VISVESVARAYA TECHNOLOGICAL UNIVERSITY

“JnanaSangama”, Belgaum -590014, Karnataka.

LAB REPORT

ON

MACHINE LEARNING

Submitted by:

NISHANT KUMAR (1BM21CS117)

in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING

(Autonomous Institution under VTU)

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B. M. S. College of Engineering,

Bull Temple Road, Bangalore 560019

(Affiliated To Visvesvaraya Technological University, Belgaum)

Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Lab work entitled "**MACHINE LEARNING**" carried out by **NISHANT KUMAR (1BM21CS117),** who is bonafide student of **B. M. S. College of Engineering.** It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum during the year 2023-24. The Lab report has been approved as it satisfies the academic requirements in respect of Machine Learning Lab **- (22CS3PCMAL)** work prescribed for the said degree.

Sonika Sharma D
Assistant Professor
Department of CSE
BMSCE, Bengaluru

Dr. Jyothi S Nayak
Professor and Head
Department of CSE
BMSCE, Bengaluru

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PROGRAM 1

Date:05-04-2024

Write a python program to import and export data using Pandas library functions

05/04/24

Program-1

Write a python program to import and export data using Pandas library functions

IMPORT:

```
import pandas as pd
airbnb_data = pd.read_csv ("listings.csv")
airbnb_data.head()
```

EXPORT:

```
airbnb_data.to_csv ("exported_listings.csv")
```

READING DATA FROM URL:

```
url = "https://archive.ics.uci.edu/ml/machine-learning
        -databases/iris/iris.data"
col_names = ["sepal_length_in_cm", "sepal_width_
             in_cm", "petal_length_in_cm",
             "petal_width_in_cm", "class"]
iris_data = pd.read_csv (url, names= col_names)
iris_data.head()
```

Import:

import pandas as pd

Read the CSV file

airbnb_data = pd.read_csv("listings.csv")

View the first 5 rows

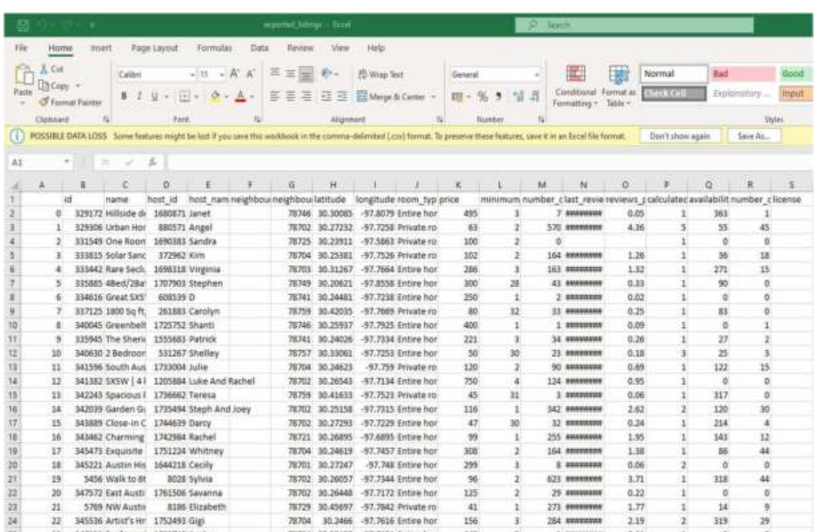
airbnb_data.head()

[1]:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_reviews	last_r
0	329172	Hillside designer home,10 min.dwntn	1680871	Janet	NaN	78746	30.30085	-97.80794	Entire home/apt	495	3	7	2022-
1	329306	Urban Homestead, 5 minutes to downtown	880571	Angel	NaN	78702	30.27232	-97.72579	Private room	63	2	570	2022-
2	331549	One Room with Private Bathroom	1690383	Sandra	NaN	78725	30.23911	-97.58625	Private room	100	2	0	
3	333815	Solar Sanctuary - Austin Room	372962	Kim	NaN	78704	30.25381	-97.75262	Private room	102	2	164	2022-
4	333442	Rare Secluded 1940s Estate	1698318	Virginia	NaN	78703	30.31267	-97.76641	Entire home/apt	286	3	163	2022-

Export:

airbnb_data.to_csv("exported_listings.csv")



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1		id	name	host_id	host_nam	neighbou	neighbou	latitude	longitude	room_typ	price	minimum	number_c	last_revie	reviews_p	calculatec	availabilit	number_c	license
2	0	329172	Hillside de	1680871	Janet		78746	30.30085	-97.8079	Entire hor	495	3	7	########	0.05	1	363	1	
3	1	329306	Urban Hor	880571	Angel		78702	30.27232	-97.7258	Private ro	63	2	570	########	4.36	5	55	45	
4	2	331549	One Roon	1690383	Sandra		78725	30.23911	-97.5863	Private ro	100	2	0			1	0	0	
5	3	333815	Solar Sanc	372962	Kim		78704	30.25381	-97.7526	Private ro	102	2	164	########	1.26	1	36	18	
6	4	333442	Rare Sech	1698318	Virginia		78703	30.31267	-97.7664	Entire hor	286	3	163	########	1.32	1	271	15	
7	5	335885	4Bed/2Ba	1707903	Stephen		78749	30.20621	-97.8558	Entire hor	300	28	43	########	0.33	1	90	0	
8	6	334616	Great SXS	608539	D		78741	30.24481	-97.7238	Entire hor	250	1	2	########	0.02	1	0	0	
9	7	337125	1800 Sq ft,	261883	Carolyn		78759	30.42035	-97.7669	Private ro	80	32	33	########	0.25	1	83	0	
10	8	340045	Greenbelt	1725752	Shanti		78746	30.25937	-97.7925	Entire hor	400	1	1	########	0.09	1	0	1	
11	9	335945	The Sheri	1555683	Patrick		78741	30.24026	-97.7334	Entire hor	221	3	34	########	0.26	1	27	2	
12	10	340630	2 Bedroor	331267	Shelley		78757	30.33061	-97.7253	Entire hor	50	30	23	########	0.18	3	25	3	
13	11	341596	South Aus	1733004	Julie		78704	30.24623	-97.759	Private ro	120	2	90	########	0.69	1	122	15	
14	12	341382	SXSW | 4 I	1205884	Luke And Rachel		78702	30.26543	-97.7134	Entire hor	750	4	124	########	0.95	1	0	0	
15	13	342243	Spacious I	1736662	Teresa		78759	30.41633	-97.7523	Private ro	45	31	3	########	0.06	1	317	0	
16	14	342039	Garden Gu	1735494	Steph And Joey		78702	30.25158	-97.7315	Entire hor	116	1	342	########	2.62	2	120	30	
17	15	343889	Close-in C	1744639	Darcy		78702	30.27293	-97.7229	Entire hor	47	30	32	########	0.24	1	214	4	
18	16	343462	Charming	1742984	Rachel		78721	30.26895	-97.6895	Entire hor	99	1	255	########	1.95	1	143	12	
19	17	345473	Exquisite	1751224	Whitney		78704	30.24619	-97.7457	Entire hor	308	2	164	########	1.38	1	86	44	
20	18	345221	Austin His	1644218	Cecily		78701	30.27247	-97.748	Entire hor	299	3	8	########	0.06	2	0	0	
21	19	5456	Walk to 6t	8028	Sylvia		78702	30.26057	-97.7344	Entire hor	96	2	623	########	3.71	1	318	44	
22	20	347572	East Austi	1761506	Savanna		78702	30.26448	-97.7172	Entire hor	125	2	29	########	0.22	1	0	0	
23	21	5769	NW Austir	8186	Elizabeth		78729	30.45697	-97.7842	Private ro	41	1	273	########	1.77	1	14	9	
24	22	345536	Artist's Hr	1752493	Gigi		78704	30.2466	-97.7616	Entire hor	156	3	284	########	2.19	2	319	29	
25	23	347935	for formul	1763742	Amber		78704	30.25152	-97.7621	Entire hor	643	5	1	########	0.01	1	0	0	

Reading data from URL:

```
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"

# Define the column names
col_names = ["sepal_length_in_cm",
          "sepal_width_in_cm",
          "petal_length_in_cm",
          "petal_width_in_cm",
          "class"]

# Read data from URL
iris_data = pd.read_csv(url, names=col_names)

iris_data.head()
```

[10]:

	sepal_length_in_cm	sepal_width_in_cm	petal_length_in_cm	petal_width_in_cm	class
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

PROGRAM 2

Date:05-04-2024

Demonstrate various data pre-processing techniques for a given dataset

Code and Output

2. Importing and Exploration of the dataset

In [2]:
```
# Loading the data and setting the unique client_id as the index::

df = pd.read_csv('/content/loans.csv', index_col = 'client_id')
```

In [3]:
```
# # showing the first 5 rows of the dataset:
df.head()
```

Out[3]:

client_id	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate
46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15
46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25
46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68
46109	cash	12518	1	10596	2010-12-08	2013-05-05	1.24
46109	credit	14049	1	11415	2010-07-07	2012-05-21	3.13

In [4]:
```
# To check the Dimensions of the dataset:
df.shape
```

Out[4]: (443, 7)

In [5]:
```
# Checking the info of the data:
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 443 entries, 46109 to 26945
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   loan_type    443 non-null    object
 1   loan_amount  443 non-null    int64
 2   repaid       443 non-null    int64
 3   loan_id      443 non-null    int64
 4   loan_start   443 non-null    object
 5   loan_end     443 non-null    object
 6   rate         443 non-null    float64
dtypes: float64(1), int64(3), object(3)
memory usage: 27.7+ KB
```

3. Checking the datatypes of the columns

In [6]:
```
df.dtypes
```

Out[6]:
```
loan_type       object
loan_amount      int64
repaid           int64
loan_id          int64
loan_start      object
loan_end        object
rate           float64
dtype: object
```

4. Converting the data types of columns

```
- loan_id to object
- repaid to category dtype
- loan_start and loan_end to date type
```

In [7]:
```
# loan_id:

df['loan_id'] = df['loan_id'].astype('object')

# repaid:

df['repaid'] = df['repaid'].astype('category')
```

In [8]:
```
# loan_start:

df['loan_start'] = pd.to_datetime(df['loan_start'], format = '%Y-%m-%d')


# loan_end:

df['loan_end'] = pd.to_datetime(df['loan_end'], format = '%Y-%m-%d')
```

Checking the datatypes again:

In [9]:
```
df.dtypes
```

Out[9]:
```
loan_type              object
loan_amount             int64
repaid               category
loan_id                object
loan_start     datetime64[ns]
loan_end       datetime64[ns]
rate                  float64
dtype: object
```

5. Summary Statistics of the data

In [10]:
```
# Summary Statistics for Numerical data:
df.describe()
```

Out[10]:

	loan_amount	loan_start	loan_end	rate
count	443.000000	443	443	443.000000
mean	7982.311512	2007-08-02 12:56:53.092550912	2009-08-23 11:35:37.246049536	3.217156
min	559.000000	2000-01-26 00:00:00	2001-08-02 00:00:00	0.010000
25%	4232.500000	2003-10-19 00:00:00	2005-09-12 12:00:00	1.220000
50%	8320.000000	2007-03-10 00:00:00	2009-03-19 00:00:00	2.780000
75%	11739.000000	2011-07-31 00:00:00	2013-09-11 12:00:00	4.750000
max	14971.000000	2014-11-11 00:00:00	2017-05-07 00:00:00	12.620000
std	4172.891992	NaN	NaN	2.397168

In [11]:
```
# Summary Statistics for Categorical data:
df.describe(exclude=[np.number])
```

Out[11]:

	loan_type	repaid	loan_id	loan_start	loan_end
count	443	443.0	443.0	443	443
unique	4	2.0	443.0	NaN	NaN
top	home	1.0	10243.0	NaN	NaN
freq	121	237.0	1.0	NaN	NaN
mean	NaN	NaN	NaN	2007-08-02 12:56:53.092550912	2009-08-23 11:35:37.246049536
min	NaN	NaN	NaN	2000-01-26 00:00:00	2001-08-02 00:00:00
25%	NaN	NaN	NaN	2003-10-19 00:00:00	2005-09-12 12:00:00
50%	NaN	NaN	NaN	2007-03-10 00:00:00	2009-03-19 00:00:00
75%	NaN	NaN	NaN	2011-07-31 00:00:00	2013-09-11 12:00:00
max	NaN	NaN	NaN	2014-11-11 00:00:00	2017-05-07 00:00:00

6. Missing Values

In [12]:
```
# use isnull().sum() to check for missing values
df.isnull().sum()
```

Out[12]:
```
loan_type      0
loan_amount    0
repaid         0
loan_id        0
loan_start     0
loan_end       0
rate           0
dtype: int64
```

There are no missing values in the data.

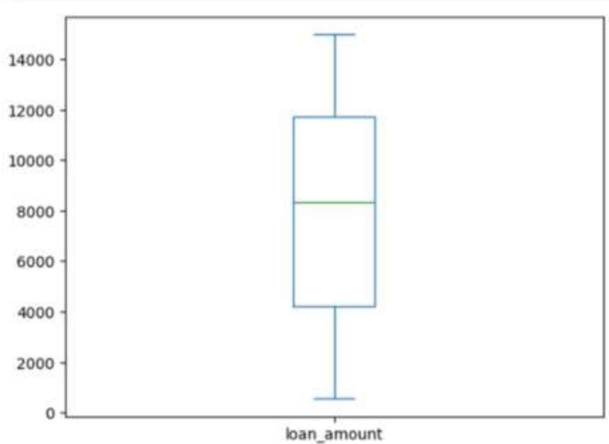
Sk-learn library has an in-built function called Iterative Imputer to impute the missing values. Its sklearn domcumentation: https://scikit-learn.org/stable/modules/generated/sklearn.impute.IterativeImputer.html

---

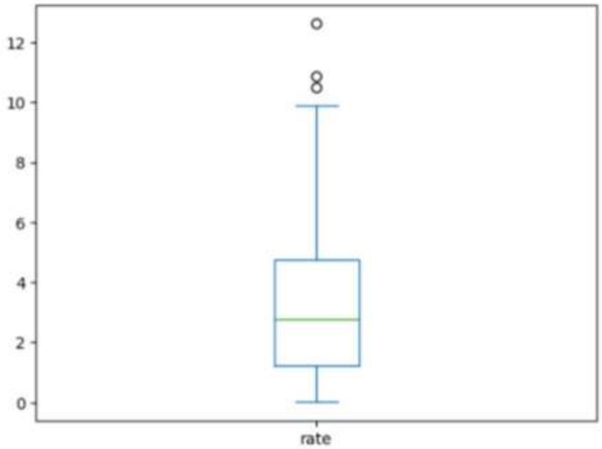
7. Outliers Treatment

To check for the presence of outliers, we plot Boxplot.

In [13]:
```
# For Loan_amount
df['loan_amount'].plot(kind='box')
plt.show()
```



In [14]:
```
# For rate
df['rate'].plot(kind='box')
plt.show()
```



We can see that there are no outliers in the loan_amount column and some outliers are present in the rate column. To treat for outliers can either cap the values or transform the data. Shall demonstrate both the approaches here.

8. Transformation

8a. SQRT transformation

In [15]:
```
df['SQRT_RATE'] = df['rate']**0.5
```

In [16]:
```
df['sqrt_rate'] = np.sqrt(df['rate'])
```

In [17]:
```
df.head()
```

Out[17]:

client_id	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate	SQRT_RATE	sqrt_rate
46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15	1.466288	1.466288
46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25	1.118034	1.118034
46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68	0.824621	0.824621
46109	cash	12518	1	10596	2010-12-08	2013-05-05	1.24	1.113553	1.113553
46109	credit	14049	1	11415	2010-07-07	2012-05-21	3.13	1.769181	1.769181

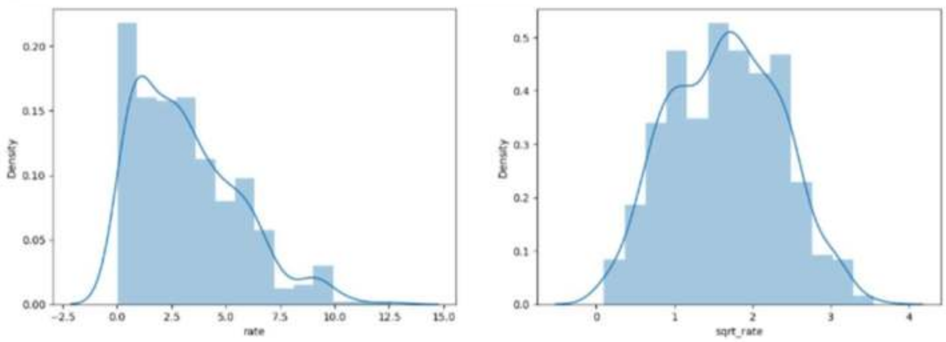
In [18]:

```
#checking the skewness, kurtosis between the original and transformed data:
print("The skewness of the original data is {}".format(df.rate.skew()))
print('The skewness of the SQRT transformed data is {}'.format(df.SQRT_RATE.skew()))

print('')

print("The kurtosis of the original data is {}".format(df.rate.kurt()))
print("The kurtosis of the SQRT transformed data is {}".format(df.SQRT_RATE.kurt()))
```

```
The skewness of the original data is 0.884204614329943
The skewness of the SQRT transformed data is 0.04964154055528862

The kurtosis of the original data is 0.42437165143736433
The kurtosis of the SQRT transformed data is -0.6318437642052039
```

In [19]:

```
# plotting the distribution

fig, axes = plt.subplots(1,2, figsize=(15,5))
sns.distplot(df['rate'], ax=axes[0])
sns.distplot(df['sqrt_rate'], ax=axes[1])

plt.show()
```



Result:

The Rate column was right skewed earlier. The skewness and kurtosis as reduced significantly. The transformed SQRT rate, on the right graph resembles normal distribution now.

8b. Log Transformation

In [20]:

```
df['Log Rate'] = np.log(df['rate'])
```

In [21]:

```
df.head()
```

Out[21]:

client_id	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate	SQRT_RATE	sqrt_rate	Log Rate
46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15	1.466288	1.466288	0.765468
46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25	1.118034	1.118034	0.223144
46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68	0.824621	0.824621	-0.385662
46109	cash	12518	1	10596	2010-12-08	2013-05-05	1.24	1.113553	1.113553	0.215111
46109	credit	14049	1	11415	2010-07-07	2012-05-21	3.13	1.769181	1.769181	1.141033

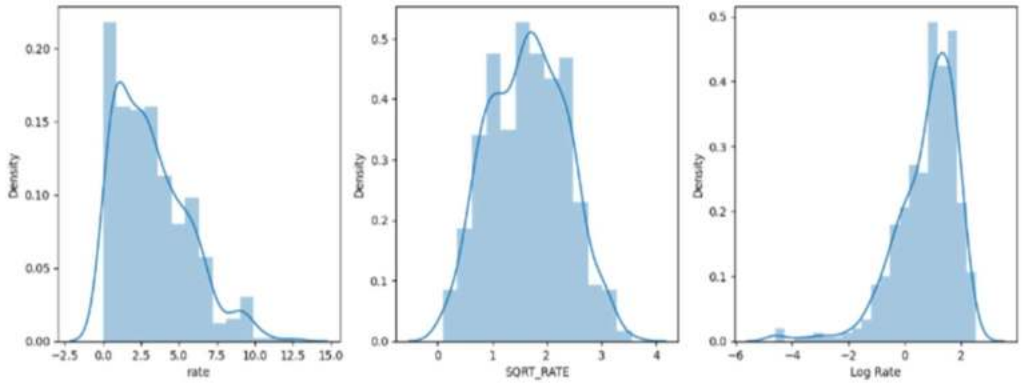
In [22]:

```
print("The skewness of the original data is {}".format(df.rate.skew()))
print('The skewness of the SQRT transformed data is {}'.format(df.SQRT_RATE.skew()))
print("The skewnss of the LOG transformed data is {}".format(df['Log Rate'].skew()))

print('')


print("The kurtosis of the original data is {}".format(df.rate.kurt()))
print("The kurtosis of the SQRT transformed data is {}".format(df.SQRT_RATE.kurt()))
print("The kurtosis of the LOG transformed data is {}".format(df['Log Rate'].kurt()))
```

```
The skewness of the original data is 0.884204614329943
The skewness of the SQRT transformed data is 0.04964154055528862
The skewnss of the LOG transformed data is -1.5943217626331552

The kurtosis of the original data is 0.42437165143736433
The kurtosis of the SQRT transformed data is -0.6318437642052039
The kurtosis of the LOG transformed data is 4.157026150198228
```

In [23]:

```
# plot the graph:

fig, axes = plt.subplots(1,3,figsize=(15,5))

sns.distplot(df['rate'], ax=axes[0])
sns.distplot(df['SQRT_RATE'], ax=axes[1])
sns.distplot(df['Log Rate'], ax=axes[2])

plt.show()
```



Inference:

Log Transformation made the rate left skewed and more peaked.

However, Log transformation is more closer to 0 and hence is more normal. Though it heavily maniupulates the data.

In our case, square root transformation is more suitable.

In [24]:

```
## Using Lambda function :

df['LOG_Rate'] = df['rate'].apply(lambda x:np.log(x))
```

In [25]:

```
df.head()
```

Out[25]:

client_id	loan_type	loan_amount	repaid	loan_id	loan_start	loan_end	rate	SQRT_RATE	sqrt_rate	Log Rate	LOG_Rate
46109	home	13672	0	10243	2002-04-16	2003-12-20	2.15	1.466288	1.466288	0.765468	0.765468
46109	credit	9794	0	10984	2003-10-21	2005-07-17	1.25	1.118034	1.118034	0.223144	0.223144
46109	home	12734	1	10990	2006-02-01	2007-07-05	0.68	0.824621	0.824621	-0.385662	-0.385662
46109	cash	12518	1	10596	2010-12-08	2013-05-05	1.24	1.113553	1.113553	0.215111	0.215111
46109	credit	14049	1	11415	2010-07-07	2012-05-21	3.13	1.769181	1.769181	1.141033	1.141033

PROGRAM 3

Date:12-04-2024

Use an appropriate data set for building the decision tree (ID3) and apply this knowledge to classify a new sample

Algorithm:

12/04/24

Program - 2

Decision Tree ID3

Algorithm:

ID3 (Examples, Target_attribute, Attributes)

- Create a Root node for the tree.
- ~~Retu~~ If all Examples are positive, Return the single-node tree Root, with label = +
- If all Examples are negative, Return the single-node tree Root, with Label = -
- If attributes is empty, Return the single-node tree Root, with label = most common value of Target_attribute in Examples
- Otherwise Begin:
  - A ← the attribute from Attributes that best* classifies Examples.
  - The decision attribute for Root ← A.
  - For each possible value, v_i, of A,
    - Add a new tree branch below Root, corresponding to the test A = v_i
    - Let Examples$_{v_i}$, be the subset of Examples that have values v_i for A.
    - If Examples$_{v_i}$ is empty.
      - Then below this new branch add a leaf node with label = most common value of Target_attribute
      - Else below this new branch add the subtree ID3.
- End
- Return Root

Code:

Importing Database

In [2]:
```
# Importing the required libraries
import pandas as pd
import numpy as np
import math

# Reading the dataset (Tennis-dataset)
data = pd.read_csv('/content/PlayTennis.csv')
```

In [ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

In [3]:
```
def highlight(cell_value):
    '''
    Highlight yes / no values in the dataframe
    '''
    color_1 = 'background-color: pink;'
    color_2 = 'background-color: lightgreen;'

    if cell_value == 'no':
        return color_1
    elif cell_value == 'yes':
        return color_2

data.style.applymap(highlight)\
    .set_properties(subset=data.columns, **{'width': '100px'})\
    .set_table_styles([{'selector': 'th', 'props': [('background-color', 'lightgray'), ('border', '1px solid gray'),
                                                     ('font-weight', 'bold')]},
     {'selector': 'tr:hover', 'props': [('background-color', 'white'), ('border', '1.5px solid black')]}])
```

Out[3]:

	outlook	temp	humidity	windy	play
0	sunny	hot	high	False	no
1	sunny	hot	high	True	no
2	overcast	hot	high	False	yes
3	rainy	mild	high	False	yes
4	rainy	cool	normal	False	yes
5	rainy	cool	normal	True	no
6	overcast	cool	normal	True	yes
7	sunny	mild	high	False	no
8	sunny	cool	normal	False	yes
9	rainy	mild	normal	False	yes
10	sunny	mild	normal	True	yes
11	overcast	mild	high	True	yes
12	overcast	hot	normal	False	yes
13	rainy	mild	high	True	no

Entropy of the dataset

In [4]:

```
def find_entropy(data):
    """
    Returns the entropy of the class or features
    formula: - ∑ P(X)logP(X)
    """
    entropy = 0
    for i in range(data.nunique()):
        x = data.value_counts()[i]/data.shape[0]
        entropy += (- x * math.log(x,2))
    return round(entropy,3)



def information_gain(data, data_):
    """
    Returns the information gain of the features
    """
    info = 0
    for i in range(data_.nunique()):
        df = data[data_ == data_.unique()[i]]
        w_avg = df.shape[0]/data.shape[0]
        entropy = find_entropy(df.play)
        x = w_avg * entropy
        info += x
    ig = find_entropy(data.play) - info
    return round(ig, 3)



def entropy_and_infogain(datax, feature):
    """
    Grouping features with the same class and computing their
    entropy and information gain for splitting
    """
    for i in range(data[feature].nunique()):
        df = datax[datax[feature]==data[feature].unique()[i]]
        if df.shape[0] < 1:
            continue

        display(df[[feature, 'play']].style.applymap(highlight)\
                .set_properties(subset=[feature, 'play'], **{'width': '80px'})\
                .set_table_styles([{'selector': 'th', 'props': [('background-color', 'lightgray'),
                                                                ('border', '1px solid gray'),
                                                                ('font-weight', 'bold')]},
                                   {'selector': 'td', 'props': [('border', '1px solid gray')]},
                                   {'selector': 'tr:hover', 'props': [('background-color', 'white'),
                                                                      ('border', '1.5px solid black')]}]))

        print(f'Entropy of {feature} - {data[feature].unique()[i]} = {find_entropy(df.play)}')
    print(f'Information Gain for {feature} = {information_gain(datax, datax[feature])}')
```

In [5]:

```
print(f'Entropy of the entire dataset: {find_entropy(data.play)}')
```

```
Entropy of the entire dataset: 0.94
```

Entropy and Information Gain of temperature

In [6]:
```
entropy_and_infogain(data, 'temp')
```

	temp	play
0	hot	no
1	hot	no
2	hot	yes
12	hot	yes

```
Entropy of temp - hot = 1.0
```

	temp	play
3	mild	yes
7	mild	no
9	mild	yes
10	mild	yes
11	mild	yes
13	mild	no

```
Entropy of temp - mild = 0.918
```

	temp	play
4	cool	yes
5	cool	no
6	cool	yes
8	cool	yes

```
Entropy of temp - cool = 0.811
Information Gain for temp = 0.029
```

Entropy and Information Gain of humidity

In [7]:
```
entropy_and_infogain(data, 'humidity')
```

	humidity	play
0	high	no
1	high	no
2	high	yes
3	high	yes
7	high	no
11	high	yes
13	high	no

```
Entropy of humidity - high = 0.985
```

	humidity	play
4	normal	yes
5	normal	no
6	normal	yes
8	normal	yes
9	normal	yes
10	normal	yes
12	normal	yes

```
Entropy of humidity - normal = 0.592
Information Gain for humidity = 0.151
```

Entropy and Information Gain of windy

```
In [8]: entropy_and_infogain(data, 'windy')
```

	windy	play
0	False	no
2	False	yes
3	False	yes
4	False	yes
7	False	no
8	False	yes
9	False	yes
12	False	yes

```
Entropy of windy - False = 0.811
```

	windy	play
1	True	no
5	True	no
6	True	yes
10	True	yes
11	True	yes
13	True	no

```
Entropy of windy - True = 1.0
Information Gain for windy = 0.048
```

Rainy Outlook

Rainy -outlook

In [9]:
```
rainy = data[data['outlook'] == 'rainy']
rainy.style.applymap(highlight)\
    .set_properties(subset=data.columns, **{'width': '100px'})\
    .set_table_styles([{'selector': 'th', 'props': [('background-color', 'lightgray'), ('border', '1px solid gray'),
                                                   ('font-weight', 'bold')]},
     {'selector': 'tr:hover', 'props': [('background-color', 'white'), ('border', '1.5px solid black')]}])
```

Out[9]:

	outlook	temp	humidity	windy	play
3	rainy	mild	high	False	yes
4	rainy	cool	normal	False	yes
5	rainy	cool	normal	True	no
9	rainy	mild	normal	False	yes
13	rainy	mild	high	True	no

In [10]:
```
print(f'Entropy of the Rainy dataset: {find_entropy(rainy.play)}')
```

```
Entropy of the Rainy dataset: 0.971
```

In [11]:
```
entropy_and_infogain(rainy, 'temp')
```

	temp	play
3	mild	yes
9	mild	yes
13	mild	no

```
Entropy of temp - mild = 0.918
```

	temp	play
4	cool	yes
5	cool	no

```
Entropy of temp - cool = 1.0
Information Gain for temp = 0.02
```

In [12]:
```
entropy_and_infogain(rainy, 'humidity')
```

	humidity	play
3	high	yes
13	high	no

```
Entropy of humidity - high = 1.0
```

	humidity	play
4	normal	yes
5	normal	no
9	normal	yes

```
Entropy of humidity - normal = 0.918
Information Gain for humidity = 0.02
```

In [13]:
```
entropy_and_infogain(rainy, 'windy')
```

	windy	play
3	False	yes
4	False	yes
9	False	yes

```
Entropy of windy - False = 0.0
```

	windy	play
5	True	no
13	True	no

```
Entropy of windy - True = 0.0
Information Gain for windy = 0.971
```

wind has highest information gain

Output

Output:

Entropy of the dataset : 0.9331

Pregnancies - Entropy : 3.482, IG : 0.062
Glucose - Entropy : 6.751, IG : 0.304
BloodPressure - Entropy : 4.792, IG : 0.059
SkinThickness - Entropy : 4.586, IG : 0.082
Insulin - Entropy : 4.682, IG : 0.277
BMI - Entropy : 7.594, IG : 0.344
DiabetesPedigreeFunction - Entropy : 8.829, IG : 0.65
Age - Entropy : 5.029, IG : 0.141

PROGRAM 4

Date:19-04-2024

Implement Linear and Multi-Linear Regression algorithm using appropriate dataset

LINEAR REGRESSION:

Algorithm

03/05/2024

Program - 4

Implement Linear and Multi-Linear Regression algorithm.

Linear Regression:

```
function linear regression (x, y, learning_rate
                              num: iterations)
  Initialize random values for slope (m)
  & intercept (b)

  for i = 1 to num_iterations :

  predictions = m * x + b

  errors = predictions - y

  loss = mean_squared_error (errors)

  gradient_m = (2/N) * sum (errors * x)
  gradient_m = (2/N) * sum (errors)
   m = m - learningrate * gradient_m
   b = b - learningrate * gradient_b
Return m, b

function mean_squared error (errors) :
  squared_errors = errors²
  mse = sum (squared_errors) / sum (errors)
  return mse.
```

Code

Importing Dataset

In [1]:

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

In [18]:

```
df=pd.read_csv("/Salary_Data.csv")
df
```

Out[18]:

	YearsExperience	Salary
0	1.1	39343.0
1	1.3	46205.0
2	1.5	37731.0
3	2.0	43525.0
4	2.2	39891.0
5	2.9	56642.0
6	3.0	60150.0
7	3.2	54445.0
8	3.2	64445.0
9	3.7	57189.0
10	3.9	63218.0
11	4.0	55794.0
12	4.0	56957.0
13	4.1	57081.0
14	4.5	61111.0
15	4.9	67938.0
16	5.1	66029.0
17	5.3	83088.0
18	5.9	81363.0
19	6.0	93940.0
20	6.8	91738.0
21	7.1	98273.0
22	7.9	101302.0
23	8.2	113812.0
24	8.7	109431.0
25	9.0	105582.0
26	9.5	116969.0
27	9.6	112635.0
28	10.3	122391.0
29	10.5	121872.0

Slope and Intercept calculation

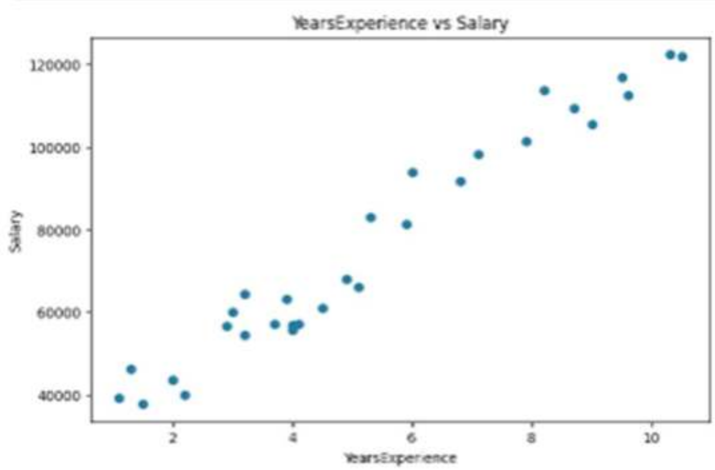
In [19]:
```
def linear(X, b0, b1):
    return [b0+b1*x for x in X]
```

In [20]:
```
# b0 - Intercept
def intercept(X, Y, b1):
    x_ = np.mean(X)
    y_ = np.mean(Y)

    return y_-b1*x_
```

In [21]:
```
# b1 - Slope
def slope(X, Y):
    x_ = np.mean(X)
    y_ = np.mean(Y)

    rise = sum([(x-x_) * (y-y_) for x,y in zip(X,Y)])
    run = sum([(x-x_)**2 for x,y in zip(X,Y)])

    return rise / run
```

Predicted Values Graph

In [23]:
```
plt.figure(figsize=(8,5))
plt.title("YearsExperience vs Salary")
plt.scatter(predictor, target, color = "#247ba0")
plt.xlabel('YearsExperience')
plt.ylabel('Salary')
plt.show()
```

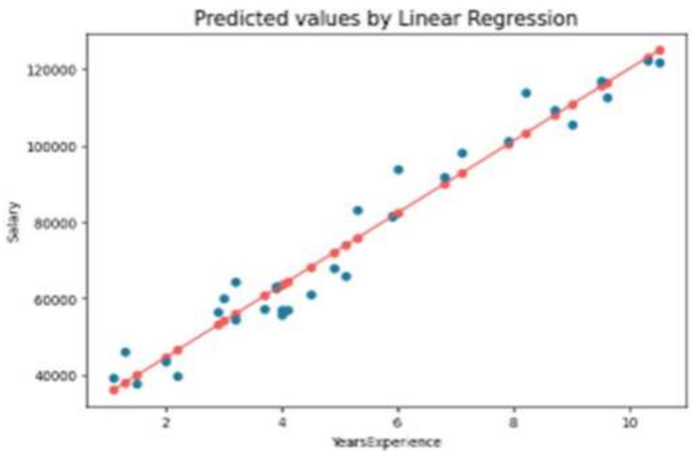


In [24]:
```
b1 = slope(predictor, target)
b0 = intercept(predictor, target, b1)
predicted = linear(predictor, b0, b1)
```

In [28]:
```
plt.figure(figsize = (8, 5))
plt.plot(predictor, predicted, color = '#f25f5c')
plt.scatter(predictor, predicted, color = '#f25f5c')  #Red Line is predicted data
plt.title('Predicted values by Linear Regression', fontsize = 15)
plt.xlabel('YearsExperience')
plt.ylabel('Salary')
plt.scatter(predictor, target, color = "#247ba0")
plt.show()
```

Output

```
In [26]: print("Coefficients:\n=============")
         print("b0 : ", b0)
         print("b1 : ", b1)

Coefficients:
=============
b0 :  25792.20019866869
b1 :  9449.962321455077
```



MULTIPLE LINEAR REGRESSION:

Algorithm

Multi-Linear Regression

```
function initialize_parameters ( ):
    randomly initialize β0, β1, ...

function hypothesis_function ( X, β ):
    h = β0 + β1 * X[1] + β2 * X[2] + ... + βm * X[m]
    return h.

function cost_function (X, y, β):
    n = length (X)
    total_error = 0
    for i = 1 to n:
        h = hypothesis_function (X[i], β)
        total_error += (h - y[i])^2
    cost = (1/(2*n)) * total_error
    return cost.

function gradient_descent (X, y, β, α, iterations,
                          threshold)
    n = length (X)
    for iter = 1 to iterations:
        error_sum = 0
        for i = 1 to n:
            h = hypothesis_function (X[i], β)
            error = h - y[i]
            error_sum += error
            for j = 0 to m:
                β[j] = β[j] - α * (1/n) * error
                                 * X[i][j]
        cost = cost_function (X, y, β)
        if cost < threshold : break
    return β.
```

Code

In [19]:
```
house = pd.read_csv('https://github.com/YBIFoundation/Dataset/raw/main/Boston.csv')
```

In [20]:
```
house.head()
```

Out[20]:

	CRIM	ZN	INDUS	CHAS	NX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
0	0.00632	18.0	2.31	0	0.538	6.575	65.2	4.0900	1	296.0	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0	0.469	6.421	78.9	4.9671	2	242.0	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0	0.469	7.185	61.1	4.9671	2	242.0	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0	0.458	6.998	45.8	6.0622	3	222.0	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0	0.458	7.147	54.2	6.0622	3	222.0	18.7	396.90	5.33	36.2

In [21]:
```
house.describe()
```

Out[21]:

	CRIM	ZN	INDUS	CHAS	NX	RM	AGE	DIS	RAD	TAX	PTRAT
count	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000000	506.000
mean	3.613524	11.363636	11.136779	0.069170	0.554695	6.284634	68.574901	3.795043	9.549407	408.237154	18.455
std	8.601545	23.322453	6.860353	0.253994	0.115878	0.702617	28.148861	2.105710	8.707259	168.537116	2.164
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600
25%	0.082045	0.000000	5.190000	0.000000	0.449000	5.885500	45.025000	2.100175	4.000000	279.000000	17.400
50%	0.256510	0.000000	9.690000	0.000000	0.538000	6.208500	77.500000	3.207450	5.000000	330.000000	19.050
75%	3.677083	12.500000	18.100000	0.000000	0.624000	6.623500	94.075000	5.188425	24.000000	666.000000	20.200
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000

In [22]:
```
house.columns
```

Out[22]:
```
Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
       'PTRATIO', 'B', 'LSTAT', 'MEDV'],
      dtype='object')
```

In [23]:
```
y = house['MEDV']
```

In [24]:
```
X = house.drop(['MEDV'],axis=1)
```

In [25]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, train_size=0.7, random_state=2529)
```

In [26]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[26]:
```
((354, 13), (152, 13), (354,), (152,))
```

In [25]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, train_size=0.7, random_state=2529)
```

In [26]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[26]:
```
((354, 13), (152, 13), (354,), (152,))
```

In [27]:
```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
```

In [28]:
```
# Step 6 : train or fit model
model.fit(X_train,y_train)
```

Out[28]:
```
LinearRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [29]:
```
model.intercept_
```

Out[29]:
```
34.21916368862993
```

In [30]:
```
model.coef_
```

Out[30]:
```
array([-1.29e-01,  3.65e-02,  1.54e-02,  2.35e+00, -2.04e+01,  4.41e+00,
        4.61e-03, -1.59e+00,  2.51e-01, -9.60e-03, -9.64e-01,  1.01e-02,
       -5.43e-01])
```

In [31]:
```
# Step 7 : predict model
y_pred = model.predict(X_test)
```

Output

In [32]:
```
y_pred
```

Out[32]:
```
array([31.72, 22.02, 21.17, 39.78, 20.1 , 22.86, 18.36, 14.79, 22.56,
       21.35, 18.38, 27.97, 29.86,  6.45, 10.68, 26.25, 21.89, 25.23,
        3.62, 36.22, 24.08, 22.94, 14.27, 20.79, 24.23, 16.74, 18.75,
       20.97, 28.51, 20.86,  9.23, 17.07, 22.07, 22.23, 39.26, 26.17,
       42.5 , 19.35, 34.52, 14.07, 13.81, 23.28, 11.79,  9.01, 21.65,
       25.55, 18.17, 16.82, 14.66, 14.86, 33.79, 33.27, 15.49, 24.08,
       27.64, 19.58, 45.02, 20.97, 20.07, 27.67, 34.59, 12.71, 23.66,
       31.66, 28.97, 32.46, 13.93, 35.49, 19.36, 19.6 ,  1.44, 24.1 ,
       33.67, 20.62, 26.89, 21.29, 31.95, 29.74, 13.93, 13.82, 19.76,
       21.54, 20.87, 23.63, 28.8 , 23.64,  6.95, 22.2 , -6.82, 16.97,
       16.77, 25.44, 14.95,  3.72, 15.03, 16.91, 21.46, 31.66, 30.72,
       23.73, 22.19, 13.76, 18.47, 18.15, 36.6 , 27.49, 11.  , 17.26,
       22.49, 16.53, 29.49, 22.89, 24.68, 20.38, 19.69, 22.55, 27.32,
       24.86, 20.2 , 29.14,  7.43,  5.85, 25.35, 38.73, 23.94, 25.28,
       20.11, 19.75, 25.07, 35.16, 27.32, 27.26, 31.4 , 16.55, 14.3 ,
       23.77,  7.65, 23.35, 21.37, 26.12, 25.32, 13.12, 17.67, 36.2 ,
       20.5 , 27.95, 22.46, 18.15, 31.24, 20.85, 27.36, 30.53])
```

In [33]:
```
# Step 8 : model accuracy
from sklearn.metrics import mean_absolute_error, mean_absolute_percentage_error, mean_squared_error
```

In [34]:
```
mean_absolute_error(y_test,y_pred)
```

Out[34]:
```
3.155030927602485
```

PROGRAM 5

Date:03-05-2024

Build Logistic Regression Model for a given dataset

Algorithm

03/05/24.

Program-5

Build logistic Regression Model for a given dataset.

```
function logistic_regression (x, y, learning_rate,
                              num_itr) :
    Initialize random values for weights (w)
                                   & bias (b)
    for i=1 to num_itr
        logits = x·w+b
        pred = sigmoid (logits)
        loss = compute_loss (y, pred)
    update weights & bias using gradients
Return w, b

function sigmoid (x)
    return 1(1+exp(-x))

function compute_loss (y_true, y_pred):
    loss = mean (y_true * log(y_pred) + (1-y_true)
                                   * log(1-y_pred))
    return loss
```

Code

```
In [2]: import numpy as np # linear algebra
        import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
        import matplotlib.pyplot as plt
        # Input data files are available in the "../input/" directory.
        # For example, running this (by clicking run or pressing Shift+Enter) will list the files in the input directory

        import os

In [4]: data = pd.read_csv('/content/data.csv')

In [5]: data.drop(['Unnamed: 32',"id"], axis=1, inplace=True)
        data.diagnosis = [1 if each == "M" else 0 for each in data.diagnosis]
        y = data.diagnosis.values
        x_data = data.drop(['diagnosis'], axis=1)

In [7]: # Assuming x_data is a numpy array or pandas DataFrame
        x = (x_data - np.min(x_data)) / (np.max(x_data) - np.min(x_data))

In [8]: from sklearn.model_selection import train_test_split

        x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.15, random_state=42)

        x_train = x_train.T
        x_test = x_test.T
        y_train = y_train.T
        y_test = y_test.T

        print("x train: ",x_train.shape)
        print("x test: ",x_test.shape)
        print("y train: ",y_train.shape)
        print("y test: ",y_test.shape)

        x train:  (30, 483)
        x test:  (30, 86)
        y train:  (483,)
        y test:  (86,)

In [9]: def initialize_weights_and_bias(dimension):
            w = np.full((dimension,1),0.01)
            b = 0.0
            return w, b

In [10]: def sigmoid(z):
             y_head = 1/(1+np.exp(-z))
             return y_head

In [ ]: def forward_backward_propagation(w,b,x_train,y_train):
            # forward propagation
            z = np.dot(w.T,x_train) + b
            y_head = sigmoid(z)
            loss = -y_train*np.log(y_head)-(1-y_train)*np.log(1-y_head)
            cost = (np.sum(loss))/x_train.shape[1]      # x_train.shape[1]  is for scaling
            # backward propagation
            derivative_weight = (np.dot(x_train,((y_head-y_train).T)))/x_train.shape[1] # x_train.shape[1]  is for scaling
            derivative_bias = np.sum(y_head-y_train)/x_train.shape[1]                 # x_train.shape[1]  is for scaling
            gradients = {"derivative_weight": derivative_weight,"derivative_bias": derivative_bias}
            return cost,gradients
```

In [ ]:

```
def update(w, b, x_train, y_train, learning_rate,number_of_iterarion):
    cost_list = []
    cost_list2 = []
    index = []
    # updating(learning) parameters is number_of_iterarion times
    for i in range(number_of_iterarion):
        # make forward and backward propagation and find cost and gradients
        cost,gradients = forward_backward_propagation(w,b,x_train,y_train)
        cost_list.append(cost)
        w = w - learning_rate * gradients["derivative_weight"]
        b = b - learning_rate * gradients["derivative_bias"]
        if i % 10 == 0:
            cost_list2.append(cost)
            index.append(i)
            print ("Cost after iteration %i: %f" %(i, cost))
    # we update(learn) parameters weights and bias
    parameters = {"weight": w,"bias": b}
    plt.plot(index,cost_list2)
    plt.xticks(index,rotation='vertical')
    plt.xlabel("Number of Iterarion")
    plt.ylabel("Cost")
    plt.show()
    return parameters, gradients, cost_list
```

In [11]:

```
def predict(w,b,x_test):
    # x_test is a input for forward propagation
    z = sigmoid(np.dot(w.T,x_test)+b)
    Y_prediction = np.zeros((1,x_test.shape[1]))
    # if z is bigger than 0.5, our prediction is sign one (y_head=1),
    # if z is smaller than 0.5, our prediction is sign zero (y_head=0),
    for i in range(z.shape[1]):
        if z[0,i]<= 0.5:
            Y_prediction[0,i] = 0
        else:
            Y_prediction[0,i] = 1

    return Y_prediction
```

In [18]:

```
def sigmoid(z):
    return 1 / (1 + np.exp(-z))

def initialize_weights_and_bias(dim):
    w = np.zeros((dim, 1))
    b = 0
    return w, b

def compute_cost(w, b, x, y):
    m = x.shape[1]
    A = sigmoid(np.dot(w.T, x) + b)
    cost = -1 / m * np.sum(y * np.log(A) + (1 - y) * np.log(1 - A))
    return cost

def propagate(w, b, x, y):
    m = x.shape[1]
    A = sigmoid(np.dot(w.T, x) + b)
    dw = 1 / m * np.dot(x, (A - y).T)
    db = 1 / m * np.sum(A - y)
    return dw, db
```

```python
def logistic_regression(x_train, y_train, x_test, y_test, learning_rate, num_iterations):
    # Initialize
    dimension = x_train.shape[0]  # Number of features
    w, b = initialize_weights_and_bias(dimension)
    costs = []

    # Gradient Descent
    for i in range(num_iterations):
        # Forward and Backward Propagation
        dw, db = propagate(w, b, x_train, y_train)

        # Update parameters
        w -= learning_rate * dw
        b -= learning_rate * db

        # Record the costs
        if i % 100 == 0:
            cost = compute_cost(w, b, x_train, y_train)
            costs.append(cost)
            print(f"Cost after iteration {i}: {cost}")

    # Evaluate model
    y_prediction_train = predict(w, b, x_train)
    y_prediction_test = predict(w, b, x_test)

    train_accuracy = 100 - np.mean(np.abs(y_prediction_train - y_train)) * 100
    test_accuracy = 100 - np.mean(np.abs(y_prediction_test - y_test)) * 100

    print("Train accuracy: {} %".format(train_accuracy))
    print("Test accuracy: {} %".format(test_accuracy))

    return w, b

# Assuming you have defined the predict function
# def predict(w, b, x):
#     ...

# Assuming you have defined x_train, y_train, x_test, y_test, learning_rate, and num_iterations
logistic_regression(x_train, y_train, x_test, y_test, learning_rate=1, num_iterations=100)
```

Output

```
Cost after iteration 0: 0.6782740160052536
Train accuracy: 80.74534161490683 %
Test accuracy: 81.3953488372093 %
```

```
Out[18]:  (array([[ 1.77806654e-02],
                  [ 1.10160388e-02],
                  [ 1.27806976e-01],
                  [ 1.95749649e+00],
                  [ 1.85931875e-05],
                  [ 2.68863405e-04],
                  [ 4.89020048e-04],
                  [ 2.63106803e-04],
                  [ 3.49357933e-05],
                  [-2.02145931e-05],
                  [ 1.25690784e-03],
                  [-3.98285024e-04],
                  [ 8.96937014e-03],
                  [ 2.02426962e-01],
                  [-3.60718647e-06],
                  [ 4.19150446e-05],
                  [ 6.03411729e-05],
                  [ 2.00740406e-05],
                  [-6.24803672e-06],
                  [ 6.24944780e-07],
                  [ 2.79506973e-02],
                  [ 1.99326360e-02],
                  [ 1.98774929e-01],
                  [ 3.39189908e+00],
                  [ 5.79135019e-05],
                  [ 8.53041205e-04],
                  [ 1.25862280e-03],
                  [ 4.60695564e-04],
                  [ 1.89671301e-04],
                  [ 3.52490835e-05]]),
           -1.5161875221606185)
```

PROGRAM 6

Date:19-04-2024

Build KNN Classification model for a given dataset.

Algorithm

03/05/24

Program - 5

KNN Classification Model

Algorithm:

1) Define the value of K and a distance metric.
2) For the given point, calculate the distance between the given point and every other point in the dataset.
3) Choose K closest points.
4) The class/value of the given point is the majority of that of K points. If euclidean distance is used as the distance matrix then $d = \sqrt{(x_1-x_2)^2+(y_1-y_2)^2}$

Code

```
In [1]: import numpy as np # linear algebra
        import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
        import matplotlib.pyplot as plt # for data visualization purposes
        import seaborn as sns # for data visualization
        %matplotlib inline

In [2]: data = '/content/cancer_detector.txt'
        df = pd.read_csv(data, header=None)

In [3]: df.shape

Out[3]: (699, 11)

In [4]: col_names = ['Id', 'Clump_thickness', 'Uniformity_Cell_Size', 'Uniformity_Cell_Shape', 'Marginal_Adhesion',
                     'Single_Epithelial_Cell_Size', 'Bare_Nuclei', 'Bland_Chromatin', 'Normal_Nucleoli', 'Mitoses', 'Class']

        df.columns = col_names

        df.columns

Out[4]: Index(['Id', 'Clump_thickness', 'Uniformity_Cell_Size',
               'Uniformity_Cell_Shape', 'Marginal_Adhesion',
               'Single_Epithelial_Cell_Size', 'Bare_Nuclei', 'Bland_Chromatin',
               'Normal_Nucleoli', 'Mitoses', 'Class'],
              dtype='object')

In [5]: df.head()

Out[5]:
```

	Id	Clump_thickness	Uniformity_Cell_Size	Uniformity_Cell_Shape	Marginal_Adhesion	Single_Epithelial_Cell_Size	Bare_Nuclei	Bla
0	1000025	5	1	1	1	2	1	
1	1002945	5	4	4	5	7	10	
2	1015425	3	1	1	1	2	2	
3	1016277	6	8	8	1	3	4	
4	1017023	4	1	1	3	2	1	

In [18]:
```python
import numpy as np
```

In [21]:
```python
# view summary statistics in numerical variables

print(round(df.describe(),2))
```

```
       Clump_thickness  Uniformity_Cell_Size  Uniformity_Cell_Shape  \
count           699.00                699.00                 699.00
mean              4.42                  3.13                   3.21
std               2.82                  3.05                   2.97
min               1.00                  1.00                   1.00
25%               2.00                  1.00                   1.00
50%               4.00                  1.00                   1.00
75%               6.00                  5.00                   5.00
max              10.00                 10.00                  10.00

       Marginal_Adhesion  Single_Epithelial_Cell_Size  Bare_Nuclei  \
count             699.00                       699.00       683.00
mean                2.81                         3.22         3.54
std                 2.86                         2.21         3.64
min                 1.00                         1.00         1.00
25%                 1.00                         2.00         1.00
50%                 1.00                         2.00         1.00
75%                 4.00                         4.00         6.00
max                10.00                        10.00        10.00

       Bland_Chromatin  Normal_Nucleoli  Mitoses   Class
count           699.00           699.00   699.00  699.00
mean              3.44             2.87     1.59    2.69
std               2.44             3.05     1.72    0.95
min               1.00             1.00     1.00    2.00
25%               2.00             1.00     1.00    2.00
50%               3.00             1.00     1.00    2.00
75%               5.00             4.00     1.00    4.00
max              10.00            10.00    10.00    4.00
```

In [22]:
```python
X = df.drop(['Class'], axis=1)

y = df['Class']
```

In [23]:
```python
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
```

In [24]:
```python
X_train.shape, X_test.shape
```

Out[24]:
```
((559, 9), (140, 9))
```

In [25]:
```python
for col in X_train.columns:
    if X_train[col].isnull().mean()>0:
        print(col, round(X_train[col].isnull().mean(),4))
```

```
Bare_Nuclei 0.0233
```

In [26]:
```python
for df1 in [X_train, X_test]:
    for col in X_train.columns:
        col_median=X_train[col].median()
        df1[col].fillna(col_median, inplace=True)
```

In [27]:
```python
cols = X_train.columns
```

In [28]:
```python
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)

X_test = scaler.transform(X_test)
```

In [29]:
```python
X_train = pd.DataFrame(X_train, columns=[cols])
```

In [30]:
```python
X_test = pd.DataFrame(X_test, columns=[cols])
```

Output

```
In [33]: y_pred = knn.predict(X_test)

         y_pred

Out[33]: array([2, 2, 4, 2, 4, 2, 4, 2, 4, 2, 2, 2, 4, 4, 4, 2, 2, 4, 4, 2, 4, 4,
                2, 2, 2, 4, 2, 2, 4, 4, 2, 2, 2, 2, 2, 2, 2, 4, 2, 2, 2, 2, 2, 2,
                4, 4, 2, 4, 2, 4, 4, 2, 2, 4, 2, 2, 2, 2, 2, 2, 4, 2, 2, 4, 4, 4,
                4, 2, 2, 4, 2, 2, 4, 4, 2, 2, 2, 2, 4, 2, 2, 2, 4, 2, 2, 2, 4, 2,
                4, 4, 2, 2, 2, 4, 2, 2, 2, 4, 2, 4, 4, 2, 2, 2, 4, 2, 2, 2, 2, 2,
                4, 4, 4, 2, 2, 2, 2, 2, 4, 4, 4, 4, 2, 4, 2, 2, 4, 4, 4, 4, 4, 2,
                2, 4, 4, 2, 2, 4, 2, 2])

In [34]: knn.predict_proba(X_test)[:,0]

Out[34]: array([1.        , 1.        , 0.33333333, 1.        , 0.        ,
                1.        , 0.        , 1.        , 0.        , 0.66666667,
                1.        , 1.        , 0.        , 0.33333333, 0.        ,
                1.        , 1.        , 0.        , 0.        , 1.        ,
                0.        , 0.        , 1.        , 1.        , 1.        ,
                0.        , 1.        , 1.        , 0.        , 0.        ,
                1.        , 1.        , 1.        , 1.        , 1.        ,
                0.66666667, 1.        , 0.        , 1.        , 1.        ,
                1.        , 1.        , 1.        , 1.        , 0.        ,
                0.        , 1.        , 0.        , 1.        , 0.        ,
                0.        , 1.        , 1.        , 0.        , 1.        ,
                1.        , 1.        , 1.        , 0.66666667, 1.        ,
                0.        , 1.        , 1.        , 0.        , 0.        ,
                0.33333333, 0.        , 1.        , 1.        , 0.        ,
                1.        , 1.        , 0.        , 0.        , 1.        ,
                1.        , 1.        , 1.        , 0.        , 1.        ,
                1.        , 1.        , 0.        , 1.        , 1.        ,
                1.        , 0.        , 1.        , 0.        , 0.        ,
                1.        , 1.        , 0.66666667, 0.        , 1.        ,
                1.        , 1.        , 0.        , 1.        , 0.        ,
                0.        , 1.        , 1.        , 1.        , 0.        ,
                1.        , 1.        , 1.        , 1.        , 1.        ,
                0.        , 0.33333333, 0.        , 1.        , 1.        ,
                1.        , 1.        , 1.        , 0.        , 0.        ,
                0.        , 0.33333333, 1.        , 0.        , 1.        ,
                1.        , 0.33333333, 0.33333333, 0.        , 0.        ,
                0.        , 1.        , 1.        , 0.33333333, 0.        ,
                1.        , 1.        , 0.        , 1.        , 1.        ])

In [35]: from sklearn.metrics import accuracy_score

         print('Model accuracy score: {0:0.4f}'. format(accuracy_score(y_test, y_pred)))

Model accuracy score: 0.9714

In [36]: y_pred_train = knn.predict(X_train)

In [37]: print('Training-set accuracy score: {0:0.4f}'. format(accuracy_score(y_train, y_pred_train)))

Training-set accuracy score: 0.9821
```

PROGRAM 7

Date:24-05-2024

Build Support vector machine model for a given dataset

Algorithm

31/05/24

Program - 7

Build support vector machine model for a given dataset.

1. Define kernel function $K(x_1, x_2) = x_1 \cdot x_2$
2. Solve the quadratic programming problem to find the α.
3. Compute the bias
4. Identify the support vectors.
5. Make prediction

Output:

Model = SVM ()
Model.fit (x_train, y_train)
prediction = model.predict (x_test)
accuracy = (y_test, prediction)

0.98230088

Model predict ([-0.43096, -0.16048964,
-0.4481
-0.8244122, -0.19956318])

Code

Open in Colab

```
In [ ]: import seaborn as sns
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import plotly.express as px
```

```
In [ ]: df = pd.read_csv('/content/breast-cancer.csv')
        df.head()
```

Out[ ]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mear
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.300
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.086
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.197
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.241
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.198

5 rows × 32 columns

```
In [ ]: df.drop('id', axis=1, inplace=True) #drop redundant columns
```

```
In [ ]: df.describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%	75%	max
radius_mean	569.0	14.127292	3.524049	6.981000	11.700000	13.370000	15.780000	28.11000
texture_mean	569.0	19.289649	4.301036	9.710000	16.170000	18.840000	21.800000	39.28000
perimeter_mean	569.0	91.969033	24.298981	43.790000	75.170000	86.240000	104.100000	188.50000
area_mean	569.0	654.889104	351.914129	143.500000	420.300000	551.100000	782.700000	2501.00000
smoothness_mean	569.0	0.096360	0.014064	0.052630	0.086370	0.095870	0.105300	0.16340
compactness_mean	569.0	0.104341	0.052813	0.019380	0.064920	0.092630	0.130400	0.34540
concavity_mean	569.0	0.088799	0.079720	0.000000	0.029560	0.061540	0.130700	0.42680
concave points_mean	569.0	0.048919	0.038803	0.000000	0.020310	0.033500	0.074000	0.20120
symmetry_mean	569.0	0.181162	0.027414	0.106000	0.161900	0.179200	0.195700	0.30400
fractal_dimension_mean	569.0	0.062798	0.007060	0.049960	0.057700	0.061540	0.066120	0.09744
radius_se	569.0	0.405172	0.277313	0.111500	0.232400	0.324200	0.478900	2.87300
texture_se	569.0	1.216853	0.551648	0.360200	0.833900	1.108000	1.474000	4.88500
perimeter_se	569.0	2.866059	2.021855	0.757000	1.606000	2.287000	3.357000	21.98000
area_se	569.0	40.337079	45.491006	6.802000	17.850000	24.530000	45.190000	542.20000
smoothness_se	569.0	0.007041	0.003003	0.001713	0.005169	0.006380	0.008146	0.03113
compactness_se	569.0	0.025478	0.017908	0.002252	0.013080	0.020450	0.032450	0.13540
concavity_se	569.0	0.031894	0.030186	0.000000	0.015090	0.025890	0.042050	0.39600
concave points_se	569.0	0.011796	0.006170	0.000000	0.007638	0.010930	0.014710	0.05279
symmetry_se	569.0	0.020542	0.008266	0.007882	0.015160	0.018730	0.023480	0.07895
fractal_dimension_se	569.0	0.003795	0.002646	0.000895	0.002248	0.003187	0.004558	0.02984
radius_worst	569.0	16.269190	4.833242	7.930000	13.010000	14.970000	18.790000	36.04000
texture_worst	569.0	25.677223	6.146258	12.020000	21.080000	25.410000	29.720000	49.54000
perimeter_worst	569.0	107.261213	33.602542	50.410000	84.110000	97.660000	125.400000	251.20000
area_worst	569.0	880.583128	569.356993	185.200000	515.300000	686.500000	1084.000000	4254.00000
smoothness_worst	569.0	0.132369	0.022832	0.071170	0.116600	0.131300	0.146000	0.22260
compactness_worst	569.0	0.254265	0.157336	0.027290	0.147200	0.211900	0.339100	1.05800
concavity_worst	569.0	0.272188	0.208624	0.000000	0.114500	0.226700	0.382900	1.25200
concave points_worst	569.0	0.114606	0.065732	0.000000	0.064930	0.099930	0.161400	0.29100
symmetry_worst	569.0	0.290076	0.061867	0.156500	0.250400	0.282200	0.317900	0.66380
fractal_dimension_worst	569.0	0.083946	0.018061	0.055040	0.071460	0.080040	0.092080	0.20750

```
In [ ]: df['diagnosis'] = (df['diagnosis'] == 'M').astype(int) #encode the label into 1/0
```

```
In [ ]: corr = df.corr()
```

```
In [ ]: # Get the absolute value of the correlation
        cor_target = abs(corr["diagnosis"])

        # Select highly correlated features (thresold = 0.2)
        relevant_features = cor_target[cor_target>0.2]

        # Collect the names of the features
        names = [index for index, value in relevant_features.items()]

        # Drop the target variable from the results
        names.remove('diagnosis')

        # Display the results
        print(names)
```

```
['radius_mean', 'texture_mean', 'perimeter_mean', 'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_mean', 'conc
ave points_mean', 'symmetry_mean', 'radius_se', 'perimeter_se', 'area_se', 'compactness_se', 'concavity_se', 'concave points_
se', 'radius_worst', 'texture_worst', 'perimeter_worst', 'area_worst', 'smoothness_worst', 'compactness_worst', 'concavity_wo
rst', 'concave points_worst', 'symmetry_worst', 'fractal_dimension_worst']
```

```
In [ ]: X = df[names].values
        y = df['diagnosis']
```

```
In [ ]: def scale(X):
            """
            Standardizes the data in the array X.

            Parameters:
                X (numpy.ndarray): Features array of shape (n_samples, n_features).

            Returns:
                numpy.ndarray: The standardized features array.
            """
            # Calculate the mean and standard deviation of each feature
            mean = np.mean(X, axis=0)
            std = np.std(X, axis=0)

            # Standardize the data
            X = (X - mean) / std
            return X
```

```
In [ ]: X = scale(X)
```

```
In [ ]: def train_test_split(X, y, random_state=41, test_size=0.2):
            """
            Splits the data into training and testing sets.

            Parameters:
                X (numpy.ndarray): Features array of shape (n_samples, n_features).
                y (numpy.ndarray): Target array of shape (n_samples,).
                random_state (int): Seed for the random number generator. Default is 42.
                test_size (float): Proportion of samples to include in the test set. Default is 0.2.

            Returns:
                Tuple[numpy.ndarray]: A tuple containing X_train, X_test, y_train, y_test.
            """
            # Get number of samples
            n_samples = X.shape[0]

            # Set the seed for the random number generator
            np.random.seed(random_state)

            # Shuffle the indices
            shuffled_indices = np.random.permutation(np.arange(n_samples))

            # Determine the size of the test set
            test_size = int(n_samples * test_size)

            # Split the indices into test and train
            test_indices = shuffled_indices[:test_size]
            train_indices = shuffled_indices[test_size:]

            # Split the features and target arrays into test and train
            X_train, X_test = X[train_indices], X[test_indices]
            y_train, y_test = y[train_indices], y[test_indices]

            return X_train, X_test, y_train, y_test
```

```
In [ ]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state=42) #split the  data into traing an
```

```python
class SVM:


    def __init__(self, iterations=1000, lr=0.01, lambdaa=0.01):

        self.lambdaa = lambdaa
        self.iterations = iterations
        self.lr = lr
        self.w = None
        self.b = None
    def initialize_parameters(self, X):

        m, n = X.shape
        self.w = np.zeros(n)
        self.b = 0

    def gradient_descent(self, X, y):

        y_ = np.where(y <= 0, -1, 1)
        for i, x in enumerate(X):
            if y_[i] * (np.dot(x, self.w) - self.b) >= 1:
                dw = 2 * self.lambdaa * self.w
                db = 0
            else:
                dw = 2 * self.lambdaa * self.w - np.dot(x, y_[i])
                db = y_[i]
            self.update_parameters(dw, db)

    def update_parameters(self, dw, db):

        self.w = self.w - self.lr * dw
        self.b = self.b - self.lr * db
    def fit(self, X, y):

        self.initialize_parameters(X)
        for i in range(self.iterations):
            self.gradient_descent(X, y)


    def predict(self, X):

        # get the outputs
        output = np.dot(X, self.w) - self.b
        # get the signs of the labels depending on if it's greater/less than zero
        label_signs = np.sign(output)
        #set predictions to 0 if they are less than or equal to -1 else set them to 1
        predictions = np.where(label_signs <= -1, 0, 1)
        return predictions
```

```python
def accuracy(y_true, y_pred):

    total_samples = len(y_true)
    correct_predictions = np.sum(y_true == y_pred)
    return (correct_predictions / total_samples)
```

Output

```python
model = SVM()
model.fit(X_train,y_train)
predictions = model.predict(X_test)

accuracy(y_test, predictions)
```

```
0.9823008849557522
```

PROGRAM 8

Date: 31-05-2024

Build Artificial Neural Network model with back propagation on a given dataset

Algorithm

31/5/24

Program 8

Build Artificial Neural Network model with back propagation on a given dataset

Algorithm :

1. Create a feed-forward network with ni inputs, nhidden hidden units, and nout output units.
2. Initialize all network weights to small random numbers.
3. Until the termination condition is met, Do
   - For each $(\vec{x}, \vec{t})$, in training examples, Do
     - Propogate the input forward through the network:
       1. Input the instance $\vec{x}$, to the network and compute the output o_u of every unit u in the network.

     Propogate the error backward through the network:

     2. For each network output unit k, calculate its error term δ_k

        $$\delta_k \leftarrow o_k(1-o_k)(t_k-o_k)$$

     3. For each hidden unit h, calculate its error term δ_h

        $$\delta_h \leftarrow o_h(1-o_h) \sum_{k \in outputs} w_{h,k}\delta_k$$

     4. Update each network weight w_{ji}

        $$w_{ji} \leftarrow w_{ji} + \Delta w_{ji}$$

        where

        $$\Delta w_{ji} = \eta \delta_j x_{ij}$$

Output : Learning Accuracy = 0.66233, Testing Accuracy = 1.0

Code

In [1]:
```
import numpy as np
from sklearn.model_selection import train_test_split

db = np.loadtxt("/content/duke-breast-cancer.txt")
print("Database raw shape (%s,%s)" % np.shape(db))
```

```
Database raw shape (86,7130)
```

In [2]:
```
np.random.shuffle(db)
y = db[:, 0]
x = np.delete(db, [0], axis=1)
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.1)
print(np.shape(x_train),np.shape(x_test))
```

```
(77, 7129) (9, 7129)
```

In [3]:
```
hidden_layer = np.zeros(72)
weights = np.random.random((len(x[0]), 72))
output_layer = np.zeros(2)
hidden_weights = np.random.random((72, 2))
```

In [4]:
```
def sum_function(weights, index_locked_col, x):
    result = 0
    for i in range(0, len(x)):
        result += x[i] * weights[i][index_locked_col]
    return result
```

In [5]:
```
def activate_layer(layer, weights, x):
    for i in range(0, len(layer)):
        layer[i] = 1.7159 * np.tanh(2.0 * sum_function(weights, i, x) / 3.0)
```

In [6]:
```
def soft_max(layer):
    soft_max_output_layer = np.zeros(len(layer))
    for i in range(0, len(layer)):
        denominator = 0
        for j in range(0, len(layer)):
            denominator += np.exp(layer[j] - np.max(layer))
        soft_max_output_layer[i] = np.exp(layer[i] - np.max(layer)) / denominator
    return soft_max_output_layer
```

In [7]:
```
def recalculate_weights(learning_rate, weights, gradient, activation):
    for i in range(0, len(weights)):
        for j in range(0, len(weights[i])):
            weights[i][j] = (learning_rate * gradient[j] * activation[i]) + weights[i][j]
```

In [8]:
```
def back_propagation(hidden_layer, output_layer, one_hot_encoding, learning_rate, x):
    output_derivative = np.zeros(2)
    output_gradient = np.zeros(2)
    for i in range(0, len(output_layer)):
        output_derivative[i] = (1.0 - output_layer[i]) * output_layer[i]
    for i in range(0, len(output_layer)):
        output_gradient[i] = output_derivative[i] * (one_hot_encoding[i] - output_layer[i])
    hidden_derivative = np.zeros(72)
    hidden_gradient = np.zeros(72)
    for i in range(0, len(hidden_layer)):
        hidden_derivative[i] = (1.0 - hidden_layer[i]) * (1.0 + hidden_layer[i])
    for i in range(0, len(hidden_layer)):
        sum_ = 0
        for j in range(0, len(output_gradient)):
            sum_ += output_gradient[j] * hidden_weights[i][j]
        hidden_gradient[i] = sum_ * hidden_derivative[i]
    recalculate_weights(learning_rate, hidden_weights, output_gradient, hidden_layer)
    recalculate_weights(learning_rate, weights, hidden_gradient, x)
```

Output

```
In [9]:
one_hot_encoding = np.zeros((2,2))
for i in range(0, len(one_hot_encoding)):
    one_hot_encoding[i][i] = 1
training_correct_answers = 0
for i in range(0, len(x_train)):
    activate_layer(hidden_layer, weights, x_train[i])
    activate_layer(output_layer, hidden_weights, hidden_layer)
    output_layer = soft_max(output_layer)
    training_correct_answers += 1 if y_train[i] == np.argmax(output_layer) else 0
    back_propagation(hidden_layer, output_layer, one_hot_encoding[int(y_train[i])], -1, x_train[i])
print("MLP Correct answers while learning: %s / %s (Accuracy = %s) on %s database." % (training_correct_answers, len(x_trai
                                                                                       training_correct_answers/len(x_train
```

```
MLP Correct answers while learning: 51 / 77 (Accuracy = 0.6623376623376623) on Duke breast cancer database.
```

```
In [10]:
testing_correct_answers = 0
for i in range(0, len(x_test)):
    activate_layer(hidden_layer, weights, x_test[i])
    activate_layer(output_layer, hidden_weights, hidden_layer)
    output_layer = soft_max(output_layer)
    testing_correct_answers += 1 if y_test[i] == np.argmax(output_layer) else 0
print("MLP Correct answers while testing: %s / %s (Accuracy = %s) on %s database" % (testing_correct_answers, len(x_test),
                                                                                     testing_correct_answers/len(x_test), "I
```

```
MLP Correct answers while testing: 9 / 9 (Accuracy = 1.0) on Duke breast cancer database
```

PROGRAM 9

Date: 31-05-2024

a) Implement Random forest ensemble method on a given dataset.

Algorithm

31/5/24

Program 9

(a) Implement Random forest ensemble method on a given dataset.

Algorithm:

1. Select Random K data points from the training dataset.
2. Build the decision trees associated with the selected data points
3. Choose the number N for decision trees that you want to build.
4. Repeat step 1 & 2.
5. For new data points, find the predictions of each decision tree and assign the new data points to the category that wins the majority votes.

Output:

Mean Absolute Error : 3.92 degrees

Accuracy : 93.76%.

Code

Open in Colab

In [1]:
```
# Pandas is used for data manipulation
import pandas as pd
# Read in data and display first 5 rows
features = pd.read_csv('/content/temps.csv')
features.head(5)
```

Out[1]:

	year	month	day	week	temp_2	temp_1	average	actual	forecast_noaa	forecast_acc	forecast_under	friend
0	2016	1	1	Fri	45	45	45.6	45	43	50	44	29
1	2016	1	2	Sat	44	45	45.7	44	41	50	44	61
2	2016	1	3	Sun	45	44	45.8	41	43	46	47	56
3	2016	1	4	Mon	44	41	45.9	40	44	48	46	53
4	2016	1	5	Tues	41	40	46.0	44	46	46	46	41

In [2]:
```
print('The shape of our features is:', features.shape)
```

```
The shape of our features is: (348, 12)
```

In [3]:
```
# Descriptive statistics for each column
features.describe()
```

Out[3]:

	year	month	day	temp_2	temp_1	average	actual	forecast_noaa	forecast_acc	forecast_under	
count	348.0	348.000000	348.000000	348.000000	348.000000	348.000000	348.000000	348.000000	348.000000	348.000000	348.(
mean	2016.0	6.477011	15.514368	62.652299	62.701149	59.760632	62.543103	57.238506	62.373563	59.772989	60.(
std	0.0	3.498380	8.772982	12.165398	12.120542	10.527306	11.794146	10.605746	10.549381	10.705256	15.(
min	2016.0	1.000000	1.000000	35.000000	35.000000	45.100000	35.000000	41.000000	46.000000	44.000000	28.(
25%	2016.0	3.000000	8.000000	54.000000	54.000000	49.975000	54.000000	48.000000	53.000000	50.000000	47.:
50%	2016.0	6.000000	15.000000	62.500000	62.500000	58.200000	62.500000	56.000000	61.000000	58.000000	60.(
75%	2016.0	10.000000	23.000000	71.000000	71.000000	69.025000	71.000000	66.000000	72.000000	69.000000	71.(
max	2016.0	12.000000	31.000000	117.000000	117.000000	77.400000	92.000000	77.000000	82.000000	79.000000	95.(

In [4]:
```
# One-hot encode the data using pandas get_dummies
features = pd.get_dummies(features)
# Display the first 5 rows of the last 12 columns
features.iloc[:,5:].head(5)
```

Out[4]:

	average	actual	forecast_noaa	forecast_acc	forecast_under	friend	week_Fri	week_Mon	week_Sat	week_Sun	week_Thurs	week_Tu
0	45.6	45	43	50	44	29	True	False	False	False	False	Fa
1	45.7	44	41	50	44	61	False	False	True	False	False	Fa
2	45.8	41	43	46	47	56	False	False	False	True	False	Fa
3	45.9	40	44	48	46	53	False	True	False	False	False	Fa
4	46.0	44	46	46	46	41	False	False	False	False	False	T

In [5]:

```
# Use numpy to convert to arrays
import numpy as np
# Labels are the values we want to predict
labels = np.array(features['actual'])
# Remove the labels from the features
# axis 1 refers to the columns
features= features.drop('actual', axis = 1)
# Saving feature names for later use
feature_list = list(features.columns)
# Convert to numpy array
features = np.array(features)
```

In [6]:

```
# Using Skicit-learn to split data into training and testing sets
from sklearn.model_selection import train_test_split
# Split the data into training and testing sets
train_features, test_features, train_labels, test_labels = train_test_split(features, labels, test_size = 0.25, random_stat
```

In [7]:

```
print('Training Features Shape:', train_features.shape)
print('Training Labels Shape:', train_labels.shape)
print('Testing Features Shape:', test_features.shape)
print('Testing Labels Shape:', test_labels.shape)
```

```
Training Features Shape: (261, 17)
Training Labels Shape: (261,)
Testing Features Shape: (87, 17)
Testing Labels Shape: (87,)
```

In [8]:

```
# The baseline predictions are the historical averages
baseline_preds = test_features[:, feature_list.index('average')]
# Baseline errors, and display average baseline error
baseline_errors = abs(baseline_preds - test_labels)
print('Average baseline error: ', round(np.mean(baseline_errors), 2))
```

```
Average baseline error:  5.06
```

In [9]:

```
# Import the model we are using
from sklearn.ensemble import RandomForestRegressor
# Instantiate model with 1000 decision trees
rf = RandomForestRegressor(n_estimators = 1000, random_state = 42)
# Train the model on training data
rf.fit(train_features, train_labels);
```

In [10]:

```
# Use the forest's predict method on the test data
predictions = rf.predict(test_features)
# Calculate the absolute errors
errors = abs(predictions - test_labels)
# Print out the mean absolute error (mae)
print('Mean Absolute Error:', round(np.mean(errors), 2), 'degrees.')
```

```
Mean Absolute Error: 3.87 degrees.
```

In [11]:

```
# Calculate mean absolute percentage error (MAPE)
mape = 100 * (errors / test_labels)
# Calculate and display accuracy
accuracy = 100 - np.mean(mape)
print('Accuracy:', round(accuracy, 2), '%.')
```

```
Accuracy: 93.93 %.
```

In [12]:

```
# Import tools needed for visualization
from sklearn.tree import export_graphviz
import pydot
# Pull out one tree from the forest
tree = rf.estimators_[5]
# Import tools needed for visualization
from sklearn.tree import export_graphviz
import pydot
# Pull out one tree from the forest
tree = rf.estimators_[5]
# Export the image to a dot file
export_graphviz(tree, out_file = 'tree.dot', feature_names = feature_list, rounded = True, precision = 1)
# Use dot file to create a graph
(graph, ) = pydot.graph_from_dot_file('tree.dot')
# Write graph to a png file
graph.write_png('tree.png')
```

In [13]:

```
# Limit depth of tree to 3 levels
rf_small = RandomForestRegressor(n_estimators=10, max_depth = 3)
rf_small.fit(train_features, train_labels)
# Extract the small tree
tree_small = rf_small.estimators_[5]
# Save the tree as a png image
export_graphviz(tree_small, out_file = 'small_tree.dot', feature_names = feature_list, rounded = True, precision = 1)
(graph, ) = pydot.graph_from_dot_file('small_tree.dot')
graph.write_png('small_tree.png');
```

In [14]:

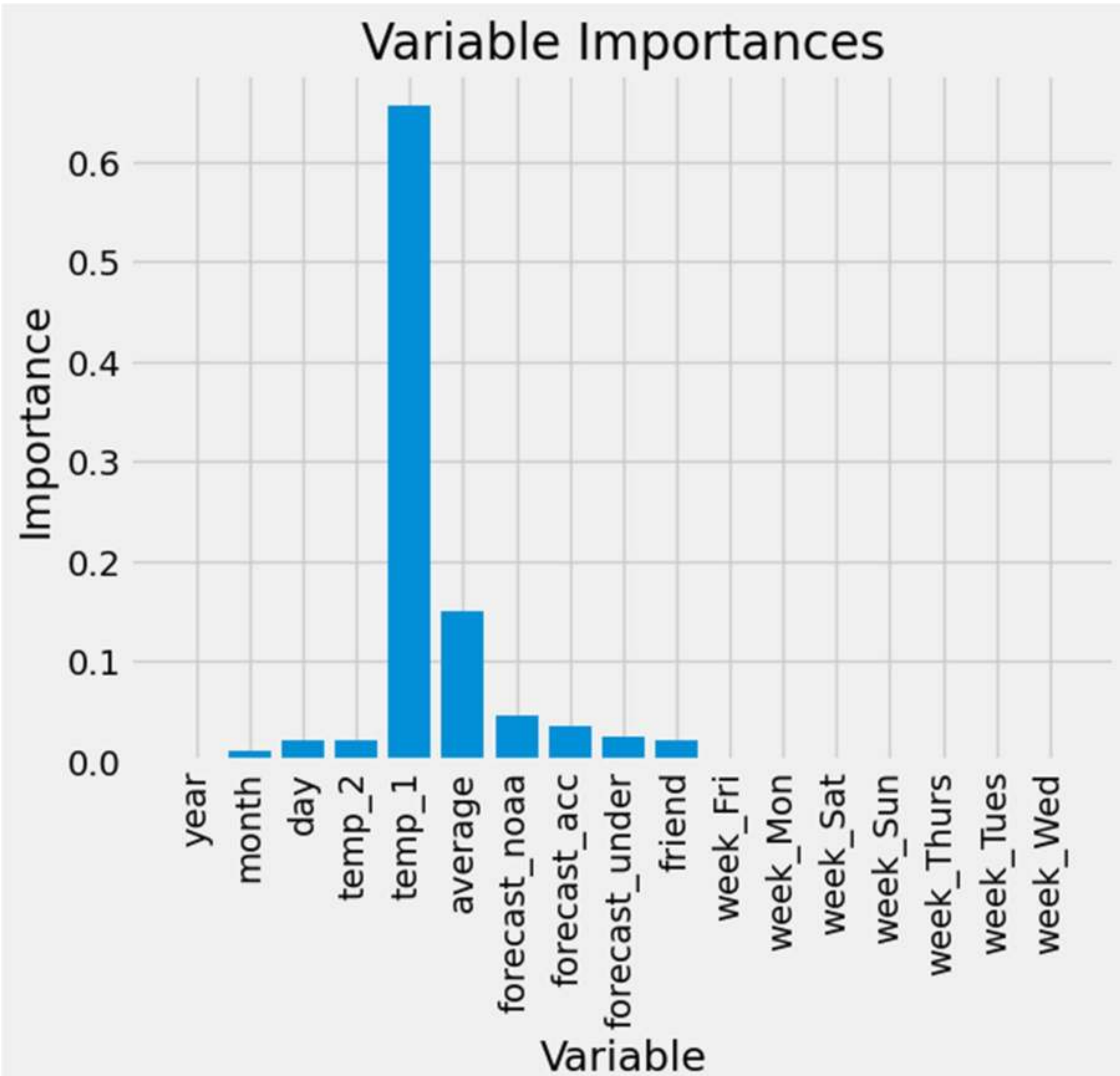
```
# Get numerical feature importances
importances = list(rf.feature_importances_)
# List of tuples with variable and importance
feature_importances = [(feature, round(importance, 2)) for feature, importance in zip(feature_list, importances)]
# Sort the feature importances by most important first
feature_importances = sorted(feature_importances, key = lambda x: x[1], reverse = True)
# Print out the feature and importances
[print('Variable: {:20} Importance: {}'.format(*pair)) for pair in feature_importances];
```

```
Variable: temp_1               Importance: 0.66
Variable: average              Importance: 0.15
Variable: forecast_noaa        Importance: 0.05
Variable: forecast_acc         Importance: 0.03
Variable: day                  Importance: 0.02
Variable: temp_2               Importance: 0.02
Variable: forecast_under       Importance: 0.02
Variable: friend               Importance: 0.02
Variable: month                Importance: 0.01
Variable: year                 Importance: 0.0
Variable: week_Fri             Importance: 0.0
Variable: week_Mon             Importance: 0.0
Variable: week_Sat             Importance: 0.0
Variable: week_Sun             Importance: 0.0
Variable: week_Thurs           Importance: 0.0
Variable: week_Tues            Importance: 0.0
Variable: week_Wed             Importance: 0.0
```

In [15]:

```
# New random forest with only the two most important variables
rf_most_important = RandomForestRegressor(n_estimators= 1000, random_state=42)
# Extract the two most important features
important_indices = [feature_list.index('temp_1'), feature_list.index('average')]
train_important = train_features[:, important_indices]
test_important = test_features[:, important_indices]
# Train the random forest
rf_most_important.fit(train_important, train_labels)
# Make predictions and determine the error
predictions = rf_most_important.predict(test_important)
errors = abs(predictions - test_labels)
# Display the performance metrics
print('Mean Absolute Error:', round(np.mean(errors), 2), 'degrees.')
mape = np.mean(100 * (errors / test_labels))
accuracy = 100 - mape
print('Accuracy:', round(accuracy, 2), '%.')
```

Output



Variable Importances
Importance
0.6
0.5
0.4
0.3
0.2
0.1
0.0
year
month
day
temp_2
temp_1
average
forecast_noaa
forecast_acc
forecast_under
friend
week_Fri
week_Mon
week_Sat
week_Sun
week_Thurs
week_Tues
week_Wed
Variable

b) Implement Boosting ensemble method on a given dataset.

Algorithm

(b) Implement Boosting Ensemble on a given dataset.

Algorithm:

1. Initialize the dataset and assign equal weight to each of the data point.
2. Provide this as input to the model and identify the wrongly classified datapoints
3. Increase the weight of the wrongly classified data points and decrease the weights of correctly classified data points. And then normalize the weights of all data points.
4. If (got required results)
   Goto step - 5
   Else
   Goto step - 2
5. End.

Output

Confusion Matrix : [[116 35]
[26 54]]

Accuracy score : 0.7359.

Code

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
sns.set_style("whitegrid")
plt.style.use("fivethirtyeight")
```

In [2]:
```
df = pd.read_csv("/content/diabetes.csv")
df.head()
```

Out[2]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

In [3]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

In [4]:
```
df.isnull().sum()
```

Out[4]:
```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

In [5]:
```
pd.set_option('display.float_format', '{:.2f}'.format)
df.describe()
```

Out[5]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
count	768.00	768.00	768.00	768.00	768.00	768.00	768.00	768.00	768.00
mean	3.85	120.89	69.11	20.54	79.80	31.99	0.47	33.24	0.35
std	3.37	31.97	19.36	15.95	115.24	7.88	0.33	11.76	0.48
min	0.00	0.00	0.00	0.00	0.00	0.00	0.08	21.00	0.00
25%	1.00	99.00	62.00	0.00	0.00	27.30	0.24	24.00	0.00
50%	3.00	117.00	72.00	23.00	30.50	32.00	0.37	29.00	0.00
75%	6.00	140.25	80.00	32.00	127.25	36.60	0.63	41.00	1.00
max	17.00	199.00	122.00	99.00	846.00	67.10	2.42	81.00	1.00

```
In [6]: categorical_val = []
        continous_val = []
        for column in df.columns:
        #     print('==============================')
        #     print(f"{column} : {df[column].unique()}")
            if len(df[column].unique()) <= 10:
                categorical_val.append(column)
            else:
                continous_val.append(column)
```

```
In [7]: df.columns
```

```
Out[7]: Index(['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulin',
               'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome'],
              dtype='object')
```

```
In [8]: # How many missing zeros are mising in each feature
        feature_columns = [
            'Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness',
            'Insulin', 'BMI', 'DiabetesPedigreeFunction', 'Age'
        ]

        for column in feature_columns:
            print("============================================")
            print(f"{column} ==> Missing zeros : {len(df.loc[df[column] == 0])}")
```

```
============================================
Pregnancies ==> Missing zeros : 111
============================================
Glucose ==> Missing zeros : 5
============================================
BloodPressure ==> Missing zeros : 35
============================================
SkinThickness ==> Missing zeros : 227
============================================
Insulin ==> Missing zeros : 374
============================================
BMI ==> Missing zeros : 11
============================================
DiabetesPedigreeFunction ==> Missing zeros : 0
============================================
Age ==> Missing zeros : 0
```

```
In [9]: from sklearn.impute import SimpleImputer


        fill_values = SimpleImputer(missing_values=0, strategy="mean", copy=False)
        df[feature_columns] = fill_values.fit_transform(df[feature_columns])

        for column in feature_columns:
            print("============================================")
            print(f"{column} ==> Missing zeros : {len(df.loc[df[column] == 0])}")
```

```
============================================
Pregnancies ==> Missing zeros : 0
============================================
Glucose ==> Missing zeros : 0
============================================
BloodPressure ==> Missing zeros : 0
============================================
SkinThickness ==> Missing zeros : 0
============================================
Insulin ==> Missing zeros : 0
============================================
BMI ==> Missing zeros : 0
============================================
DiabetesPedigreeFunction ==> Missing zeros : 0
============================================
Age ==> Missing zeros : 0
```

```
In [10]: from sklearn.model_selection import train_test_split


         X = df[feature_columns]
         y = df.Outcome

         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
```

```
In [11]: from sklearn.metrics import confusion_matrix, accuracy_score, classification_report


         def evaluate(model, X_train, X_test, y_train, y_test):
             y_test_pred = model.predict(X_test)
             y_train_pred = model.predict(X_train)

             print("TRAINIG RESULTS: \n===============================")
             clf_report = pd.DataFrame(classification_report(y_train, y_train_pred, output_dict=True))
             print(f"CONFUSION MATRIX:\n{confusion_matrix(y_train, y_train_pred)}")
             print(f"ACCURACY SCORE:\n{accuracy_score(y_train, y_train_pred):.4f}")
             print(f"CLASSIFICATION REPORT:\n{clf_report}")

             print("TESTING RESULTS: \n===============================")
             clf_report = pd.DataFrame(classification_report(y_test, y_test_pred, output_dict=True))
             print(f"CONFUSION MATRIX:\n{confusion_matrix(y_test, y_test_pred)}")
             print(f"ACCURACY SCORE:\n{accuracy_score(y_test, y_test_pred):.4f}")
             print(f"CLASSIFICATION REPORT:\n{clf_report}")
```

```
In [12]: from sklearn.ensemble import AdaBoostClassifier

         ada_boost_clf = AdaBoostClassifier(n_estimators=30)
         ada_boost_clf.fit(X_train, y_train)
         evaluate(ada_boost_clf, X_train, X_test, y_train, y_test)
```

Output-AdaBoost

```
TRAINIG RESULTS:
===============================
CONFUSION MATRIX:
[[310  39]
 [ 51 137]]
ACCURACY SCORE:
0.8324
CLASSIFICATION REPORT:
                0      1  accuracy  macro avg  weighted avg
precision    0.86   0.78      0.83       0.82          0.83
recall       0.89   0.73      0.83       0.81          0.83
f1-score     0.87   0.75      0.83       0.81          0.83
support    349.00 188.00      0.83     537.00        537.00
TESTING RESULTS:
===============================
CONFUSION MATRIX:
[[123  28]
 [ 27  53]]
ACCURACY SCORE:
0.7619
CLASSIFICATION REPORT:
                0     1  accuracy  macro avg  weighted avg
precision    0.82  0.65      0.76       0.74          0.76
recall       0.81  0.66      0.76       0.74          0.76
f1-score     0.82  0.66      0.76       0.74          0.76
support    151.00 80.00      0.76     231.00        231.00
```

Output- GradientBoost

```
TRAINIG RESULTS:
===============================
CONFUSION MATRIX:
[[342   7]
 [ 19 169]]
ACCURACY SCORE:
0.9516
CLASSIFICATION REPORT:
                0      1  accuracy  macro avg  weighted avg
precision    0.95   0.96      0.95       0.95          0.95
recall       0.98   0.90      0.95       0.94          0.95
f1-score     0.96   0.93      0.95       0.95          0.95
support    349.00 188.00      0.95     537.00        537.00
TESTING RESULTS:
===============================
CONFUSION MATRIX:
[[116  35]
 [ 26  54]]
ACCURACY SCORE:
0.7359
CLASSIFICATION REPORT:
                0     1  accuracy  macro avg  weighted avg
precision    0.82  0.61      0.74       0.71          0.74
recall       0.77  0.68      0.74       0.72          0.74
f1-score     0.79  0.64      0.74       0.72          0.74
support    151.00 80.00      0.74     231.00        231.00
```

PROGRAM 10

Date: 24-05-2024

Build k-Means algorithm to cluster a set of data stored in a .CSV file.

Algorithm

31/5/24

Program-10

K Means Clustering Algorithm

Algorithm:

1. Select the number K decide the number of cluster
2. Select random k points of centroids
3. Assign each point to the nearest centroid which will form the predefined k clusters
4. Calculate the variance and place a new centroid of each cluster.
5. Repeat 3 step, reassign the centroid.
6. If any reassignment occurs go to step 4 else go to finish.
7. The mode is ready

Code

Importing and initializing the data points

In [5]:
```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.cluster import KMeans
```

In [6]:
```
from sklearn.datasets import make_blobs
X, y_true = make_blobs(n_samples=550, centers=4, cluster_std=0.60, random_state=0)
```

In [7]:
```
import plotly.express as px
fig = px.scatter(x =X[:, 0], y =X[:, 1],width=800,height=500)
fig.show()
```

Elbow Method to find optimal K

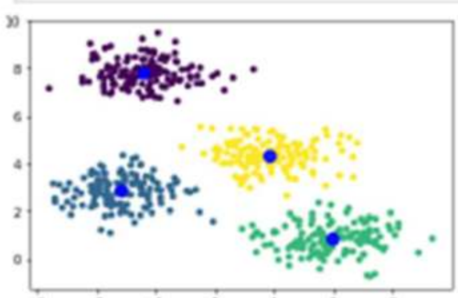
In [8]:
```
cost =[]
for i in range(1, 11):
        KM = KMeans(n_clusters = i, max_iter = 500)
        KM.fit(X)

        cost.append(KM.inertia_)

# plot the cost against K values
fig = px.line(x=range(1, 11), y=cost, width=600, height=400)
fig.show()
# the point of the elbow is the
# most optimal value for choosing k
```

Defining Model and fitting the same

In [9]:
```
kmeans = KMeans(n_clusters=4)
kmeans.fit(X)
y_kmeans = kmeans.predict(X)
```

In [10]:
```
fig = px.scatter(x =X[:, 0], y = X[:, 1], color=y_kmeans, width=700,height=400)
trace = px.scatter(x =X[:, 0], y = X[:, 1],  width=700,height=400)
fig.show()
```

In [11]:
```
plt.scatter(X[:, 0], X[:, 1], c=y_kmeans, s=20)
centers = kmeans.cluster_centers_
plt.scatter(centers[:, 0], centers[:, 1], c='blue', s=100, alpha=0.9);
plt.show()
```



Iris Dataset

In [12]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import datasets
```

In [24]:

```
iris = datasets.load_iris()
df = pd.DataFrame(iris.data)
df['class']=iris.target
df.columns=['sepal_len', 'sepal_wid', 'petal_len', 'petal_wid', 'class']
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   sepal_len  150 non-null    float64
 1   sepal_wid  150 non-null    float64
 2   petal_len  150 non-null    float64
 3   petal_wid  150 non-null    float64
 4   class      150 non-null    int64
dtypes: float64(4), int64(1)
memory usage: 6.0 KB
```

In [52]:

```
px.histogram(df, x ='class', color='class')
```

In [56]:

```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X = df.iloc[:,0:4].values
```

In [63]:

```
scaled_x = scaler.fit_transform(X)
```

In [74]:

```
model = KMeans(n_clusters=3,init='k-means++',random_state=0)
labels = model.fit_predict(scaled_x)
```

In [81]:

```
import plotly.graph_objects as go
fig = go.Figure()

 # Add trace
fig.add_trace(go.Histogram(x=labels,name="Predicted Labels"))
fig.add_trace(go.Histogram(x=df['class'],name="True Labels"))

# Overlay both histograms
fig.update_layout(barmode='overlay')
# Reduce opacity to see both histograms
fig.update_traces(opacity=0.75)
fig.show()
```

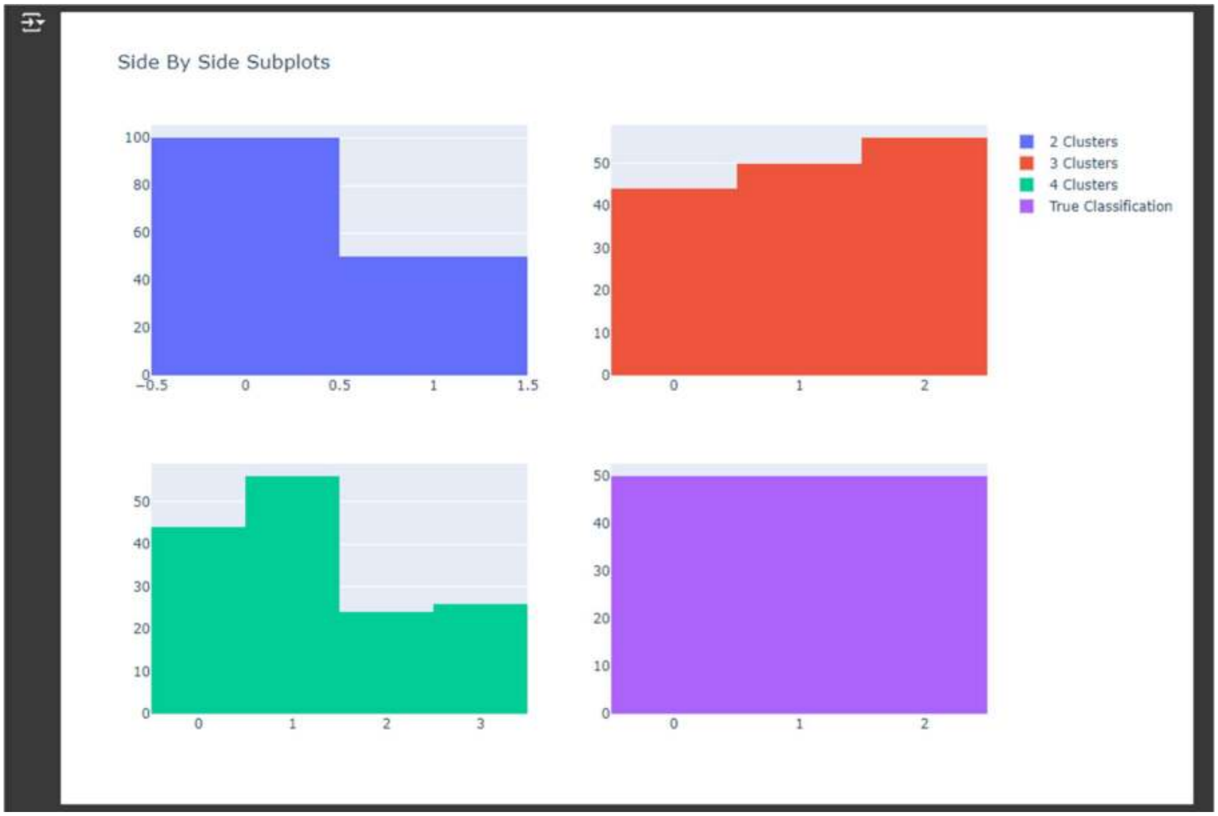
In [89]:

```
labels =[]
for i in range(2, 5):
        model = KMeans(n_clusters = i, max_iter = 500)
        model.fit(scaled_x)
        labels.append(model.fit_predict(scaled_x))
```

In [97]:

```
from plotly.subplots import make_subplots
import plotly.graph_objects as go
fig = make_subplots(rows=2, cols=2)
for i in range(0, 3):
    fig.add_trace(go.Histogram(x=labels[i],name="{} Clusters".format(i+2)),
              row=(i//2 + 1), col=(i%2 + 1))
fig.add_trace(go.Histogram(x=df['class'],name="True Classification"),
              row=(2), col=(2))
fig.update_layout(height=700, width=1000, title_text="Side By Side Subplots")

fig.show()
```

Output



Side By Side Subplots
2 Clusters
3 Clusters
4 Clusters
True Classification

PROGRAM 11

Date: 24-05-2024

Implement Dimensionality reduction using Principle Component Analysis (PCA) method.

31/5/24

Program 11

Principal Component Analysis

Algorithm:

1. Calculate Mean.
2. Calculations of Covariance Matrix
3. Calculate Eigen values of the covariance matrix.
4. Computation of the Eigen vector.
5. Calculation of first principle component
6. Geometric meaning of first principle component

Output:

pca.explained_variance ratio

array([0.9837746, 0.01620498])

Code

Open in Colab

```
In [ ]: from google.colab import drive
        drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
In [ ]: import seaborn as sns
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import plotly.express as px
        import plotly.graph_objects as go
        from plotly.subplots import make_subplots
```

```
In [ ]: df = pd.read_csv('/content/drive/MyDrive/breast-cancer.csv')
        df.head()
```

Out[ ]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mear
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.198C

5 rows × 32 columns

```
In [ ]: df.drop('id', axis=1, inplace=True) #drop redundant columns
```

```
In [ ]: df['diagnosis'] = (df['diagnosis'] == 'M').astype(int) #encode the label into 1/0
```

```
In [ ]: corr = df.corr()
```

```
In [ ]: # Get the absolute value of the correlation
        cor_target = abs(corr["diagnosis"])

        # Select highly correlated features (thresold = 0.2)
        relevant_features = cor_target[cor_target>0.2]

        # Collect the names of the features
        names = [index for index, value in relevant_features.items()]

        # Drop the target variable from the results
        names.remove('diagnosis')

        # Display the results
        print(names)
```

```
['radius_mean', 'texture_mean', 'perimeter_mean', 'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_mean', 'conc
ave points_mean', 'symmetry_mean', 'radius_se', 'perimeter_se', 'area_se', 'compactness_se', 'concavity_se', 'concave points_
se', 'radius_worst', 'texture_worst', 'perimeter_worst', 'area_worst', 'smoothness_worst', 'compactness_worst', 'concavity_wo
rst', 'concave points_worst', 'symmetry_worst', 'fractal_dimension_worst']
```

```
In [ ]: X = df[names].values
```

```python
In [ ]: class PCA:
    """
    Principal Component Analysis (PCA) class for dimensionality reduction.
    """

    def __init__(self, n_components):
        """
        Constructor method that initializes the PCA object with the number of components to retain.

        Args:
        - n_components (int): Number of principal components to retain.
        """
        self.n_components = n_components
    def fit(self, X):
        """
        Fits the PCA model to the input data and computes the principal components.

        Args:
        - X (numpy.ndarray): Input data matrix with shape (n_samples, n_features).
        """
        # Compute the mean of the input data along each feature dimension.
        mean = np.mean(X, axis=0)

        # Subtract the mean from the input data to center it around zero.
        X = X - mean

        # Compute the covariance matrix of the centered input data.
        cov = np.cov(X.T)

        # Compute the eigenvectors and eigenvalues of the covariance matrix.
        eigenvalues, eigenvectors = np.linalg.eigh(cov)
        # Reverse the order of the eigenvalues and eigenvectors.
        eigenvalues = eigenvalues[::-1]
        eigenvectors = eigenvectors[:,::-1]

        # Keep only the first n_components eigenvectors as the principal components.
        self.components = eigenvectors[:,:self.n_components]

        # Compute the explained variance ratio for each principal component.
        # Compute the total variance of the input data
        total_variance = np.sum(np.var(X, axis=0))

        # Compute the variance explained by each principal component
        self.explained_variances = eigenvalues[:self.n_components]

        # Compute the explained variance ratio for each principal component
        self.explained_variance_ratio_ = self.explained_variances / total_variance
    def transform(self, X):
        """
        Transforms the input data by projecting it onto the principal components.

        Args:
        - X (numpy.ndarray): Input data matrix with shape (n_samples, n_features).

        Returns:
        - transformed_data (numpy.ndarray): Transformed data matrix with shape (n_samples, n_components).
        """
        # Center the input data around zero using the mean computed during the fit step.
        X = X - np.mean(X, axis=0)

        # Project the centered input data onto the principal components.
        transformed_data = np.dot(X, self.components)

        return transformed_data

    def fit_transform(self, X):
        """
        Fits the PCA model to the input data and computes the principal components then
        transforms the input data by projecting it onto the principal components.

        Args:
        - X (numpy.ndarray): Input data matrix with shape (n_samples, n_features).
        """
        self.fit(X)
        transformed_data = self.transform(X)
        return transformed_data
```

```
In [ ]: pca = PCA(2)

In [ ]: pca.fit(X)

In [ ]: pca.explained_variance_ratio_

Out[ ]: array([0.98377428, 0.01620498])

In [ ]: X_transformed = pca.transform(X)

In [ ]: X_transformed[:,1].shape

Out[ ]: (569,)

In [ ]: fig = px.scatter(x=X_transformed[:,0], y=X_transformed[:,1])
        fig.update_layout(
            title="PCA transformed data for breast cancer dataset",
            xaxis_title="PC1",
            yaxis_title="PC2"
        )
        fig.show()
```

Output