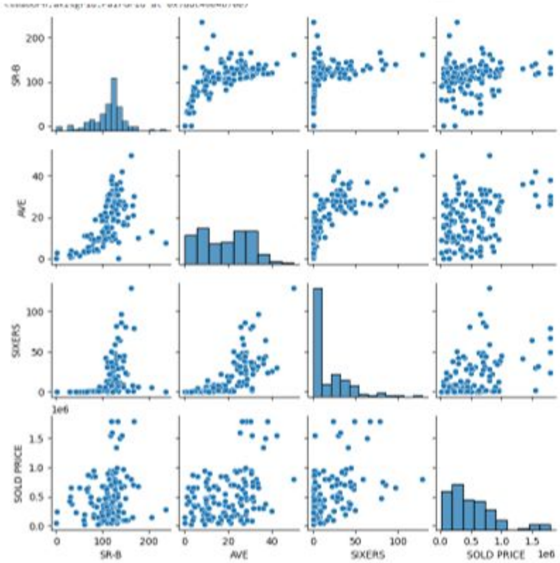
```
<Axes: xlabel='SIXERS', ylabel='SOLD PRICE'>
```



Pair plot

```
influential_features = ['SR-B', 'AVE', 'SIXERS', 'SOLD PRICE']
```

```
sn.pairplot(ipl_auction_df[influential_features], size=2)
```



Correlation and Heatmap

- Correlation is used for measuring the strength and direction of the linear relationship between two continuous random variables X and Y
- It is a statistical measure that indicates the extent to which two variables change together
- Positive correlation – the variables increase/ decrease together
- Negative correlation – if one variable increases, the other decreases
- The correlation value lies between -1.0 and 1.0. The sign indicates whether it is positive or negative correlation.
- -1.0 indicates a perfect negative correlation, whereas +1.0 indicates perfect positive correlation.

Correlation and Heatmap

```
ipl_auction_df[influential_features].corr()
```

	SR-B	AVE	SIXERS	SOLD PRICE
SR-B	1.000000	0.583579	0.425394	0.184278
AVE	0.583579	1.000000	0.705365	0.396519
SIXERS	0.425394	0.705365	1.000000	0.450609
SOLD PRICE	0.184278	0.396519	0.450609	1.000000

Correlation and Heatmap

```
sn.heatmap(ipl_auction_df[influential_features].corr(), annot=True);
```

Thank you!