VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
On

MACHINE LEARNING

Submitted by

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in partial fulfillment for the award of the degree of
BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
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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 **JYOTHIKA C N(1BM21CS083)**, 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 - **(22CS6PCMAL)**work prescribed for the said degree.

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Course outcomes:

CO1	Apply machine learning techniques in computing systems
CO2	Evaluate the model using metrics
CO3	Design a model using machine learning to solve a problem
CO4	Conduct experiments to solve real-world problems using appropriate machine learning techniques

5.04.2024 1BM21CS083

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

05/04/2024

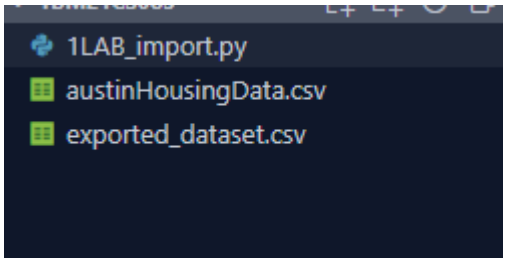
1) Write a python program to import and export data using pandas library function.

→ import pandas as pd
df= pd.read_csv ("austinHousingData.csv")
print (df.head())
df.to_csv ("exported_dataset.csv")

```
# -*- coding: utf-8 -*-
#JYOTHIKA C N
#1BM21CS083
import pandas as pd
df=pd.read_csv("austinHousingData.csv")
print(df.head())
df.to_csv("exported_dataset.csv")
```

Output:

```
PS C:\Users\student\Documents\1BM21CS083> python -u "c:\Users\student\Documents\1BM21CS083\1LAB_import.py"
         zpid          city          streetAddress  zipcode  ... numOfBathrooms  numOfBedrooms  numOfStories                                                homeImage
0   111373431  pflugerville   14424 Lake Victor Dr    78660  ...            3.0              4             2  111373431_ffce26843283d3365c11d81b8e6bdc6f-p_f...
1   120900430  pflugerville      1104 Strickling Dr   78660  ...            2.0              4             1  120900430_8255c127be8dcf0a1a18b7563d987088-p_f...
2  2084491383  pflugerville    1408 Fort Dessau Rd    78660  ...            2.0              3             1  2084491383_a2ad649e1a7a098111dcea084a11c855-p_...
3   120901374  pflugerville      1025 Strickling Dr   78660  ...            2.0              3             1  120901374_b469367a619da85b1f5ceb69b675d88e-p_f...
4    60134862  pflugerville  15005 Donna Jane Loop    78660  ...            3.0              3             2  60134862_b1a48a3df3f111e005bb913873e98ce2-p_f.jpg

[5 rows x 47 columns]
PS C:\Users\student\Documents\1BM21CS083>
```

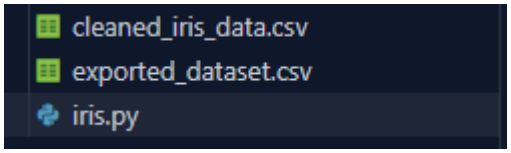


```
→ import pandas as pd
  url = "https://archive.ics.uci.edu/ml/machine-learning-
    databases/iris/iris.data"

  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)
  print(iris_data.head())
  iris_data.to_csv("cleaned_iris_data.csv")
```

```
import pandas as pd
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)

print(iris_data.head())

iris_data.to_csv("cleaned_iris_data.csv")
```

Output:

```
PS C:\Users\student\Documents\1BM21CS083> python -u "c:\Users\student\Documents\1BM21CS083\1lab\iris.py"
   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
PS C:\Users\student\Documents\1BM21CS083>
```


cleaned_iris_data.csv
exported_dataset.csv
iris.py

2. Demonstrate various data pre-processing techniques for a given dataset

05/04/2024

2. Data preprocessing

1) Import dataset using pandas
2) Perform dataset.shape() to analyse shape of dataset
3) Use is.null() function from pandas to analyse missing values.
4) Drop or fill missing values according to your use case. Example dropna() and fill().
5) We can generate dummy variables (is a binary variable that indicates whether a seperate categorical variable takes on a specific value).

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

```
dataset = pd.read_csv("Data.csv")
df = pd.DataFrame(dataset)
print(df.head())
```

```
   Country   Age   Salary Purchased
0   France  44.0  72000.0        No
1    Spain  27.0  48000.0       Yes
2  Germany  30.0  54000.0        No
3    Spain  38.0  61000.0        No
4  Germany  40.0      NaN       Yes
```

```
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values
```

```
print(X)
```

```
[['France' 44.0 72000.0]
 ['Spain' 27.0 48000.0]
 ['Germany' 30.0 54000.0]
 ['Spain' 38.0 61000.0]
 ['Germany' 40.0 nan]
 ['France' 35.0 58000.0]
 ['Spain' nan 52000.0]
 ['France' 48.0 79000.0]
 ['Germany' 50.0 83000.0]
 ['France' 37.0 67000.0]]
```

```
print(y)
```

```
['No' 'Yes' 'No' 'No' 'Yes' 'Yes' 'No' 'Yes' 'No' 'Yes']
```

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

```
Country      0
Age          1
Salary       1
Purchased    0
dtype: int64
```

```python
df1 = df.copy()
```

```python
# summarize the shape of the raw data
print("Before:",df1.shape)

# drop rows with missing values
df1.dropna(inplace=True)

# summarize the shape of the data with missing rows removed
print("After:",df1.shape)
```

```
Before: (10, 4)
After: (8, 4)
```

```python
df2
```

	Country	Age	Salary	Purchased
0	France	44.0	72000.0	No
1	Spain	27.0	48000.0	Yes
2	Germany	30.0	54000.0	No
3	Spain	38.0	61000.0	No
4	Germany	40.0	NaN	Yes
5	France	35.0	58000.0	Yes
6	Spain	NaN	52000.0	No
7	France	48.0	79000.0	Yes
8	Germany	50.0	83000.0	No
9	France	37.0	67000.0	Yes

```python
pd.get_dummies(df2)
```

	Age	Salary	Country_France	Country_Germany	Country_Spain	Purchased_No	Purchased_Yes
0	44.0	72000.0	True	False	False	True	False
1	27.0	48000.0	False	False	True	False	True
2	30.0	54000.0	False	True	False	True	False
3	38.0	61000.0	False	False	True	True	False
4	40.0	NaN	False	True	False	False	True
5	35.0	58000.0	True	False	False	False	True
6	NaN	52000.0	False	False	True	True	False
7	48.0	79000.0	True	False	False	False	True
8	50.0	83000.0	False	True	False	True	False
9	37.0	67000.0	True	False	False	False	True

3.Decision Tree Algorithm

12/4/2024

Decision Tree Algorithm

- Create a Root node for the tree
- 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 branch below Root, corresponding to the test $A = v_i$
    - Let $Examples_{v_i}$, be the subset of Examples that have value 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 in Examples.
      - Else below this new branch add the subtree ID3 ($Examples_{v_i}$, Target_attribute, Attributes − {A})
  - End
  - Return Root

★ The best attribute is the one with highest information gain

Output:

Entropy of the entire dataset : 0.94

① Highest information gain = Outlook = 0.246

② Highest information gain = ~~rainy~~ ~~humidity~~ rainy = 0.971

③ Best attribute is windy.

12/4/2024

Code and output:

```
[6] import pandas as pd
    import numpy as np
    import math
    # Reading the dataset (Tennis-dataset)
    data = pd.read_csv('PlayTennis.csv')
```

```
[2] data.head()
```

	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

Next steps: View recommended plots

```
[8] 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')]}])
```

[8]

	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

```
[3]
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])}')
```

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

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

```
entropy_and_infogain(data, 'outlook')
```

	outlook	play
0	sunny	no
1	sunny	no
7	sunny	no
8	sunny	yes
10	sunny	yes

```
Entropy of outlook - sunny = 0.971
```

	outlook	play
2	overcast	yes
6	overcast	yes
11	overcast	yes
12	overcast	yes

```
Entropy of outlook - overcast = 0.0
```

	outlook	play
3	rainy	yes
4	rainy	yes
5	rainy	no
9	rainy	yes
13	rainy	no

```
Entropy of outlook - rainy = 0.971
Information Gain for outlook = 0.246
```

```
[10] 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_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
```

```
[12] 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
```

```
sunny = data[data['outlook'] == 'sunny']
sunny.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')]}])
```

	outlook	temp	humidity	windy	play
0	sunny	hot	high	False	no
1	sunny	hot	high	True	no
7	sunny	mild	high	False	no
8	sunny	cool	normal	False	yes
10	sunny	mild	normal	True	yes

```
[14] print(f'Entropy of the Sunny dataset: {find_entropy(sunny.play)}')
```

```
Entropy of the Sunny dataset: 0.971
```

```
[15] entropy_and_infogain(sunny, 'temp')
```

	temp	play
0	hot	no
1	hot	no

```
Entropy of temp - hot = 0.0
```

	temp	play
7	mild	no
10	mild	yes

```
Entropy of temp - mild = 1.0
```

	temp	play
8	cool	yes

```
Entropy of temp - cool = 0.0
Information Gain for temp = 0.571
```

```
[16] entropy_and_infogain(sunny, 'humidity')
```

	humidity	play
0	high	no
1	high	no
7	high	no

```
Entropy of humidity - high = 0.0
```

	humidity	play
8	normal	yes
10	normal	yes

```
Entropy of humidity - normal = 0.0
Information Gain for humidity = 0.971
```

```
[17] entropy_and_infogain(sunny, 'windy')
```

	windy	play
0	False	no
7	False	no
8	False	yes

```
Entropy of windy - False = 0.918
```

	windy	play
1	True	no
10	True	yes

```
Entropy of windy - True = 1.0
Information Gain for windy = 0.02
```

```
[13] 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')]}])
```

	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

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

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

```
[20] 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
```

```
[21] 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
```

```
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
```

4.Build KNN Classification model for a given dataset.:

3/5/2024

→ KNN

1) Input : unlabeled instance x_{test} for which the class label needs to be predicted

2) Calculate Euclidean distances

3) Find nearest Neighbours : select k instances with the smallest distance to x_{test}

4) For classification :

- Majority vote : If it's classification task, count the occurrences of each class label among the k nearest neighbours.
- Assign label : Assign the class label with the highest count as the predicted label for x_{test}

Output :

- model.predict([[7.7, 2.6, 6.9, 2.3]])

→ array(['Iris-virginica'], dtype='<U14')

Code and output:

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

```
[3] iris = pd.read_csv("Iris.csv") #Load Data
    iris.drop('Id',inplace=True,axis=1) #Drop Id column
```

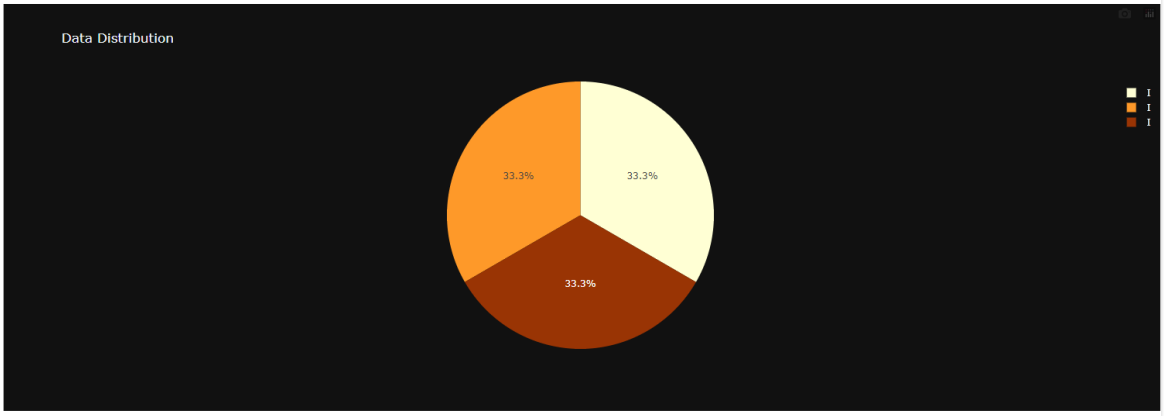
```
[4] iris.head()
```

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
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

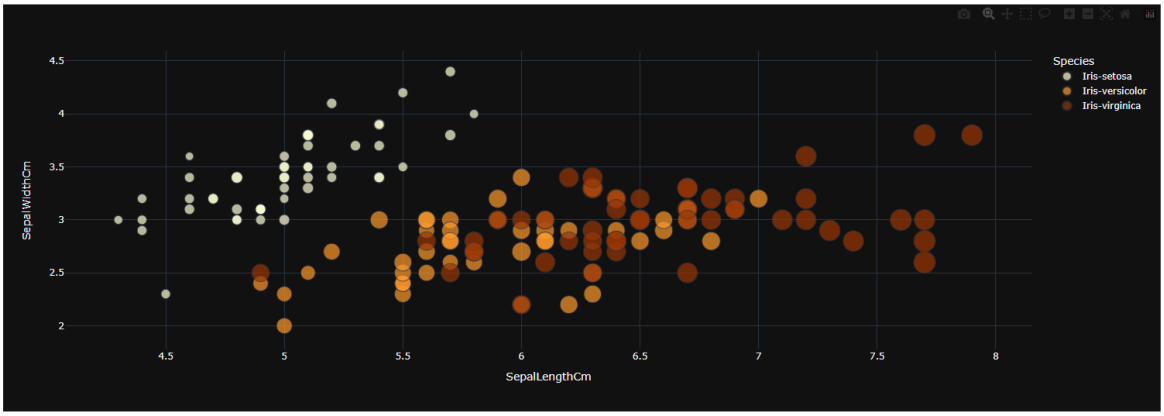
Next steps: View recommended plots

```
[5] X = iris.iloc[:,:-1] #Set our training data

    y = iris.iloc[:,-1] #Set training labels
```

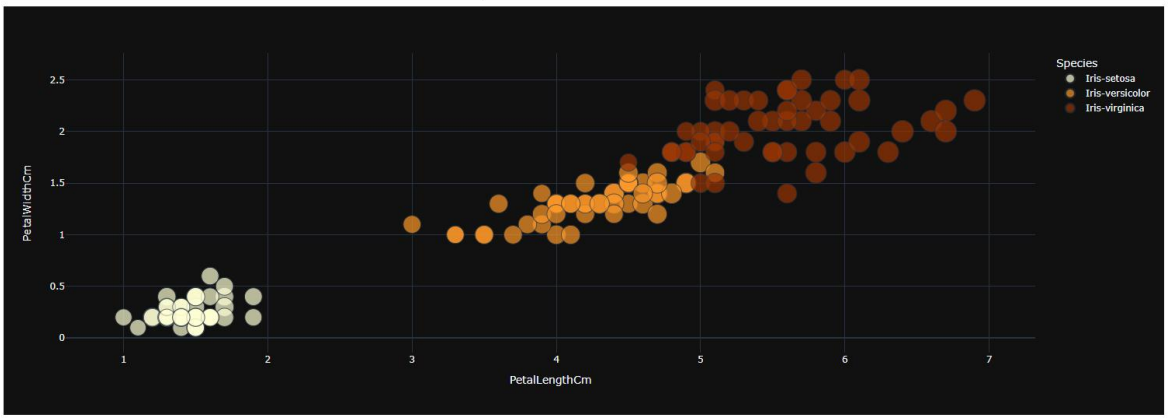
```
fig = px.pie(iris, 'Species',color_discrete_sequence=['#ffffd4 ','#fe9929 ','#993404 '],title='Data Distribution',template='plotly_dark')
fig.show()
```



```
fig = px.scatter(data_frame=iris, x='SepalLengthCm',y='SepalWidthCm'
            ,color='Species',size='PetalLengthCm', color_discrete_sequence=['#ffffd4 ','#fe9929 ','#993404 '], template='plotly_dark',)

fig.show()
```




```
fig = px.scatter(data_frame=iris, x='PetalLengthCm',y='PetalWidthCm'
            ,color='Species',size='SepalLengthCm', color_discrete_sequence=['#ffffd4 ','#fe9929 ','#993404 '], template='plotly_dark',)

fig.show()
```



```python
class KNN:
    """
    K-Nearest Neighbors (KNN) classification algorithm

    Parameters:
    -----------
    n_neighbors : int, optional (default=5)
        Number of neighbors to use in the majority vote.

    Methods:
    --------
    fit(X_train, y_train):
        Stores the values of X_train and y_train.

    predict(X):
        Predicts the class labels for each example in X.

    """
    def __init__(self, n_neighbors=5):
        self.n_neighbors = n_neighbors

    def euclidean_distance(self, x1, x2):
        """
        Calculate the Euclidean distance between two data points.

        Parameters:
        -----------
        x1 : numpy.ndarray, shape (n_features,)
            A data point in the dataset.

        x2 : numpy.ndarray, shape (n_features,)
            A data point in the dataset.

        Returns:
        --------
        distance : float
            The Euclidean distance between x1 and x2.
        """
        return np.linalg.norm(x1 - x2)
```

```python
    def fit(self, X_train, y_train):
        """
        Stores the values of X_train and y_train.

        Parameters:
        -----------
        X_train : numpy.ndarray, shape (n_samples, n_features)
            The training dataset.

        y_train : numpy.ndarray, shape (n_samples,)
            The target labels.
        """
        self.X_train = X_train
        self.y_train = y_train

    def predict(self, X):
        """
        Predicts the class labels for each example in X.

        Parameters:
        -----------
        X : numpy.ndarray, shape (n_samples, n_features)
            The test dataset.

        Returns:
        --------
        predictions : numpy.ndarray, shape (n_samples,)
            The predicted class labels for each example in X.
        """
        # Create empty array to store the predictions
        predictions = []
        # Loop over X examples
        for x in X:
            # Get prediction using the prediction helper function
            prediction = self._predict(x)
            # Append the prediction to the predictions list
            predictions.append(prediction)
        return np.array(predictions)
```

```python
def _predict(self, x):
    """
    Predicts the class label for a single example.

    Parameters:
    -----------
    x : numpy.ndarray, shape (n_features,)
        A data point in the test dataset.

    Returns:
    --------
    most_occuring_value : int
        The predicted class label for x.
    """
    # Create empty array to store distances
    distances = []
    # Loop over all training examples and compute the distance between x and all the training examples
    for x_train in self.X_train:
        distance = self.euclidean_distance(x, x_train)
        distances.append(distance)
    distances = np.array(distances)

    # Sort by ascendingly distance and return indices of the given n neighbours
    n_neighbors_idxs = np.argsort(distances)[: self.n_neighbors]

    # Get labels of n-neighbour indexes
    labels = self.y_train[n_neighbors_idxs]
    labels = list(labels)
    # Get the most frequent class in the array
    most_occuring_value = max(labels, key=labels.count)
    return most_occuring_value
```

```python
[] def train_test_split(X, y, random_state=42, 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
```

```python
[12] X_train, X_test, y_train, y_test = train_test_split(X.values, y.values, test_size = 0.2, random_state=42) #
```

```
[13] model = KNN(7)
     model.fit(X_train, y_train)
```

```
[14] def compute_accuracy(y_true, y_pred):
         """
         Computes the accuracy of a classification model.

         Parameters:
         y_true (numpy array): A numpy array of true labels for each data point.
         y_pred (numpy array): A numpy array of predicted labels for each data point.

         Returns:
         float: The accuracy of the model, expressed as a percentage.
         """
         y_true = y_true.flatten()
         total_samples = len(y_true)
         correct_predictions = np.sum(y_true == y_pred)
         return (correct_predictions / total_samples)
```

```
[15] predictions = model.predict(X_test)
     accuracy = compute_accuracy(y_test, predictions)
     print(f" our model got accuracy score of : {accuracy}")
```

```
 our model got accuracy score of : 0.9666666666666667
```

```
[16] from sklearn.neighbors import KNeighborsClassifier
     skmodel = KNeighborsClassifier(n_neighbors=7)
     skmodel.fit(X_train, y_train)
```

```
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=7)
```

```
[17] sk_predictions = skmodel.predict(X_test)
     sk_accuracy = compute_accuracy(y_test, sk_predictions)
     print(f" sklearn-model got accuracy score of : {sk_accuracy}")
```

```
 sklearn-model got accuracy score of : 0.9666666666666667
```

5.Linear Regression

→ Linear Regression

Training phase:

1. Input: Training data with one predictor (x) and one target variable (y)

2. Compute means:

3. estimate coefficients

$$\beta_1 = \frac{cov(x,y)}{var(x)}$$

$$\beta_0 = \bar{y} - \beta_1 \bar{x}$$

Prediction phase:

1. Input: New x_{test}

2. Compute prediction: use $y_{pred} = \beta_0 + \beta_1 x_{test}$ to predict y_{pred}

Output:

model.predict([[237]])

→ array([107.82727115])

Code and output:

```python
import math
import numpy as np
import pandas as pd
import plotly.express as px
import pickle
```

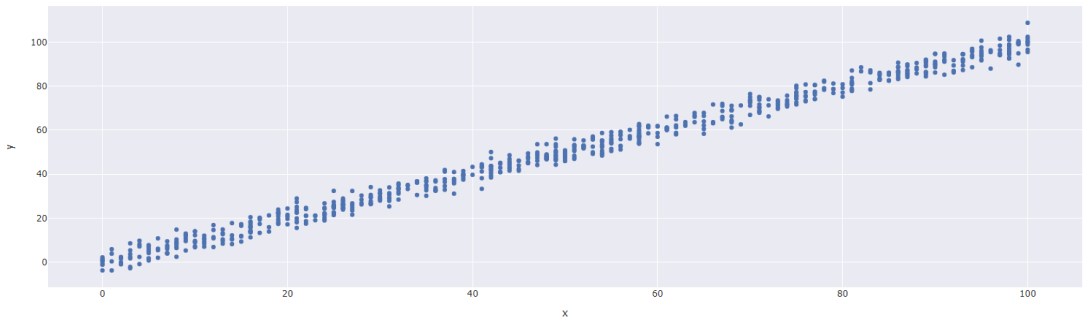
```python
[2] # Load the training and test datasets
train_data = pd.read_csv('train.csv')
test_data = pd.read_csv('test.csv')

# Remove rows with missing values
train_data = train_data.dropna()
test_data = test_data.dropna()
```

```python
[3] train_data.head()
```

	x	y
0	24.0	21.549452
1	50.0	47.464463
2	15.0	17.218656
3	38.0	36.586398
4	87.0	87.288984

Next steps: View recommended plots

```python
[4] px.scatter(x=train_data['x'], y=train_data['y'],template='seaborn')
```




```python
[5] # Set training data and target
X_train = train_data['x'].values
y_train = train_data['y'].values

# Set testing data and target
X_test = test_data['x'].values
y_test = test_data['y'].values
```

```
[6]     """
        Standardizes the input data using mean and standard deviation.

        Parameters:
            X_train (numpy.ndarray): Training data.
            X_test (numpy.ndarray): Testing data.

        Returns:
            Tuple of standardized training and testing data.
        """
        # Calculate the mean and standard deviation using the training data
        mean = np.mean(X_train, axis=0)
        std = np.std(X_train, axis=0)

        # Standardize the data
        X_train = (X_train - mean) / std
        X_test = (X_test - mean) / std

        return X_train, X_test

    X_train, X_test = standardize_data(X_train, X_test)
```

```
[7] X_train = np.expand_dims(X_train, axis=-1)
    X_test = np.expand_dims(X_test, axis=-1)
```

```
[8] class LinearRegression:
        """
        Linear Regression Model with Gradient Descent

        Linear regression is a supervised machine learning algorithm used for modeling the relationship
        between a dependent variable (target) and one or more independent variables (features) by fitting
        a linear equation to the observed data.

        This class implements a linear regression model using gradient descent optimization for training.
        It provides methods for model initialization, training, prediction, and model persistence.

        Parameters:
            learning_rate (float): The learning rate used in gradient descent.
            convergence_tol (float, optional): The tolerance for convergence (stopping criterion). Defaults to 1e-6.

        Attributes:
```

```
[8]     Attributes:
            W (numpy.ndarray): Coefficients (weights) for the linear regression model.
            b (float): Intercept (bias) for the linear regression model.

        Methods:
            initialize_parameters(n_features): Initialize model parameters.
            forward(X): Compute the forward pass of the linear regression model.
            compute_cost(predictions): Compute the mean squared error cost.
            backward(predictions): Compute gradients for model parameters.
            fit(X, y, iterations, plot_cost=True): Fit the linear regression model to training data.
            predict(X): Predict target values for new input data.
            save_model(filename=None): Save the trained model to a file using pickle.
            load_model(filename): Load a trained model from a file using pickle.

        Examples:
            >>> from linear_regression import LinearRegression
            >>> model = LinearRegression(learning_rate=0.01)
            >>> model.fit(X_train, y_train, iterations=1000)
            >>> predictions = model.predict(X_test)
        """

        def __init__(self, learning_rate, convergence_tol=1e-6):
            self.learning_rate = learning_rate
            self.convergence_tol = convergence_tol
            self.W = None
            self.b = None

        def initialize_parameters(self, n_features):
            """
            Initialize model parameters.

            Parameters:
                n_features (int): The number of features in the input data.
            """
            self.W = np.random.randn(n_features) * 0.01
            self.b = 0
        def forward(self, X):
            """
            Compute the forward pass of the linear regression model.

            Parameters:
                X (numpy.ndarray): Input data of shape (m, n_features).
```

[8]

```python
        Returns:
            numpy.ndarray: Predictions of shape (m,).
        """
        return np.dot(X, self.W) + self.b

    def compute_cost(self, predictions):
        """
        Compute the mean squared error cost.

        Parameters:
            predictions (numpy.ndarray): Predictions of shape (m,).

        Returns:
            float: Mean squared error cost.
        """
        m = len(predictions)
        cost = np.sum(np.square(predictions - self.y)) / (2 * m)
        return cost

    def backward(self, predictions):
        """
        Compute gradients for model parameters.

        Parameters:
            predictions (numpy.ndarray): Predictions of shape (m,).

        Updates:
            numpy.ndarray: Gradient of W.
            float: Gradient of b.
        """
        m = len(predictions)
        self.dW = np.dot(predictions - self.y, self.X) / m
        self.db = np.sum(predictions - self.y) / m
    def fit(self, X, y, iterations, plot_cost=True):
        """
        Fit the linear regression model to the training data.

        Parameters:
            X (numpy.ndarray): Training input data of shape (m, n_features).
            y (numpy.ndarray): Training labels of shape (m,).
            iterations (int): The number of iterations for gradient descent.
            plot_cost (bool, optional): Whether to plot the cost during training. Defaults to True.
```

[8]

```python
        Raises:
            AssertionError: If input data and labels are not NumPy arrays or have mismatched shapes.

        Plots:
            Plotly line chart showing cost vs. iteration (if plot_cost is True).
        """
        assert isinstance(X, np.ndarray), "X must be a NumPy array"
        assert isinstance(y, np.ndarray), "y must be a NumPy array"
        assert X.shape[0] == y.shape[0], "X and y must have the same number of samples"
        assert iterations > 0, "Iterations must be greater than 0"

        self.X = X
        self.y = y
        self.initialize_parameters(X.shape[1])
        costs = []

        for i in range(iterations):
            predictions = self.forward(X)
            cost = self.compute_cost(predictions)
            self.backward(predictions)
            self.W -= self.learning_rate * self.dW
            self.b -= self.learning_rate * self.db
            costs.append(cost)

            if i % 100 == 0:
                print(f'Iteration: {i}, Cost: {cost}')

            if i > 0 and abs(costs[-1] - costs[-2]) < self.convergence_tol:
                print(f'Converged after {i} iterations.')
                break

        if plot_cost:
            fig = px.line(y=costs, title="Cost vs Iteration", template="plotly_dark")
            fig.update_layout(
                title_font_color="#41BEE9",
                xaxis=dict(color="#41BEE9", title="Iterations"),
                yaxis=dict(color="#41BEE9", title="Cost")
            )

            fig.show()
```

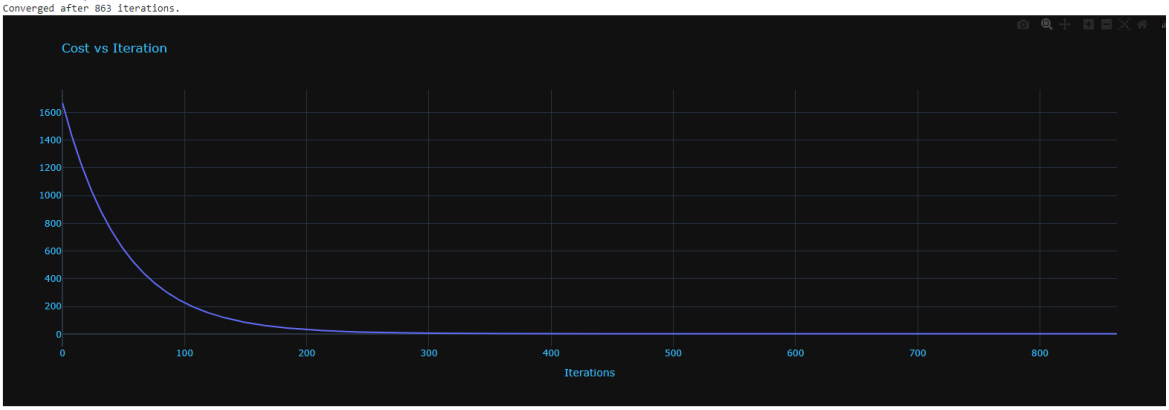
```python
            fig.show()
    def predict(self, X):
        """
        Predict target values for new input data.

        Parameters:
            X (numpy.ndarray): Input data of shape (m, n_features).

        Returns:
            numpy.ndarray: Predicted target values of shape (m,).
        """
        return self.forward(X)


    def save_model(self, filename=None):
        """
        Save the trained model to a file using pickle.

        Parameters:
            filename (str): The name of the file to save the model to.
        """
        model_data = {
            'learning_rate': self.learning_rate,
            'convergence_tol': self.convergence_tol,
            'W': self.W,
            'b': self.b
        }

        with open(filename, 'wb') as file:
            pickle.dump(model_data, file)

    @classmethod
    def load_model(cls, filename):
        """
        Load a trained model from a file using pickle.

        Parameters:
            filename (str): The name of the file to load the model from.
```

```python
8]  with open(filename, 'wb') as file:
            pickle.dump(model_data, file)

    @classmethod
    def load_model(cls, filename):
        """
        Load a trained model from a file using pickle.

        Parameters:
            filename (str): The name of the file to load the model from.

        Returns:
            LinearRegression: An instance of the LinearRegression class with loaded parameters.
        """
        with open(filename, 'rb') as file:
            model_data = pickle.load(file)

        # Create a new instance of the class and initialize it with the loaded parameters
        loaded_model = cls(model_data['learning_rate'], model_data['convergence_tol'])
        loaded_model.W = model_data['W']
        loaded_model.b = model_data['b']

        return loaded_model
```

```python
9]  lr = LinearRegression(0.01)
    lr.fit(X_train, y_train, 10000)
```

```
Iteration: 0, Cost: 1670.0184887161677
Iteration: 100, Cost: 227.15535101517312
Iteration: 200, Cost: 33.84101696145528
Iteration: 300, Cost: 7.9408253395546575
Iteration: 400, Cost: 4.4707260872934835
Iteration: 500, Cost: 4.005803317750673
Iteration: 600, Cost: 3.943513116253261
Iteration: 700, Cost: 3.9351674953098015
Iteration: 800, Cost: 3.9340493517293096
Converged after 863 iterations.
```

```
Iteration: 800, Cost: 3.9340493517293096
Converged after 863 iterations.
```




```
[10] lr.save_model('model.pkl')
```

```
[11] model = LinearRegression.load_model("model.pkl")
```

```
[12] class RegressionMetrics:
         @staticmethod
         def mean_squared_error(y_true, y_pred):
             """
             Calculate the Mean Squared Error (MSE).

             Args:
                 y_true (numpy.ndarray): The true target values.
                 y_pred (numpy.ndarray): The predicted target values.

             Returns:
                 float: The Mean Squared Error.
             """
             assert len(y_true) == len(y_pred), "Input arrays must have the same length."
             mse = np.mean((y_true - y_pred) ** 2)
             return mse

         @staticmethod
         def root_mean_squared_error(y_true, y_pred):
             """
             Calculate the Root Mean Squared Error (RMSE).

             Args:
                 y_true (numpy.ndarray): The true target values.
                 y_pred (numpy.ndarray): The predicted target values.

             Returns:
                 float: The Root Mean Squared Error.
             """
             assert len(y_true) == len(y_pred), "Input arrays must have the same length."
             mse = RegressionMetrics.mean_squared_error(y_true, y_pred)
             rmse = np.sqrt(mse)
             return rmse

         @staticmethod
         def r_squared(y_true, y_pred):
             """
             Calculate the R-squared (R^2) coefficient of determination.

             Args:
```

```
[12]    @staticmethod
        def r_squared(y_true, y_pred):
            """
            Calculate the R-squared (R^2) coefficient of determination.

            Args:
                y_true (numpy.ndarray): The true target values.
                y_pred (numpy.ndarray): The predicted target values.

            Returns:
                float: The R-squared (R^2) value.
            """
            assert len(y_true) == len(y_pred), "Input arrays must have the same length."
            mean_y = np.mean(y_true)
            ss_total = np.sum((y_true - mean_y) ** 2)
            ss_residual = np.sum((y_true - y_pred) ** 2)
            r2 = 1 - (ss_residual / ss_total)
            return r2
```

```
[13] y_pred = model.predict(X_test)
     mse_value = RegressionMetrics.mean_squared_error(y_test, y_pred)
     rmse_value = RegressionMetrics.root_mean_squared_error(y_test, y_pred)
     r_squared_value = RegressionMetrics.r_squared(y_test, y_pred)

     print(f"Mean Squared Error (MSE): {mse_value}")
     print(f"Root Mean Squared Error (RMSE): {rmse_value}")
     print(f"R-squared (Coefficient of Determination): {r_squared_value}")
```

```
Mean Squared Error (MSE): 9.44266965025894
Root Mean Squared Error (RMSE): 3.07289271701095
R-squared (Coefficient of Determination): 0.9887898724670081
```

```
model.predict([[2]])
```

```
array([107.82727115])
```

6.Logistic Regression

→ Logistic regression

Training phase:

1. Initialize parameters: Start with random or zero values for weights (θ) and bias (b)

2. Compute predictions: Calculate predictions using the equation $\hat{y} = \sigma(\theta^T x + b)$, where σ is the sigmoid function

3. Compute loss: measure the error between predictions and actual labels using binary cross-entropy loss.

4. update parameters: adjust weights and biases using gradient descent to minimize the loss

5. repeat: Iterate steps 2-4 until convergence or a maximum number of iterations.

Prediction phase:

1. Compute predictions: If the probability is above 0.5, classify as 1; otherwise, classify as 0

3/5/2024

```
import math
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import pprint
import pickle
```

```
df = pd.read_csv('breast-cancer.csv')
```

```
df.head()
```

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...	radius_worst	texture_worst	perimeter_worst	are
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	...	25.38	17.33	184.60	
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	...	24.99	23.41	158.80	
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	...	23.57	25.53	152.50	
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	...	14.91	26.50	98.87	
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	...	22.54	16.67	152.20	

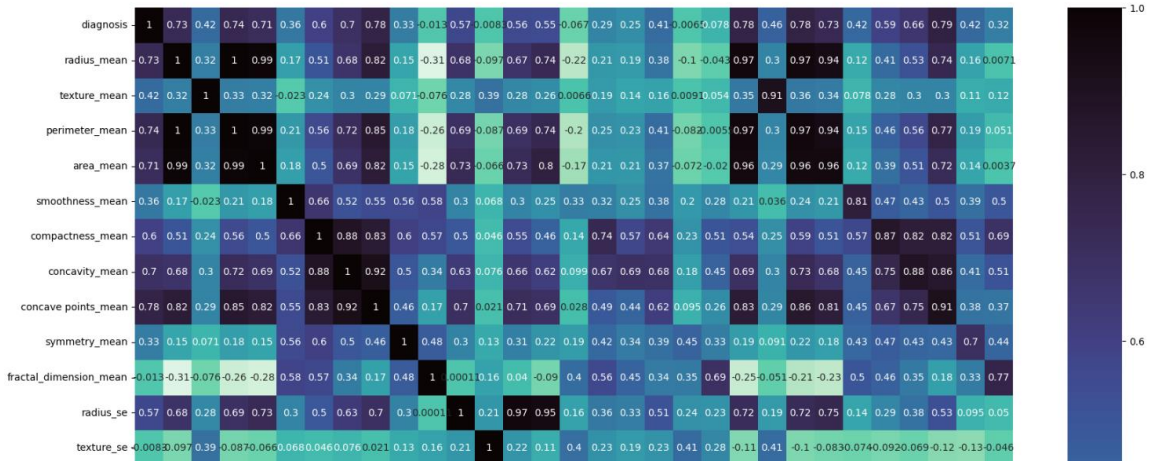
5 rows × 32 columns

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

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

```
corr = df.corr()
```

```
[9] plt.figure(figsize=(20,20))
    sns.heatmap(corr, cmap='mako_r',annot=True)
    plt.show()
```




```
[12] # 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
     pprint.pprint(names)
```

```
['radius_mean',
 'texture_mean',
 'perimeter_mean',
 'area_mean',
 'smoothness_mean',
 'compactness_mean',
 'concavity_mean',
 'concave 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_worst',
 'concave points_worst',
 'symmetry_worst',
 'fractal_dimension_worst']
```

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

```
[14] def train_test_split(X, y, random_state=42, 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
```

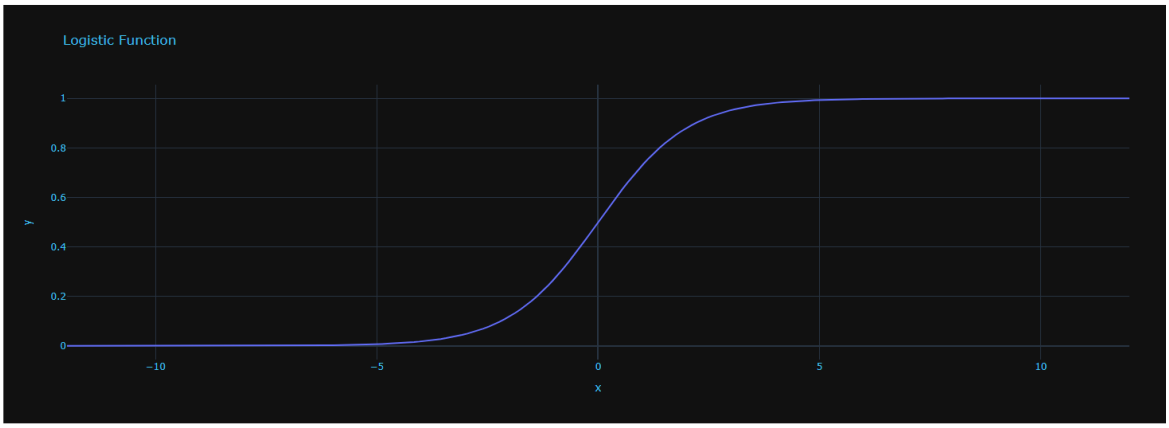
```
[15] X_train, X_test, y_train, y_test = train_test_split(X,y)
```

```
[16] def standardize_data(X_train, X_test):
         """
         Standardizes the input data using mean and standard deviation.

         Parameters:
             X_train (numpy.ndarray): Training data.
             X_test (numpy.ndarray): Testing data.

         Returns:
             Tuple of standardized training and testing data.
         """
         # Calculate the mean and standard deviation using the training data
         mean = np.mean(X_train, axis=0)
         std = np.std(X_train, axis=0)

         # Standardize the data
         X_train = (X_train - mean) / std
         X_test = (X_test - mean) / std

         return X_train, X_test

     X_train, X_test = standardize_data(X_train, X_test)
```

```
[17] def sigmoid(z):
         """
         Compute the sigmoid function for a given input.

         The sigmoid function is a mathematical function used in logistic regression and neural networks
         to map any real-valued number to a value between 0 and 1.

         Parameters:
             z (float or numpy.ndarray): The input value(s) for which to compute the sigmoid.

         Returns:
             float or numpy.ndarray: The sigmoid of the input value(s).

         Example:
             >>> sigmoid(0)
             0.5
```

```
         """
         # Compute the sigmoid function using the formula: 1 / (1 + e^(-z)).
         sigmoid_result = 1 / (1 + np.exp(-z))

         # Return the computed sigmoid value.
         return sigmoid_result
```

```
z = np.linspace(-12, 12, 200)

fig = px.line(x=z, y=sigmoid(z),title='Logistic Function',template="plotly_dark")
fig.update_layout(
    title_font_color="#41BEE9",
    xaxis=dict(color="#41BEE9"),
    yaxis=dict(color="#41BEE9")
)
fig.show()
```




```
[19] class LogisticRegression:
         """
         Logistic Regression model.

         Parameters:
             learning_rate (float): Learning rate for the model.

         Methods:
             initialize_parameter(): Initializes the parameters of the model.
             sigmoid(z): Computes the sigmoid activation function for given input z.
             forward(X): Computes forward propagation for given input X.
```

```
[19]
         def __init__(self, learning_rate=0.0001):
             np.random.seed(1)
             self.learning_rate = learning_rate

         def initialize_parameter(self):
             """
             Initializes the parameters of the model.
             """
             self.W = np.zeros(self.X.shape[1])
             self.b = 0.0


         def forward(self, X):
             """
             Computes forward propagation for given input X.

             Parameters:
                 X (numpy.ndarray): Input array.

             Returns:
                 numpy.ndarray: Output array.
             """
     #         print(X.shape, self.W.shape)
             Z = np.matmul(X, self.W) + self.b
             A = sigmoid(Z)
             return A

         def compute_cost(self, predictions):
             """
             Computes the cost function for given predictions.

             Parameters:
                 predictions (numpy.ndarray): Predictions of the model.

             Returns:
                 float: Cost of the model.
             """
             m = self.X.shape[0]  # number of training examples
             # compute the cost
             cost = np.sum((-np.log(predictions + 1e-8) * self.y) + (-np.log(1 - predictions + 1e-8)) * (
                     1 - self.y))  # we are adding small value epsilon to avoid log of 0
```

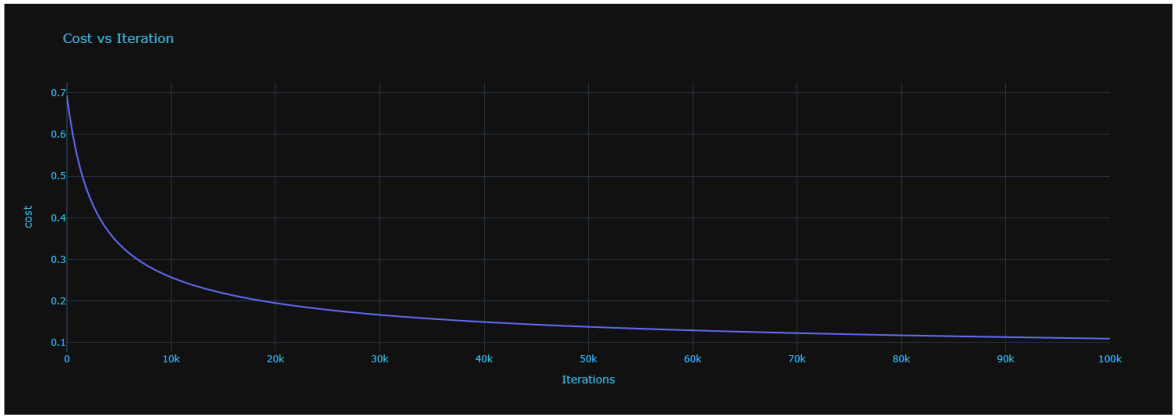
```
[19]        float: cost of the model.
            """
            m = self.X.shape[0]  # number of training examples
            # compute the cost
            cost = np.sum((-np.log(predictions + 1e-8) * self.y) + (-np.log(1 - predictions + 1e-8)) * (
                    1 - self.y))  # we are adding small value epsilon to avoid log of 0
            cost = cost / m
            return cost
        def compute_gradient(self, predictions):
            """
            Computes the gradients for the model using given predictions.

            Parameters:
                predictions (numpy.ndarray): Predictions of the model.
            """
            # get training shape
            m = self.X.shape[0]

            # compute gradients
            self.dW = np.matmul(self.X.T, (predictions - self.y))
            self.dW = np.array([np.mean(grad) for grad in self.dW])

            self.db = np.sum(np.subtract(predictions, self.y))

            # scale gradients
            self.dW = self.dW * 1 / m
            self.db = self.db * 1 / m


        def fit(self, X, y, iterations, plot_cost=True):
            """
            Trains the model on given input X and labels y for specified iterations.

            Parameters:
                X (numpy.ndarray): Input features array of shape (n_samples, n )
                y (numpy.ndarray): Labels array of shape (n_samples, 1)
                iterations (int): Number of iterations for training.
                plot_cost (bool): Whether to plot cost over iterations or not.

            Returns:
                None.
            """
            self.X = X
```

```
        self.X = X
19]     self.y = y

        self.initialize_parameter()

        costs = []
        for i in range(iterations):
            # forward propagation
            predictions = self.forward(self.X)

            # compute cost
            cost = self.compute_cost(predictions)
            costs.append(cost)

            # compute gradients
            self.compute_gradient(predictions)

            # update parameters
            self.W = self.W - self.learning_rate * self.dW
            self.b = self.b - self.learning_rate * self.db

            # print cost every 100 iterations
            if i % 10000 == 0:
                print("Cost after iteration {}: {}".format(i, cost))

        if plot_cost:
            fig = px.line(y=costs,title="Cost vs Iteration",template="plotly_dark")
            fig.update_layout(
                title_font_color="#41BEE9",
                xaxis=dict(color="#41BEE9",title="Iterations"),
                yaxis=dict(color="#41BEE9",title="cost")
            )
            fig.show()
    def predict(self, X):
        """
        Predicts the labels for given input X.

        Parameters:
            X (numpy.ndarray): Input features array.

        Returns:
            numpy.ndarray: Predicted labels.
        """
```

```
[19]        predictions = self.forward(X)
            return np.round(predictions)


        def save_model(self, filename=None):
            """
            Save the trained model to a file using pickle.

            Parameters:
                filename (str): The name of the file to save the model to.
            """
            model_data = {
                'learning_rate': self.learning_rate,
                'W': self.W,
                'b': self.b
            }

            with open(filename, 'wb') as file:
                pickle.dump(model_data, file)

        @classmethod
        def load_model(cls, filename):
            """
            Load a trained model from a file using pickle.

            Parameters:
                filename (str): The name of the file to load the model from.

            Returns:
                LogisticRegression: An instance of the LogisticRegression class with loaded parameters.
            """
            with open(filename, 'rb') as file:
                model_data = pickle.load(file)

            # Create a new instance of the class and initialize it with the loaded parameters
            loaded_model = cls(model_data['learning_rate'])
            loaded_model.W = model_data['W']
            loaded_model.b = model_data['b']

            return loaded_model
```

```
[21] lg = LogisticRegression()
     lg.fit(X_train, y_train,100000)
```

```
Cost after iteration 0: 0.6931471605599454
Cost after iteration 10000: 0.2570778370558246
Cost after iteration 20000: 0.19529178673689726
Cost after iteration 30000: 0.16685820756163852
Cost after iteration 40000: 0.14978939548676498
Cost after iteration 50000: 0.1381876134031554
Cost after iteration 60000: 0.12968141212248933
Cost after iteration 70000: 0.1231144039988139
Cost after iteration 80000: 0.11785163708790082
Cost after iteration 90000: 0.113513771386002
```



```
[22] lg.save_model("model.pkl")
```

```
[23] class ClassificationMetrics:
        @staticmethod
        def accuracy(y_true, y_pred):
            """
            Computes the accuracy of a classification model.

            Parameters:
            y_true (numpy array): A numpy array of true labels for each data point.
            y_pred (numpy array): A numpy array of predicted labels for each data point.

            Returns:
            float: The accuracy of the model, expressed as a percentage.
            """
            y_true = y_true.flatten()
            total_samples = len(y_true)
            correct_predictions = np.sum(y_true == y_pred)
            return (correct_predictions / total_samples)

        @staticmethod
        def precision(y_true, y_pred):
            """
            Computes the precision of a classification model.

            Parameters:
            y_true (numpy array): A numpy array of true labels for each data point.
            y_pred (numpy array): A numpy array of predicted labels for each data point.

            Returns:
            float: The precision of the model, which measures the proportion of true positive predictions
            out of all positive predictions made by the model.
            """
            true_positives = np.sum((y_true == 1) & (y_pred == 1))
            false_positives = np.sum((y_true == 0) & (y_pred == 1))
            return true_positives / (true_positives + false_positives)
```

```
[23]    @staticmethod
        def recall(y_true, y_pred):
            """
            Computes the recall (sensitivity) of a classification model.

            Parameters:
            y_true (numpy array): A numpy array of true labels for each data point.
            y_pred (numpy array): A numpy array of predicted labels for each data point.

            Returns:
            float: The recall of the model, which measures the proportion of true positive predictions
            out of all actual positive instances in the dataset.
            """
            true_positives = np.sum((y_true == 1) & (y_pred == 1))
            false_negatives = np.sum((y_true == 1) & (y_pred == 0))
            return true_positives / (true_positives + false_negatives)

        @staticmethod
        def f1_score(y_true, y_pred):
            """
            Computes the F1-score of a classification model.

            Parameters:
            y_true (numpy array): A numpy array of true labels for each data point.
            y_pred (numpy array): A numpy array of predicted labels for each data point.

            Returns:
            float: The F1-score of the model, which is the harmonic mean of precision and recall.
            """
            precision_value = ClassificationMetrics.precision(y_true, y_pred)
            recall_value = ClassificationMetrics.recall(y_true, y_pred)
            return 2 * (precision_value * recall_value) / (precision_value + recall_value)
```

```
[24] model = LogisticRegression.load_model("model.pkl")
```

```
[24] model = LogisticRegression.load_model("model.pkl")
```

```
[25] y_pred = model.predict(X_test)
     accuracy = ClassificationMetrics.accuracy(y_test, y_pred)
     precision = ClassificationMetrics.precision(y_test, y_pred)
     recall = ClassificationMetrics.recall(y_test, y_pred)
     f1_score = ClassificationMetrics.f1_score(y_test, y_pred)

     print(f"Accuracy: {accuracy:.2%}")
     print(f"Precision: {precision:.2%}")
     print(f"Recall: {recall:.2%}")
     print(f"F1-Score: {f1_score:.2%}")
```

```
Accuracy: 98.23%
Precision: 100.00%
Recall: 95.24%
F1-Score: 97.56%
```

7.Build Support vector machine model for a given dataset

Algorithm:

24/05/2024

→ SVM

1. Define the Kernel function
   Eg: $K(x_1, x_2) = x_1 \cdot x_2$
2. Solve the quadratic programming (QP) problem to find the α
3. Compute the weight and bias
4. Identify the support vectors
5. Make predictions

Output

```
→ model = SVM()
  model.fit(X_train, y_train)
  predictions = model.predict(X_test)
  accuracy(y_test, predictions)
```

0.98230088...

```
→ model.predict([-0.47069438, -0.16048584, -0.44810956, ...
                 ...
                 -0.02441212, -0.19956318, 0.18320441,
                 0.19695794])
```

array(0)

```
from google.colab import drive
drive.mount('/content/drive')
```

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

[2]
```
import seaborn as sns
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import plotly.express as px
```

[3]
```
df = pd.read_csv('/content/drive/MyDrive/breast-cancer.csv')
df.head()
```

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...	rad
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	...	
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	...	
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	...	
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	...	
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	...	

5 rows × 32 columns

[5]
```
df.drop('id', axis=1, inplace=True) #drop redundant columns
```

[6]
```
df.describe().T
```

	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

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

```
[8] corr = df.corr()
```

```
[10] # 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', 'concave points_mean', 'symmetry_
```

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

```
[12] 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
```

```
[13] X = scale(X)
```

```
[14] 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
```

```
[15] 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 and validatin
```

```
[18] class SVM:
         """
         A Support Vector Machine (SVM) implementation using gradient descent.

         Parameters:
         -----------
         iterations : int, default=1000
             The number of iterations for gradient descent.
         lr : float, default=0.01
             The learning rate for gradient descent.
         lambdaa : float, default=0.01
             The regularization parameter.

         Attributes:
         -----------
         lambdaa : float
             The regularization parameter.
         iterations : int
             The number of iterations for gradient descent.
         lr : float
             The learning rate for gradient descent.
         w : numpy array
             The weights.
         b : float
             The bias.

         Methods:
         --------
         initialize_parameters(X)
             Initializes the weights and bias.
         gradient_descent(X, y)
             Updates the weights and bias using gradient descent.
```

```
[18]     update_parameters(dw, db)
             Updates the weights and bias.
         fit(X, y)
             Fits the SVM to the data.
         predict(X)
             Predicts the labels for the given data.

         """

         def __init__(self, iterations=1000, lr=0.01, lambdaa=0.01):
             """
             Initializes the SVM model.

             Parameters:
             -----------
             iterations : int, default=1000
                 The number of iterations for gradient descent.
             lr : float, default=0.01
                 The learning rate for gradient descent.
             lambdaa : float, default=0.01
                 The regularization parameter.
             """
             self.lambdaa = lambdaa
             self.iterations = iterations
             self.lr = lr
             self.w = None
             self.b = None
         def initialize_parameters(self, X):
             """
             Initializes the weights and bias.

             Parameters:
             -----------
```

[18]

```
        X : numpy array
            The input data.
        """
        m, n = X.shape
        self.w = np.zeros(n)
        self.b = 0

    def gradient_descent(self, X, y):
        """
        Updates the weights and bias using gradient descent.

        Parameters:
        -----------
        X : numpy array
            The input data.
        y : numpy array
            The target values.
        """
        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):
        """
        Updates the weights and bias.

        Parameters:
```

[18]

```
            dw : numpy array
                The change in weights.
            db : float
                The change in bias.
            """
            self.w = self.w - self.lr * dw
            self.b = self.b - self.lr * db
        def fit(self, X, y):
            """
            Fits the SVM to the data.

            Parameters:
            -----------
            X : numpy array
                The input data.
            y : numpy array
                The target values.
            """
            self.initialize_parameters(X)
            for i in range(self.iterations):
                self.gradient_descent(X, y)


        def predict(self, X):
            """
            Predicts the class labels for the test data.

            Parameters
            ----------
            X : array-like, shape (n_samples, n_features)
                The input data.

            Returns
```

```
[18]
        Returns
        -------
        y_pred : array-like, shape (n_samples,)
            The predicted class labels.

        """
        # 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
```

```
[19] def accuracy(y_true, y_pred):
        """
        Computes the accuracy of a classification model.

        Parameters:
        ----------
            y_true (numpy array): A numpy array of true labels for each data point.
            y_pred (numpy array): A numpy array of predicted labels for each data point.

        Returns:
        ----------
            float: The accuracy of the model
        """
        total_samples = len(y_true)
        correct_predictions = np.sum(y_true == y_pred)
        return (correct_predictions / total_samples)
```

```
[20] model = SVM()
     model.fit(X_train,y_train)
     predictions = model.predict(X_test)

     accuracy(y_test, predictions)
```

```
0.9823008849557522
```

```
[28] model.predict([-0.47069438, -0.16048584, -0.44810956, -0.49199876,  0.23411429,
              0.02765051, -0.10984741, -0.27623152,  0.41394897, -0.03274296,
             -0.18269561, -0.22105292, -0.35591235, -0.16192949, -0.23133322,
             -0.26903951, -0.16890536, -0.33393537, -0.35629925,  0.4485028 ,
             -0.10474068, -0.02441212, -0.19956318,  0.18320441,  0.19695794])
```

```
array(0)
```

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

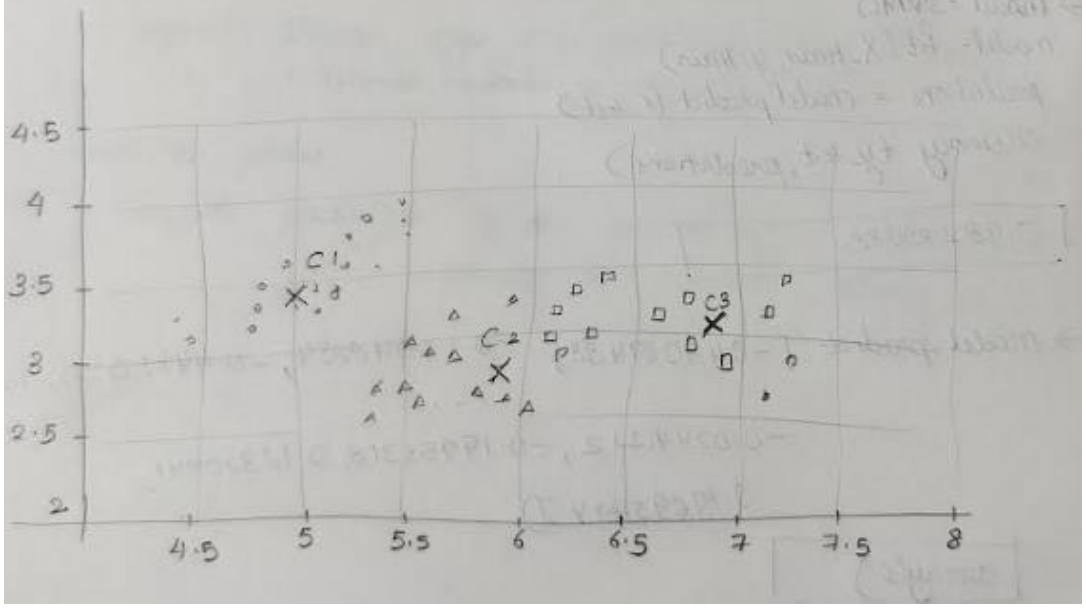
Algorithm:

24/05/2024

→ Kmeans clustering algorithm

1. Select the number K to decide the number of clusters
2. Select random K points or centroids
3. Assign each point to the closest 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 model is ready

Output:



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

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

```
[2] import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    import plotly.express as px
    import seaborn as sns
    import plotly.graph_objects as go
```

```
[3] iris = pd.read_csv("/content/drive/MyDrive/Iris.csv") #Load Data
    iris.drop('Id',inplace=True,axis=1) #Drop Id column
```

```
[4] X = iris.iloc[:,:-1] #Set our training data

    y = iris.iloc[:,-1] #We'll use this just for visualization as clustering doesn't require labels
```

```
[5] class Kmeans:
        """
        K-Means clustering algorithm implementation.

        Parameters:
            K (int): Number of clusters

        Attributes:
            K (int): Number of clusters
            centroids (numpy.ndarray): Array containing the centroids of each cluster
```

```
[5]     Methods:
            __init__(self, K): Initializes the Kmeans instance with the specified number of clusters.
            initialize_centroids(self, X): Initializes the centroids for each cluster by selecting K random points from the dataset.
            assign_points_centroids(self, X): Assigns each point in the dataset to the nearest centroid.
            compute_mean(self, X, points): Computes the mean of the points assigned to each centroid.
            fit(self, X, iterations=10): Clusters the dataset using the K-Means algorithm.
        """

        def __init__(self, K):
            assert K > 0, "K should be a positive integer."
            self.K = K

        def initialize_centroids(self, X):
            assert X.shape[0] >= self.K, "Number of data points should be greater than or equal to K."

            randomized_X = np.random.permutation(X.shape[0])
            centroid_idx = randomized_X[:self.K] # get the indices for the centroids
            self.centroids = X[centroid_idx] # assign the centroids to the selected points

        def assign_points_centroids(self, X):
            """
            Assign each point in the dataset to the nearest centroid.

            Parameters:
            X (numpy.ndarray): dataset to cluster

            Returns:
            numpy.ndarray: array containing the index of the centroid for each point
            """
            X = np.expand_dims(X, axis=1) # expand dimensions to match shape of centroids
            distance = np.linalg.norm((X - self.centroids), axis=-1) # calculate Euclidean distance between each point and each centroid
            points = np.argmin(distance, axis=1) # assign each point to the closest centroid
            assert len(points) == X.shape[0], "Number of assigned points should equal the number of data points."
```

```
[5]
        points = np.argmin(distance, axis=1) # assign each point to the closest centroid
        assert len(points) == X.shape[0], "Number of assigned points should equal the number of data points."
        return points

    def compute_mean(self, X, points):
        """
        Compute the mean of the points assigned to each centroid.

        Parameters:
        X (numpy.ndarray): dataset to cluster
        points (numpy.ndarray): array containing the index of the centroid for each point

        Returns:
        numpy.ndarray: array containing the new centroids for each cluster
        """
        centroids = np.zeros((self.K, X.shape[1])) # initialize array to store centroids
        for i in range(self.K):
            centroid_mean = X[points == i].mean(axis=0) # calculate mean of the points assigned to the current centroid
            centroids[i] = centroid_mean # assign the new centroid to the mean of its points
        return centroids

    def fit(self, X, iterations=10):
        """
        Cluster the dataset using the K-Means algorithm.

        Parameters:
        X (numpy.ndarray): dataset to cluster
        iterations (int): number of iterations to perform (default=10)

        Returns:
        numpy.ndarray: array containing the final centroids for each cluster
        numpy.ndarray: array containing the index of the centroid for each point
        """
        self.initialize_centroids(X) # initialize the centroids
```

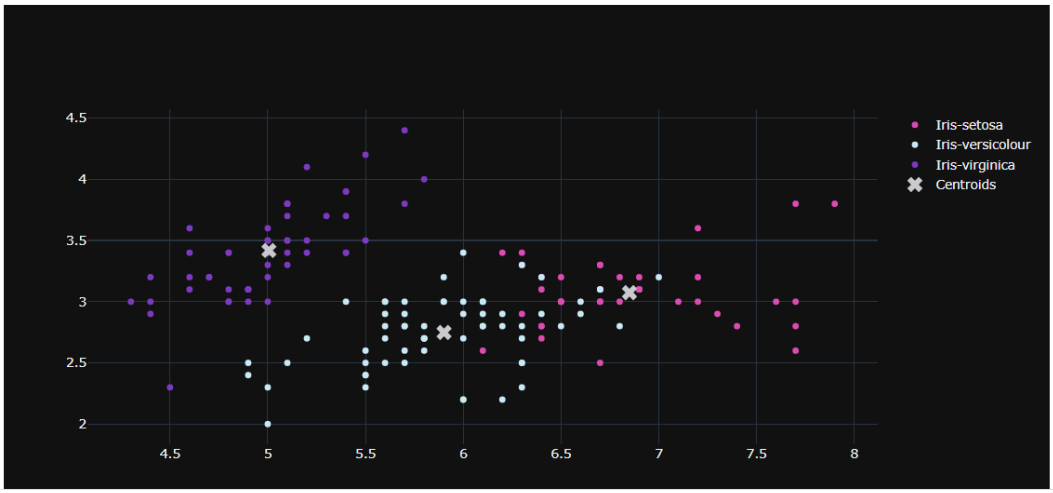
```
[5]
        """
        self.initialize_centroids(X) # initialize the centroids
        for i in range(iterations):
            points = self.assign_points_centroids(X) # assign each point to the nearest centroid
            self.centroids = self.compute_mean(X, points) # compute the new centroids based on the mean of their points

            # Assertions for debugging and validation
            assert len(self.centroids) == self.K, "Number of centroids should equal K."
            assert X.shape[1] == self.centroids.shape[1], "Dimensionality of centroids should match input data."
            assert max(points) < self.K, "Cluster index should be less than K."
            assert min(points) >= 0, "Cluster index should be non-negative."

        return self.centroids, points
```

```
[6] X = X.values
```

```
[7] kmeans = Kmeans(3)

    centroids, points = kmeans.fit(X, 1000)
```

```
[8] fig = go.Figure()
    fig.add_trace(go.Scatter(
        x=X[points == 0, 0], y=X[points == 0, 1],
        mode='markers',marker_color='#DB4CB2',name='Iris-setosa'
    ))

    fig.add_trace(go.Scatter(
        x=X[points == 1, 0], y=X[points == 1, 1],
        mode='markers',marker_color='#c9e9f6',name='Iris-versicolour'
    ))
```

```
[8]
    ))

    fig.add_trace(go.Scatter(
        x=X[points == 2, 0], y=X[points == 2, 1],
        mode='markers',marker_color='#7D3AC1',name='Iris-virginica'
    ))

    fig.add_trace(go.Scatter(
        x=centroids[:, 0], y=centroids[:,1],
        mode='markers',marker_color='#CAC9CD',marker_symbol=4,marker_size=13,name='Centroids'
    ))
    fig.update_layout(template='plotly_dark',width=1000, height=500,)
```



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

Algorithm:

24/05/2024

→ PCA

1. Calculate mean
2. Calculation of covariance matrix
3. Eigenvalues of the covariance matrix
4. Computation of the eigenvectors - unit eigenvectors
5. Computation of first principal components
6. Geometrical meaning of first principal components

Output:

→ pca.explained_variance_ratio

array([0.98377428, 0.01620498])

+ Code + Text

RAM Disk

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

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

```
[2] 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
```

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

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...	radius_worst
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	...	25.38
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	...	24.99
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	...	23.57
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	...	14.91
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	...	22.54

5 rows × 32 columns

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

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

```
[6] corr = df.corr()
```

```
[8] # 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', 'concave p
```

```
[9] X = df[names].values
```


```
[9] X = df[names].values
```


```
[11] 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)
```

```
[11]        # 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)
```

```
[11]        # 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
```

```
[12] pca = PCA(2)
```

```
[13] pca.fit(X)
```

```
[14] pca.explained_variance_ratio_
```

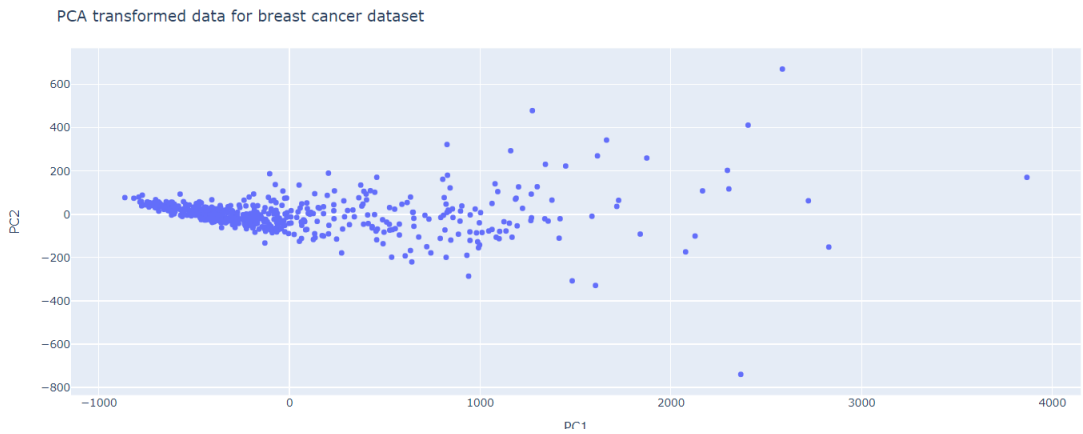
```
array([0.98377428, 0.01620498])
```

```
[15] X_transformed = pca.transform(X)
```

```
[16] X_transformed[:,1].shape
```

```
(569,)
```

```python
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()
```



31.05.2024 1BM21CS083

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

Algorithm:

31/05/2024

Build ANN with backpropagation

→ Create feed forward network with n inputs, n hidden units, n out outputs

→ Initialize all network weights to small random number

→ until the termination condition is met

do

→ for each $(\vec{x}, \vec{t})$ in training examples

→ propagate input forward

→ propagate errors backward

→ for each hidden unit h, calculate error

→ update weight

Output

MLP correct answers while testing : 8/9 (Accuracy = 0.88)

```python
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)
```

```python
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)
```

```python
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))
```

```python
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
```

```python
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)
```

```python
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
```

```python
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]
```

```python
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)
```

```
[10] 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_train),
                                                                                             training_correct_answers/len(x_train),"Duke breast cancer"))
```

```
MLP Correct answers while learning: 44 / 77 (Accuracy = 0.5714285714285714) on Duke breast cancer database.
```

```
[11] 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), "Duke breast cancer"))
```

```
MLP Correct answers while testing: 8 / 9 (Accuracy = 0.8888888888888888) on Duke breast cancer database
```

31.05.2024 1BM21CS083

11a. Implement Random forest ensemble method on a given dataset.

Algorithm:

31/05/24

Random Forest

1. Import libraries
2. Load and prepare dataset
3. Train the data before that do train test split
4. Initialize random forest regression
5. Train model
6. Make prediction
7. Evaluate using MSE (Mean Squared error)

Output

accuracy = 0.93

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

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

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

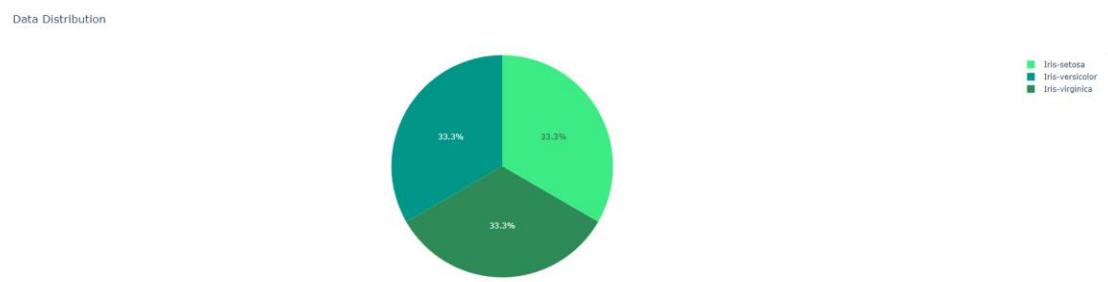
```
[19] iris = pd.read_csv("/content/drive/MyDrive/Iris.csv") #Load Data
     iris.drop('Id',inplace=True,axis=1) #Drop Id column
```

```
[20] iris.head().style.background_gradient(cmap =sns.light_palette("seagreen", as_cmap=True)
     )
```

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	5.100000	3.500000	1.400000	0.200000	Iris-setosa
1	4.900000	3.000000	1.400000	0.200000	Iris-setosa
2	4.700000	3.200000	1.300000	0.200000	Iris-setosa
3	4.600000	3.100000	1.500000	0.200000	Iris-setosa
4	5.000000	3.600000	1.400000	0.200000	Iris-setosa

```
[21] X_df = iris.iloc[:,:-1] #Set our training dataframe

     y_df = iris.iloc[:,-1] # Set our training labels dataframe
```

```
[22] fig = px.pie(iris, 'Species',color_discrete_sequence=['#3dec84 ','#009688 ','#2E8B57 '],title='Data Distribution',template='plotly')
     fig.show()
```




```
[23] iris['Species'] = iris['Species'].astype("category")
     codes = iris['Species'].cat.codes
```

```
[23] iris['Species'] = iris['Species'].astype("category")
     codes = iris['Species'].cat.codes
```

```
[24] def train_test_split(X, y, random_state=42, 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
```

```
[25] X = iris.iloc[:, :-1].values
     y = iris.iloc[:, -1].values.reshape(-1,1)
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.2, random_state=41)
```

```
[26] from sklearn.tree import DecisionTreeClassifier
     m = DecisionTreeClassifier()
```

```
[27] class RandomForest:
         """
         A random forest classifier.

         Parameters
         ----------
         n_trees : int, default=7
             The number of trees in the random forest.
         max_depth : int, default=7
             The maximum depth of each decision tree in the random forest.
         min_samples : int, default=2
             The minimum number of samples required to split an internal node
             of each decision tree in the random forest.

         Attributes
         ----------
         n_trees : int
             The number of trees in the random forest.
         max_depth : int
             The maximum depth of each decision tree in the random forest.
         min_samples : int
             The minimum number of samples required to split an internal node
             of each decision tree in the random forest.
         trees : list of DecisionTreeClassifier
             The decision trees in the random forest.
         """

         def __init__(self, n_trees=7, max_depth=7, min_samples=2):
             """
             Initialize the random forest classifier.
```

```
[27]        The decision trees in the random forest.
        """

    def __init__(self, n_trees=7, max_depth=7, min_samples=2):
        """
        Initialize the random forest classifier.

        Parameters
        ----------
        n_trees : int, default=7
            The number of trees in the random forest.
        max_depth : int, default=7
            The maximum depth of each decision tree in the random forest.
        min_samples : int, default=2
            The minimum number of samples required to split an internal node
            of each decision tree in the random forest.
        """
        self.n_trees = n_trees
        self.max_depth = max_depth
        self.min_samples = min_samples
        self.trees = []

    def fit(self, X, y):
        """
        Build a random forest classifier from the training set (X, y).

        Parameters
        ----------
        X : array-like of shape (n_samples, n_features)
            The training input samples.
        y : array-like of shape (n_samples,)
            The target values.

        Returns
        -------
        self : object
            Returns self.
        """
        # Create an empty list to store the trees.
        self.trees = []
        # Concatenate X and y into a single dataset.
        dataset = np.concatenate((X, y.reshape(-1, 1)), axis=1)
        # Loop over the number of trees.
```

```
[27]        """
        # Create an empty list to store the trees.
        self.trees = []
        # Concatenate X and y into a single dataset.
        dataset = np.concatenate((X, y.reshape(-1, 1)), axis=1)
        # Loop over the number of trees.
        for _ in range(self.n_trees):
            # Create a decision tree instance.
            tree = DecisionTreeClassifier(max_depth=self.max_depth, min_samples_split=self.min_samples)
            # Sample from the dataset with replacement (bootstrapping).
            dataset_sample = self.bootstrap_samples(dataset)
            # Get the X and y samples from the dataset sample.
            X_sample, y_sample = dataset_sample[:, :-1], dataset_sample[:, -1]
            # Fit the tree to the X and y samples.
            tree.fit(X_sample, y_sample)
            # Store the tree in the list of trees.
            self.trees.append(tree)
        return self

    def bootstrap_samples(self, dataset):
        """
        Bootstrap the dataset by sampling from it with replacement.

        Parameters
        ----------
        dataset : array-like of shape (n_samples, n_features + 1)
            The dataset to bootstrap.

        Returns
        -------
        dataset_sample : array-like of shape (n_samples, n_features + 1)
            The bootstrapped dataset sample.
        """
        # Get the number of samples in the dataset.
        n_samples = dataset.shape[0]
        # Generate random indices to index into the dataset with replacement.
        np.random.seed(1)
        indices = np.random.choice(n_samples, n_samples, replace=True)
        # Return the bootstrapped dataset sample using the generated indices.
        dataset_sample = dataset[indices]
        return dataset_sample

    def most_common_label(self, y):
```

```
[27]    def most_common_label(self, y):
            """
            Return the most common label in an array of labels.

            Parameters
            ----------
            y : array-like of shape (n_samples,)
                The array of labels.

            Returns
            -------
            most_occuring_value : int or float
                The most common label in the array.
            """
            y = list(y)
            # get the highest present class in the array
            most_occuring_value = max(y, key=y.count)
            return most_occuring_value

        def predict(self, X):
            """
            Predict class for X.

            Parameters
            ----------
            X : array-like of shape (n_samples, n_features)
                The input samples.

            Returns
            -------
            majority_predictions : array-like of shape (n_samples,)
                The predicted classes.
            """
            #get prediction from each tree in the tree list on the test data
            predictions = np.array([tree.predict(X) for tree in self.trees])
            # get prediction for the same sample from all trees for each sample in the test data
            preds = np.swapaxes(predictions, 0, 1)
            #get the most voted value by the trees and store it in the final predictions array
            majority_predictions = np.array([self.most_common_label(pred) for pred in preds])
            return majority_predictions
```

```
[28] def accuracy(y_true, y_pred):
         """
         Computes the accuracy of a classification model.

         Parameters:
         y_true (numpy array): A numpy array of true labels for each data point.
         y_pred (numpy array): A numpy array of predicted labels for each data point.

         Returns:
         float: The accuracy of the model, expressed as a percentage.
         """
         y_true = y_true.flatten()
         total_samples = len(y_true)
         correct_predictions = np.sum(y_true == y_pred)
         return (correct_predictions / total_samples)
```

```
[35] from sklearn.preprocessing import LabelEncoder

     label_encoder = LabelEncoder()
     y_train_encoded = label_encoder.fit_transform(y_train)
     y_test_encoded = label_encoder.transform(y_test)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_label.py:116: DataConversionWarning:

A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().

/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_label.py:134: DataConversionWarning:

A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
```

```
[39] from sklearn.preprocessing import LabelEncoder

     label_encoder = LabelEncoder()
     y_train_encoded = label_encoder.fit_transform(y_train.ravel())
     y_test_encoded = label_encoder.transform(y_test.ravel())
     model = RandomForest(10, 10, 2)
     model.fit(X_train, y_train_encoded)

     predictions = model.predict(X_test)
     accuracy(y_test_encoded, predictions)
```

```
0.9333333333333333
```

```
from sklearn.tree import DecisionTreeClassifier

# Create and train the decision tree model
dt = DecisionTreeClassifier()
dt.fit(X_train, y_train_encoded)

# Make predictions on the test data
predictions = dt.predict(X_test)

# Calculate accuracy
accuracy(y_test_encoded, predictions)
```

```
0.9
```

31.05.2024 1BM21CS083

11b.Implement Boosting ensemble method on a given dataset.

Algorithm:

31/05/2024

Adaboost algorithm

1. Import libraries
2. Load and prepare data
3. Initialize adaboost model - (learning rate, n_estimation)
4. Make the model train
5. Make predictions
6. Evaluate model on metrics like mean absolute error.

Output:

Accuracy : 0.944

31/5/2024

```
[15] # Compute error rate, alpha and w
     def compute_error(y, y_pred, w_i):
         '''
         Calculate the error rate of a weak classifier m. Arguments:
         y: actual target value
         y_pred: predicted value by weak classifier
         w_i: individual weights for each observation

         Note that all arrays should be the same length
         '''
         return (sum(w_i * (np.not_equal(y, y_pred)).astype(int)))/sum(w_i)

     def compute_alpha(error):
         '''
         Calculate the weight of a weak classifier m in the majority vote of the final classifier. This is called
         alpha in chapter 10.1 of The Elements of Statistical Learning. Arguments:
         error: error rate from weak classifier m
         '''
         return np.log((1 - error) / error)

     def update_weights(w_i, alpha, y, y_pred):
         '''
         Update individual weights w_i after a boosting iteration. Arguments:
         w_i: individual weights for each observation
         y: actual target value
         y_pred: predicted value by weak classifier
         alpha: weight of weak classifier used to estimate y_pred
         '''
         return w_i * np.exp(alpha * (np.not_equal(y, y_pred)).astype(int))
```

```
[16] # Define AdaBoost class
     class AdaBoost:

         def __init__(self):
             self.alphas = []
             self.G_M = []
             self.M = None
             self.training_errors = []
             self.prediction_errors = []

         def fit(self, X, y, M = 100):
             '''
             Fit model. Arguments:
             X: independent variables - array-like matrix
             y: target variable - array-like vector
             M: number of boosting rounds. Default is 100 - integer
             '''

             # Clear before calling
             self.alphas = []
             self.training_errors = []
             self.M = M

             # Iterate over M weak classifiers
             for m in range(0, M):

                 # Set weights for current boosting iteration
                 if m == 0:
                     w_i = np.ones(len(y)) * 1 / len(y)  # At m = 0, weights are all the same and equal to 1 / N
                 else:
                     # (d) Update w_i
                     w_i = update_weights(w_i, alpha_m, y, y_pred)

                 # (a) Fit weak classifier and predict labels
                 G_m = DecisionTreeClassifier(max_depth = 1)     # Stump: Two terminal-node classification tree
                 G_m.fit(X, y, sample_weight = w_i)
                 y_pred = G_m.predict(X)

                 self.G_M.append(G_m) # Save to list of weak classifiers

                 # (b) Compute error
                 error_m = compute_error(y, y_pred, w_i)
```

```
[15]                 w_i = update_weights(w_i, alpha_m, y, y_pred)

                 # (a) Fit weak classifier and predict labels
                 G_m = DecisionTreeClassifier(max_depth = 1)     # Stump: Two terminal-node classification tree
                 G_m.fit(X, y, sample_weight = w_i)
                 y_pred = G_m.predict(X)

                 self.G_M.append(G_m) # Save to list of weak classifiers

                 # (b) Compute error
                 error_m = compute_error(y, y_pred, w_i)
                 self.training_errors.append(error_m)

                 # (c) Compute alpha
                 alpha_m = compute_alpha(error_m)
                 self.alphas.append(alpha_m)

             assert len(self.G_M) == len(self.alphas)

         def predict(self, X):
             '''
             Predict using fitted model. Arguments:
             X: independent variables - array-like
             '''

             # Initialise dataframe with weak predictions for each observation
             weak_preds = pd.DataFrame(index = range(len(X)), columns = range(self.M))

             # Predict class label for each weak classifier, weighted by alpha_m
             for m in range(self.M):
                 y_pred_m = self.G_M[m].predict(X) * self.alphas[m]
                 weak_preds.iloc[:,m] = y_pred_m

             # Calculate final predictions
             y_pred = (1 * np.sign(weak_preds.T.sum())).astype(int)

             return y_pred
```

```
[17] import pandas as pd
     import numpy as np
     from sklearn.model_selection import train_test_split
     from sklearn.tree import DecisionTreeClassifier

     # Dataset
     df = pd.read_csv('/content/spambase.data', header = None)

     # Column names
     names = pd.read_csv('/content/spambase.names', sep = ':', skiprows=range(0, 33), header = None)
     col_names = list(names[0])
     col_names.append('Spam')

     # Rename df columns
     df.columns = col_names

     # Convert classes in target variable to {-1, 1}
     df['Spam'] = df['Spam'] * 2 - 1

     # Train - test split
     X_train, X_test, y_train, y_test = train_test_split(df.drop(columns = 'Spam').values,
                                                         df['Spam'].values,
                                                         train_size = 3065,
                                                         random_state = 2)
```

```
     # Fit model
     ab = AdaBoost()
     ab.fit(X_train, y_train, M = 400)

     # Predict on test set
     y_pred = ab.predict(X_test)

     from sklearn.metrics import accuracy_score

     # Calculate accuracy
     accuracy = accuracy_score(y_test, y_pred)
     print("Accuracy:", accuracy)
```

```
Accuracy: 0.9440104166666666
```