

PDV- SECOND SESSIONALS

1. Write python code to create subplot containing three rows. Each row should contain two graphs. Type of visualization need to be created is line graph. Use different colors to represent lines in each graph. Provide proper labels and line ticks. (TLO 3.1)

```
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
fig, ax = plt.subplots(3, 2)

x = np.linspace(0,5,10)
x2 = x**2
x3 = x**3

ax[0,0].set_title('Plot 1')
ax[0,0].set_xlabel('X')
ax[0,0].set_ylabel('X Squared')

ax[0,0].plot(x,x2,'r')

ax[0,1].set_title('Plot 2')
ax[0,1].set_xlabel('X')
ax[0,1].set_ylabel('X Qubed')
ax[0,1].plot(x,x3,'b')

ax[1,0].set_title('Plot 3')
ax[1,0].set_xlabel('X Squared')
ax[1,0].set_ylabel('X ')
ax[1,0].plot(x2,x,'g')

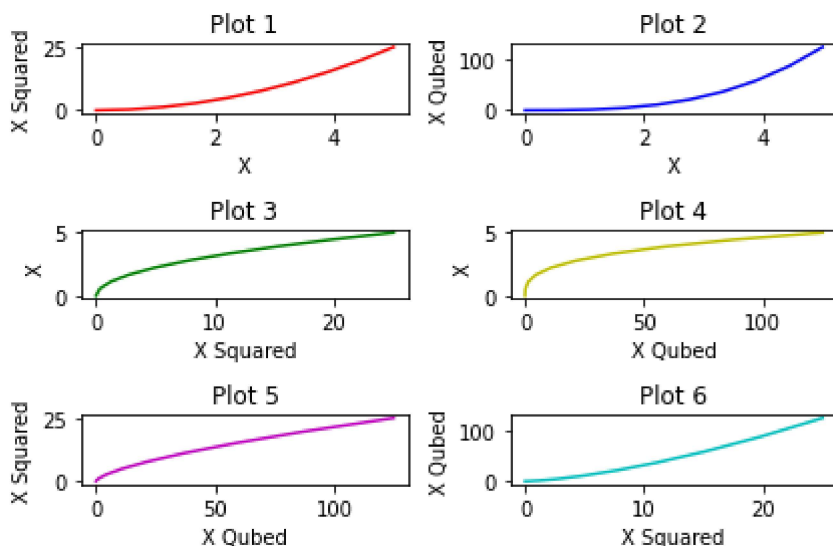
ax[1,1].set_title('Plot 4')
ax[1,1].set_xlabel('X Qubed')
ax[1,1].set_ylabel('X ')
ax[1,1].plot(x3,x,'y')

ax[2,0].set_title('Plot 5')
ax[2,0].set_xlabel('X Qubed')
ax[2,0].set_ylabel('X Squared')
```

```
ax[2,0].plot(x3,x2,'m')

ax[2,1].set_title('Plot 6')
ax[2,1].set_xlabel('X Squared')
ax[2,1].set_ylabel('X Qubed')
ax[2,1].plot(x2,x3,'c')

fig.tight_layout()
```



- 2. Write a python code to create a pie chart. Generate random data. Visualization should include legend, user defined colors for each part of the pie chart. (TLO 3.2)**

```
import matplotlib.pyplot as plt

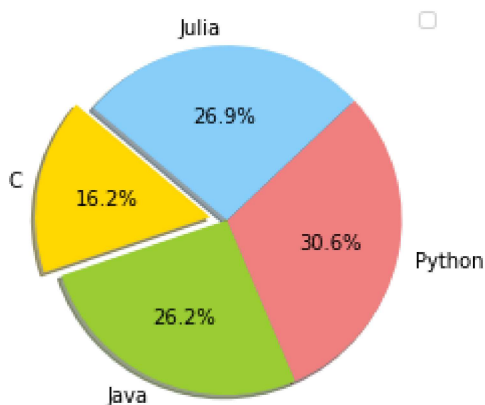
# Data to plot
labels = 'C', 'Java', 'Python', 'Julia'
sizes = [130, 210, 245, 215]
colors = ['gold', 'yellowgreen', 'lightcoral', 'lightskyblue']
explode = (0.1, 0, 0, 0) # explode 1st slice

# Plot
Sections = plt.pie(sizes, explode=explode, labels=labels, colors=colors,
autopct='%1.1f%%', shadow=True, startangle=140)
plt.legend(Sections, labels, loc='best')
plt.show()
```

```

/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:4: UserWarning: Legend does
A proxy artist may be used instead.
See: http://matplotlib.org/users/legend\_guide.html#creating-artists-specifically-for-adv
after removing the cwd from sys.path.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:4: UserWarning: Legend does
A proxy artist may be used instead.
See: http://matplotlib.org/users/legend\_guide.html#creating-artists-specifically-for-adv
after removing the cwd from sys.path.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:4: UserWarning: Legend does
A proxy artist may be used instead.
See: http://matplotlib.org/users/legend\_guide.html#creating-artists-specifically-for-adv
after removing the cwd from sys.path.

```



3. What is Exploratory Data Analysis(EDA)? Illustrate various steps performed in EDA with a reasoning for the same? specify atleast 5 EDA library. (TLO 2.3)

Exploratory Data Analysis: Exploratory data analysis is an approach to analyzing data sets to summarize their main characteristics, often with visual methods. A statistical model can be used or not, but primarily EDA is for seeing what the data can tell us beyond the formal modeling or hypothesis testing task.

Steps to Perform in EDA

- 1)Variable Identification
- 2)Univariate Analysis
- 3)Bi-variate Analysis
- 4)Missing values treatment
- 5)Outlier treatment
- 6)Variable transformation

7)Variable creation

1)Variable identification: The very first step in exploratory data analysis is to identify the type of variables in the dataset. Variables are of two types — Numerical and Categorical. They can be further classified as variable, numerical,categorical,discrete, continuous etc. Let us take any dataset as example in that indentify the type of variable the next step is to identify the Predictor (Inputs) and Target (output) variables. Next steps are Importing the Librariries Importing Data Sets Identifying Data Sets

2)Univariate Analysis: Uni-variate analysis will depend on whether the variable type is categorical or continuous. Continuous Variables:- In case of continuous variables, we need to understand the central tendency and spread of the variable. Categorical Variables:- For categorical variables, we'll use frequency table to understand distribution of each category. We can also read as percentage of values under each category. It can be be measured using two metrics, Count and Count% against each category. Bar chart can be used as visualization.

3)Bi-variate Analysis: Bi-variate Analysis finds out the relationship between two variables. Here, we look for association and disassociation between variables at a pre-defined significance level. We can perform bi-variate analysis for any combination of categorical and continuous variables. The combination can be: Categorical & Categorical, Categorical & Continuous and Continuous & Continuous.

4)Missing values treatment: Missing data in the training data set can reduce the power / fit of a model or can lead to a biased model because we have not analysed the behavior and relationship with other variables correctly. It can lead to wrong prediction or classification.

EDA Automation Libararies are: pandas-profiling (using python)

D-Tale (using python)

sweetviz (using python)

autoviz (using python)

summarytools (using R)

explore (using R)

dataMaid (using R)

4. Write a Pandas program to split a dataset to group by two columns and then sort the aggregated results within the groups. The dataset consists of ord_no purch_amt ord_date customer_id salesman_id, group on 'customer_id',

'salesman_id' and then sort sum of purch_amt within the groups (TLO 2.3)

```
import pandas as pd
pd.set_option('display.max_rows', None)
df = pd.DataFrame({
    'ord_no': [60001, 60009, 60002, 60004, 60007, 60005, 60008, 60010, 60003, 60012, 60011, 60013],
    'purch_amt': [180.5, 260.65, 85.26, 100.5, 928.5, 2300.6, 4560, 1893.43, 2480.4, 250.45, 75.29, 3045.6],
    'ord_date': ['2020-10-05', '2020-09-10', '2020-10-05', '2020-08-17', '2020-09-10', '2020-07-27', '2020-07-27', '2020-07-27', '2020-07-27', '2020-07-27', '2020-07-27', '2020-07-27'],
    'customer_id': [1001, 1001, 1002, 1001, 1002, 1001, 1002, 1001, 1002, 1001, 1002, 1002],
    'salesman_id': [2002, 2005, 2001, 2003, 2002, 2001, 2001, 2006, 2003, 2002, 2007, 2001]})
print("Original Orders DataFrame:")
print(df)
df_agg = df.groupby(['customer_id', 'salesman_id']).agg({'purch_amt': sum})
result = df_agg['purch_amt'].groupby(level=0, group_keys=False)
print("\nGroup on 'customer_id', 'salesman_id' and then sort sum of purch_amt within the groups")
print(result.nlargest())
```

Original Orders DataFrame:

	ord_no	purch_amt	ord_date	customer_id	salesman_id
0	60001	180.50	2020-10-05	1001	2002
1	60009	260.65	2020-09-10	1001	2005
2	60002	85.26	2020-10-05	1002	2001
3	60004	100.50	2020-08-17	1001	2003
4	60007	928.50	2020-09-10	1002	2002
5	60005	2300.60	2020-07-27	1001	2001
6	60008	4560.00	2020-09-10	1002	2001
7	60010	1893.43	2020-10-10	1001	2006
8	60003	2480.40	2020-10-10	1002	2003
9	60012	250.45	2020-06-27	1001	2002
10	60011	75.29	2020-08-17	1002	2007
11	60013	3045.60	2020-04-25	1002	2001

Group on 'customer_id', 'salesman_id' and then sort sum of purch_amt within the groups:

customer_id	salesman_id	purch_amt
1001	2001	2300.60
	2006	1893.43
	2002	430.95
	2005	260.65
	2003	100.50
1002	2001	7690.86
	2003	2480.40
	2002	928.50
	2007	75.29

Name: purch_amt, dtype: float64

- 5. Write a Pandas program to replace the missing values with the most frequent values present in each column of a given dataframe. Test data consists of following attributes: ord_no, purch_amt, sale_amt, ord_date, customer_id, salesman_id. (TLO 2.2)**

```
import pandas as pd
import numpy as np
pd.set_option('display.max_rows', None)
df = pd.DataFrame({
    'ord_no': [60001, np.nan, 60002, 60004, np.nan, 60005, np.nan, 60010, 60003, 60012, np.nan, 60013],
    'purch_amt': [180.5, np.nan, 85.26, 100.5, 928.5, np.nan, 4560, 1983.43, np.nan, 250.45, 75.29, 3045.6],
    'sale_amt': [10.5, 20.65, np.nan, 11.5, 98.5, np.nan, 57, 19.43, np.nan, 25.45, 75.29, 35.6],
    'ord_date': ['2020-10-05', '2020-09-10', np.nan, '2020-08-17', '2020-09-10', '2020-07-27', '2020-09-10', '2020-08-17', np.nan, '2020-07-27', '2020-09-10', '2020-08-17'],
    'customer_id': [1002, 1001, 1001, 1003, 1002, 1001, 1001, 1004, 1003, 1002, 1001, 1001],
    'salesman_id': [2002, 2003, 2001, np.nan, 2002, 2001, 2001, np.nan, 2003, 2002, 2003, np.nan]})
print("Original Orders DataFrame:")
print(df)
print("\nReplace the missing values with the most frequent values present in each column:")
result = df.fillna(df.mode().iloc[0])
print(result)
```

Original Orders DataFrame:

	ord_no	purch_amt	sale_amt	ord_date	customer_id	salesman_id
0	60001.0	180.50	10.50	2020-10-05	1002	2002.0
1	NaN	NaN	20.65	2020-09-10	1001	2003.0
2	60002.0	85.26	NaN	NaN	1001	2001.0
3	60004.0	100.50	11.50	2020-08-17	1003	NaN
4	NaN	928.50	98.50	2020-09-10	1002	2002.0
5	60005.0	NaN	NaN	2020-07-27	1001	2001.0
6	NaN	4560.00	57.00	2020-09-10	1001	2001.0
7	60010.0	1983.43	19.43	2020-10-10	1004	NaN
8	60003.0	NaN	NaN	2020-10-10	1003	2003.0
9	60012.0	250.45	25.45	2020-06-27	1002	2002.0
10	NaN	75.29	75.29	2020-08-17	1001	2003.0
11	60013.0	3045.60	35.60	2020-04-25	1001	NaN

Replace the missing values with the most frequent values present in each column:

	ord_no	purch_amt	sale_amt	ord_date	customer_id	salesman_id
0	60001.0	180.50	10.50	2020-10-05	1002	2002.0
1	60001.0	75.29	20.65	2020-09-10	1001	2003.0
2	60002.0	85.26	10.50	2020-09-10	1001	2001.0
3	60004.0	100.50	11.50	2020-08-17	1003	2001.0
4	60001.0	928.50	98.50	2020-09-10	1002	2002.0
5	60005.0	75.29	10.50	2020-07-27	1001	2001.0
6	60001.0	4560.00	57.00	2020-09-10	1001	2001.0

7	60010.0	1983.43	19.43	2020-10-10	1004	2001.0
8	60003.0	75.29	10.50	2020-10-10	1003	2003.0
9	60012.0	250.45	25.45	2020-06-27	1002	2002.0
10	60001.0	75.29	75.29	2020-08-17	1001	2003.0
11	60013.0	3045.60	35.60	2020-04-25	1001	2001.0