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,
Bull Temple Road, Bangalore 560019

(March 2024 to June 2024)

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**" is carried out by **G SAI VIKRANT (1BM21CS061)** 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 Visveswaraya Technological University, Belgaum during the year 2023-2024. The lab report has been approved as it satisfies the academic requirements in respect of **Machine Learning Lab - (22CS3PCMAL)** work prescribed for the said degree.

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Index Sheet

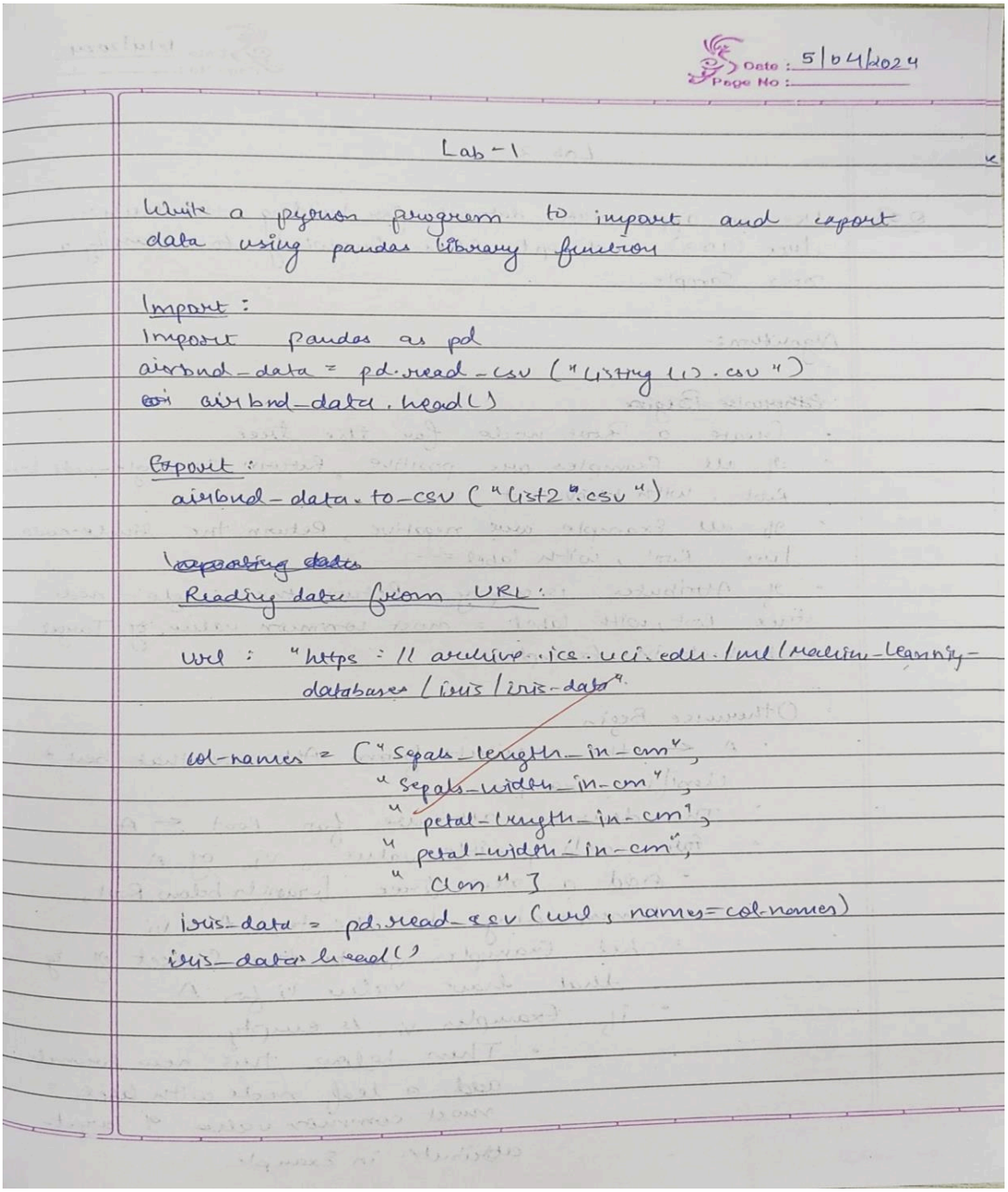
Course outcomes:

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

04.04.2024

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

Screenshot



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Lab - 1

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

Import :

```
Import pandas as pd
airbnd_data = pd.read_csv("listing (1).csv")
airbnd_data.head()
```

Export :

```
airbnd_data.to_csv("list2.csv")
```

Reading data from URL :

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

col_names = ["sepals_length_in_cm",
             "sepals_width_in_cm",
             "petal_length_in_cm",
             "petal_width_in_cm",
             "class"]
iris_data = pd.read_csv(url, names=col_names)
iris_data.head()
```

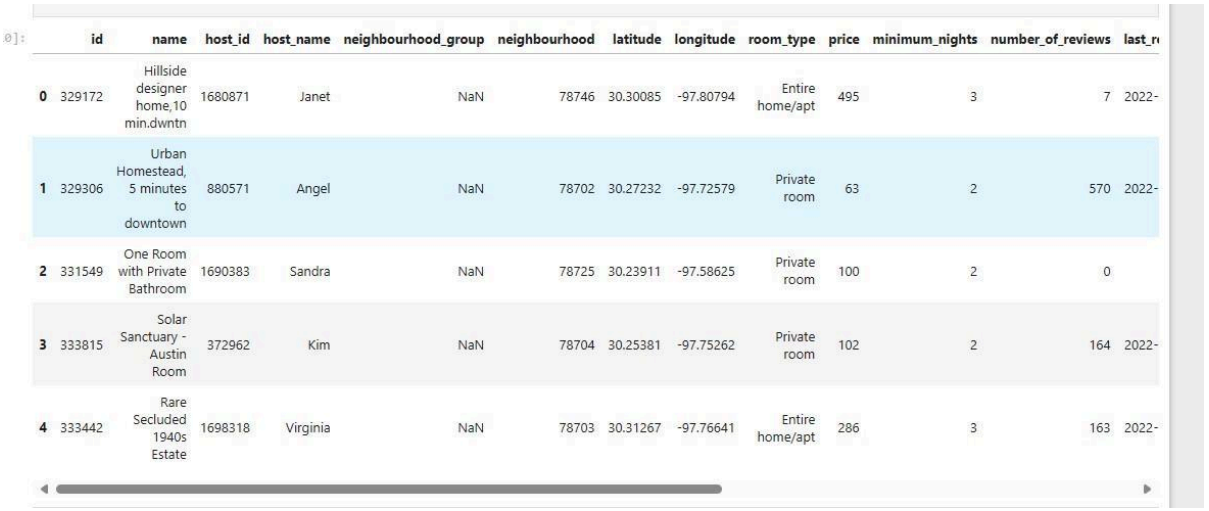
Code:

Impoít

impoít pandas as pd

aiíbnb_data = pd.íead_csv("listings (1).csv")

aiíbnb_data.head()



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

Expoít

aiíbnb_data.to_csv("list2.csv")

Reading the file from the URL:

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

col_names = ["sepal_length_in_cm",

"sepal_width_in_cm",

"petal_length_in_cm",

"petal_width_in_cm",

"class"]

iris_data = pd.read_csv(url, names=col_names)

iris_data.head()

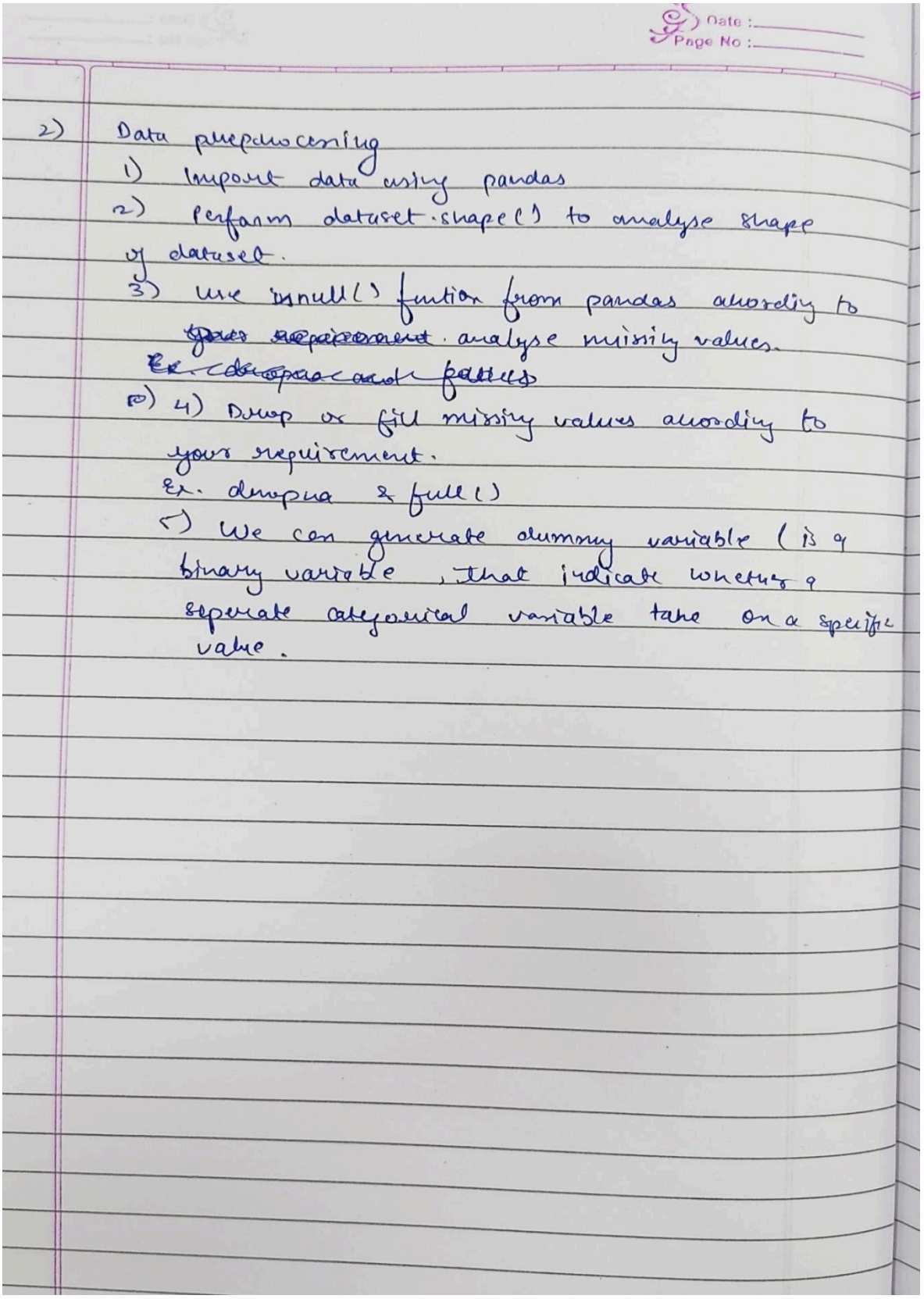
2]:

	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

04.04.2024

Demonstrate various data processing unit for a dataset.

Screenshot



2) Data preprocessing
1) Import data using pandas
2) Perform dataset.shape() to analyse shape of dataset.
3) Use isnull() funtion from pandas aloording to ~~your requirement~~. analyse missing values.
~~Ex. dropna and fillna~~
4) Drop or fill missing values aloording to your requirement.
Ex. dropna & fill()
5) We can generate dummy variable (is a binary variable, that indicate whether a seperate categorical variable take on a specific value.

Code:

```
%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']
```

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

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

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

```
# 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)
```

```
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

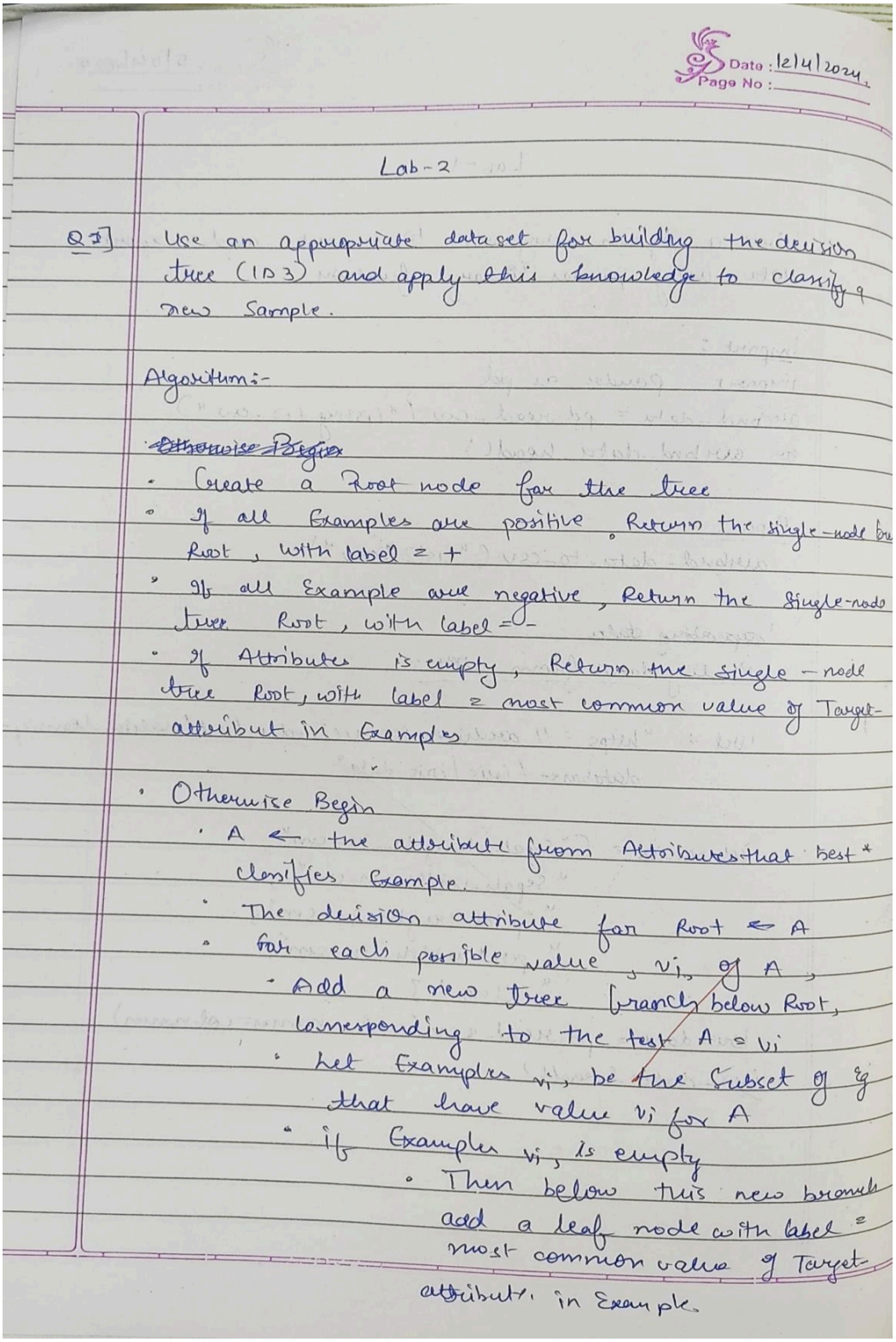
```
pd.get_dummies(df2)
```

	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

12.04.2024

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

4.snapshot



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Lab-2

Q.1] Use an appropriate data set for building the decision tree (ID3) and apply this knowledge to classify a new Sample.

Algorithm:-

~~Otherwise Begin~~

- Create a Root node for the tree
- If all Examples are positive, Return the single-node tree Root, with label = +
- If all Example 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-attribut in Examples

- Otherwise Begin
  - A ← the attribute from Attributes that best* classifies Example.
  - The decision attribute for Root ← A
  - For each possible value, v_i, of A,
    - Add a new tree branch below Root, corresponding to the test A = v_i
    - Let Examples v_i, be the Subset of E 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 Example.

- Else below this new branch add the subtree ID3

- End
- Return Root.

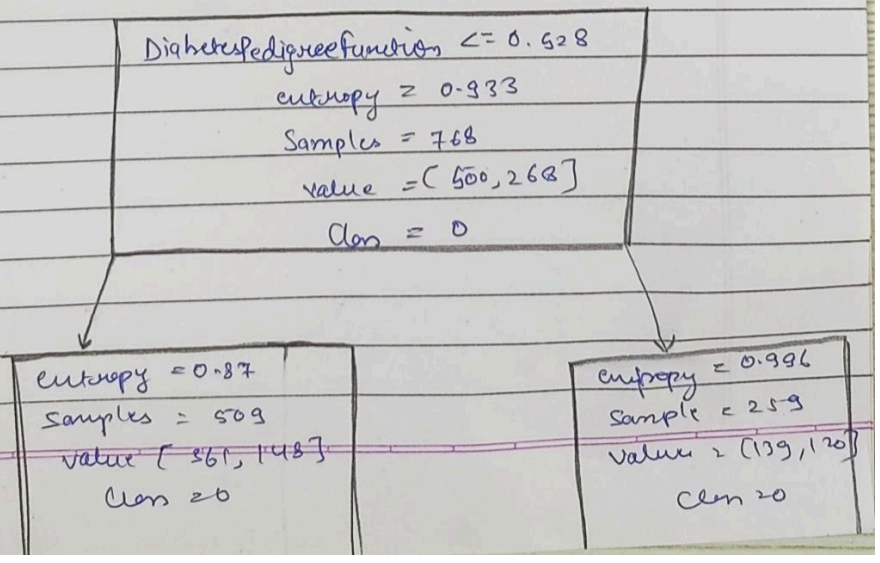
Output:

(1) Entropy of the dataset : 0.93313

(2) Calculating Entropy & IG for each case :

Pregnancies - Entropy : 3.482 , Info.gain : 0.062
Glucose - Entropy : 6.751 , Info.gain : 0.304
BP - Entropy : 4.732 , Info. gain : 0.059
Insulin - Entropy : 4.682 , Info. gain : 0.277
BMI - Entropy : 7.594 , Info. gain : 0.344.
Age - Entropy : 5.029 , Info. gain : 0.141

(3) Decision Tree :



1. importing database

```
[1] import pandas as pd
    from sklearn.tree import DecisionTreeClassifier, plot_tree
    import matplotlib.pyplot as plt
    import math
```

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

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

Next steps: View recommended plots

2. Calculating entropy and information gain.

```
def calculate_entropy(data, target_column):
  total_rows = len(data)
  target_values = data[target_column].unique()

  entropy = 0
  for value in target_values:
    value_count = len(data[data[target_column] == value])
    proportion = value_count / total_rows
    entropy -= proportion * math.log2(proportion)

  return entropy

entropy_outcome = calculate_entropy(df, 'Outcome')
print(f"Entropy of the dataset: {entropy_outcome}")
```

```
Entropy of the dataset: 0.9331343166407831
```

```
[4] def calculate_entropy(data, target_column):
      total_rows = len(data)
      target_values = data[target_column].unique()

      entropy = 0
      for value in target_values:
        value_count = len(data[data[target_column] == value])
        proportion = value_count / total_rows
        entropy -= proportion * math.log2(proportion) if proportion != 0 else 0

      return entropy

    def calculate_information_gain(data, feature, target_column):

      unique_values = data[feature].unique()
      weighted_entropy = 0

      for value in unique_values:
        subset = data[data[feature] == value]
```

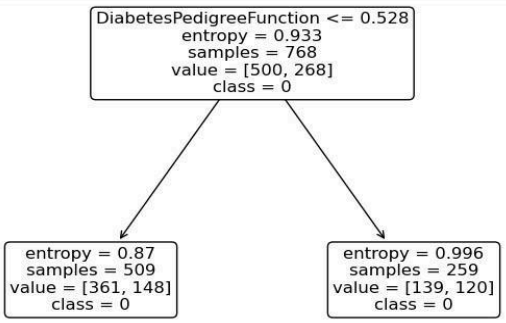
3. Making Decision tree.

```
  unique_values = data[feature].unique()
  weighted_entropy = 0

  for value in unique_values:
    subset = data[data[feature] == value]
    proportion = len(subset) / len(data)
    weighted_entropy += proportion * calculate_entropy(subset, target_column)

  information_gain = entropy_outcome - weighted_entropy

  return information_gain
```

```
for column in df.columns[:-1]:
  entropy = calculate_entropy(df, column)
  information_gain = calculate_information_gain(df, column, 'Outcome')
  print(f"{column} - Entropy: {entropy:.3f}, Information Gain: {information_gain:.3f}")
```

```
Pregnancies - Entropy: 3.482, Information Gain: 0.062
Glucose - Entropy: 6.751, Information Gain: 0.304
BloodPressure - Entropy: 4.792, Information Gain: 0.059
SkinThickness - Entropy: 4.586, Information Gain: 0.082
Insulin - Entropy: 4.682, Information Gain: 0.277
BMI - Entropy: 7.594, Information Gain: 0.344
DiabetesPedigreeFunction - Entropy: 8.829, Information Gain: 0.651
Age - Entropy: 5.029, Information Gain: 0.141
```

```
selected_feature = 'DiabetesPedigreeFunction'

clf = DecisionTreeClassifier(criterion='entropy', max_depth=1)
X = df[[selected_feature]]
y = df['Outcome']
clf.fit(X, y)

plt.figure(figsize=(8, 6))
plot_tree(clf, feature_names=[selected_feature], class_names=['0', '1'], filled=False, rounded=True)
plt.show()
```

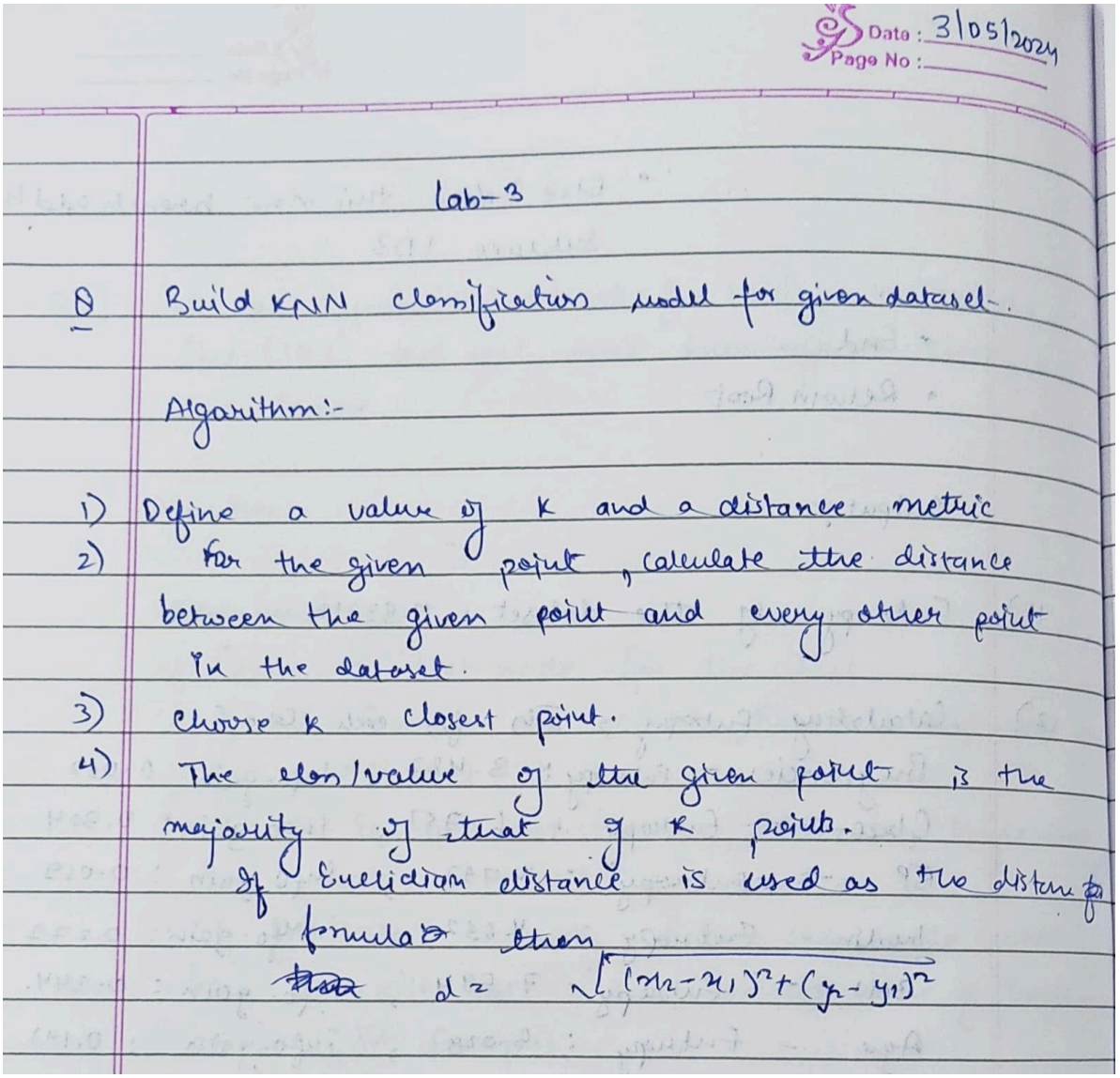



```
def id3(data, target_column, features):
  if len(data[target_column].unique()) == 1:
    return data[target_column].iloc[0]


  if len(features) == 0:
    return data[target_column].mode().iloc[0]

  best_feature = max(features, key=lambda x: calculate_information_gain(data, x, target_column))

  tree = {best_feature: {}}

  features = [f for f in features if f != best_feature]

  for value in data[best_feature].unique():
    subset = data[data[best_feature] == value]
    tree[best_feature][value] = id3(subset, target_column, features)

  return tree
```

19.04.2024

Build KNN Classification model for given dataset.

Snapshot:



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Lab-3

Q Build KNN classification model for given dataset.

Algorithm:-

1) Define a value of K and a distance metric
2) For the given point, calculate the distance between the given point and every other point in the dataset.
3) Choose K closest point.
4) The class/value of the given point is the majority of that of K points.

If Euclidian distance is used as the distance formula then

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

Code:

```
[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
```

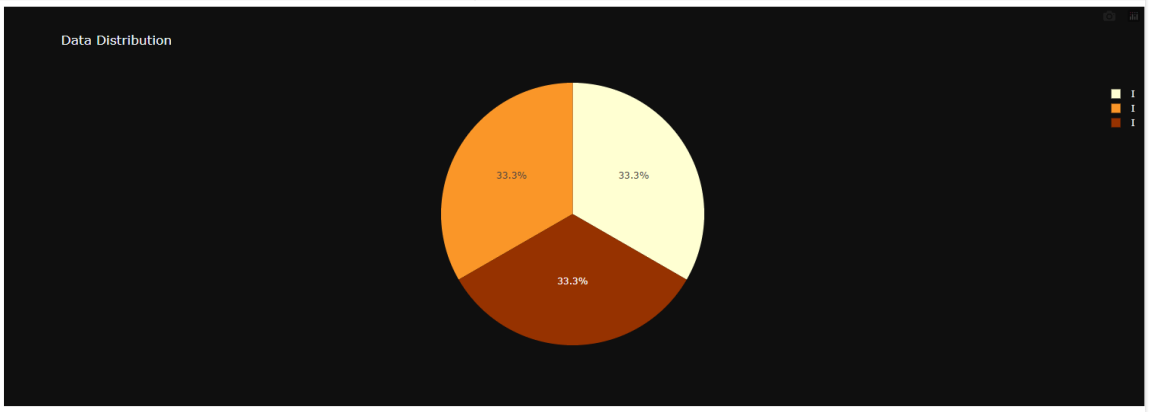
```
[4] iris.head()
```

	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

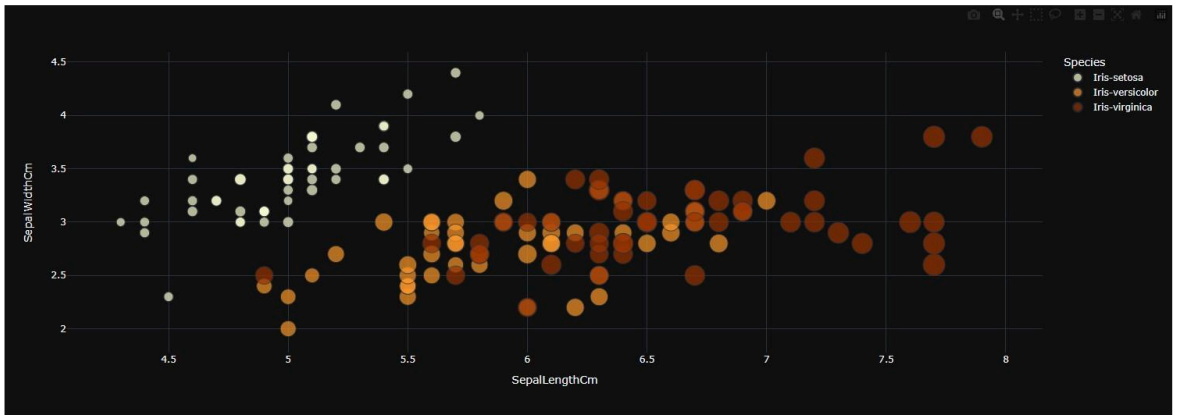
Next steps: View recommended plots

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

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

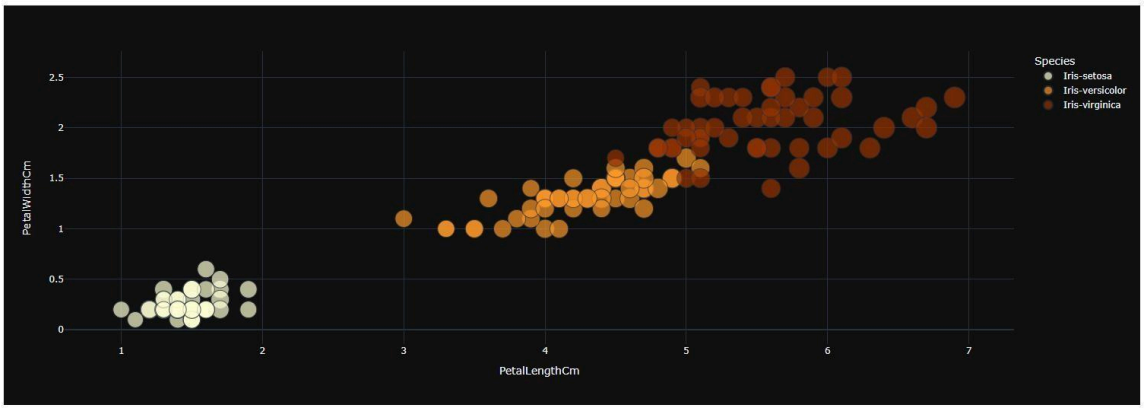
```
fig = px.pie(iris, 'Species',color_discrete_sequence=['#ffffd4 ','#fe9929 ','#993404 '],title='Data Distribution',template='plotly_dark')
fig.show()
```



```
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)
```

```
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)
```

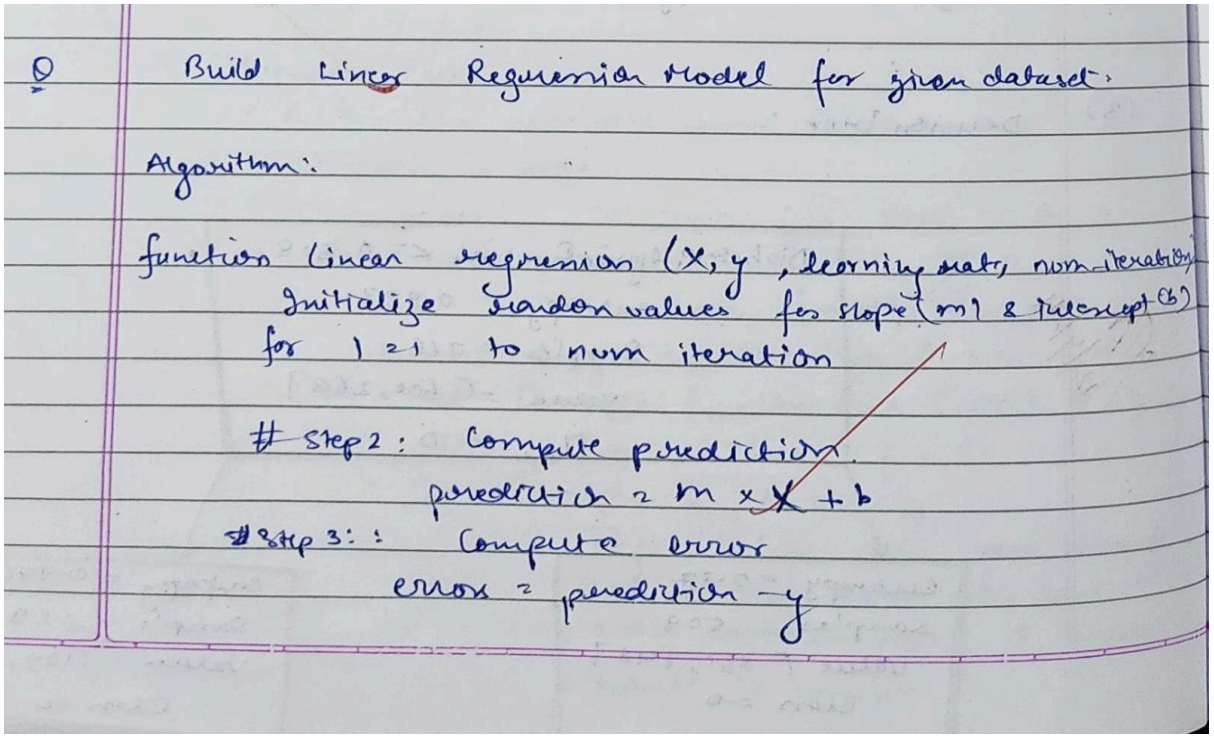
```
[17] sk_predictions = skmodel.predict(X_test)
     sk_accuracy = compute_accuracy(y_test, sk_predictions)
     print(f" sklearn-model got accuracy score of : {sk_accuracy}")
```

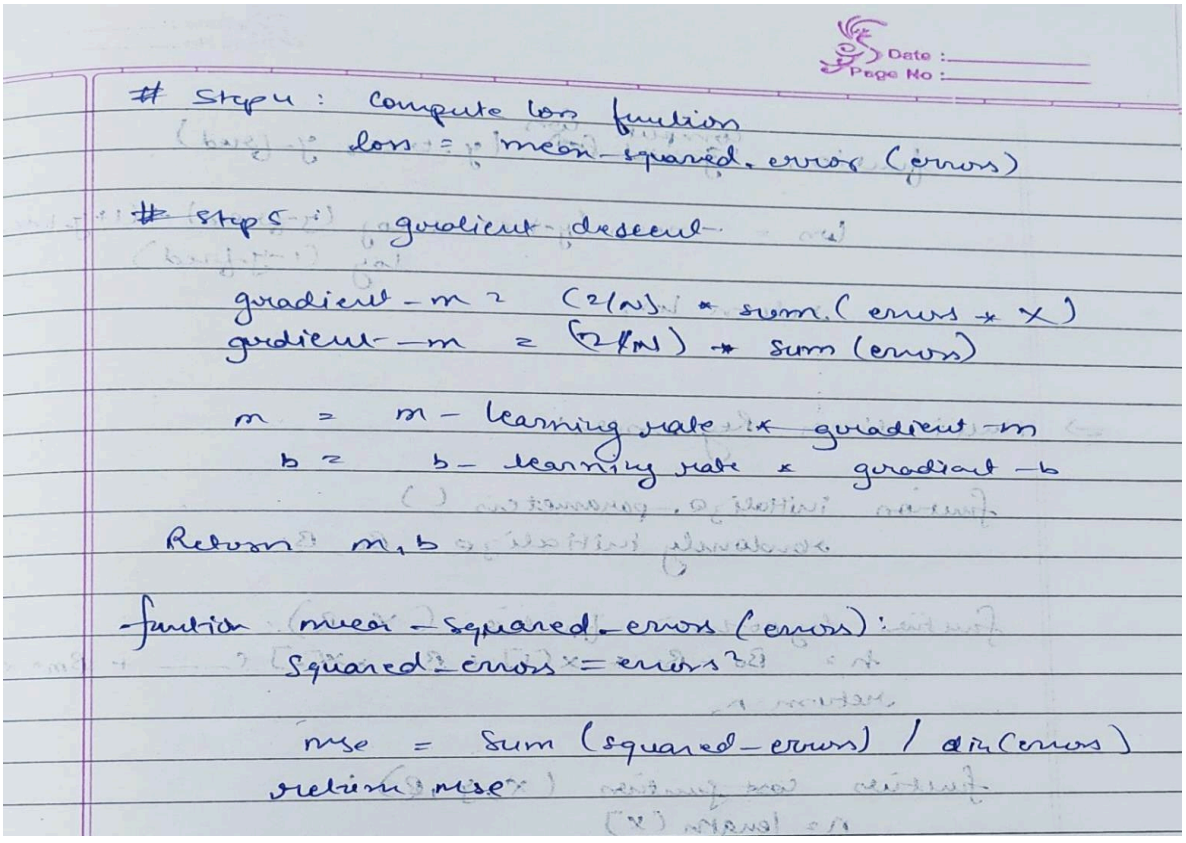
```
 sklearn-model got accuracy score of : 0.9666666666666667
```

19.04.2024

Build linear regression model for the dataset:

Snapshot:





Code:

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

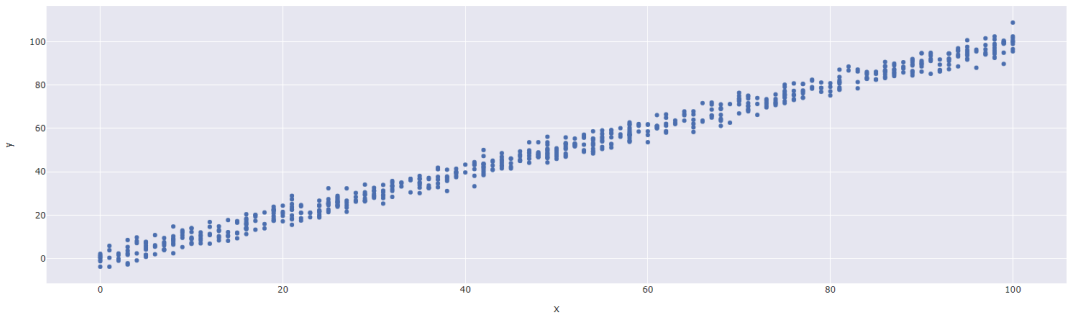
```
[2] # Load the training and test datasets
    train_data = pd.read_csv('train.csv')
    test_data = pd.read_csv('test.csv')

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

```
[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

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




```
[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:
        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]
```
        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]
```
        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()
```

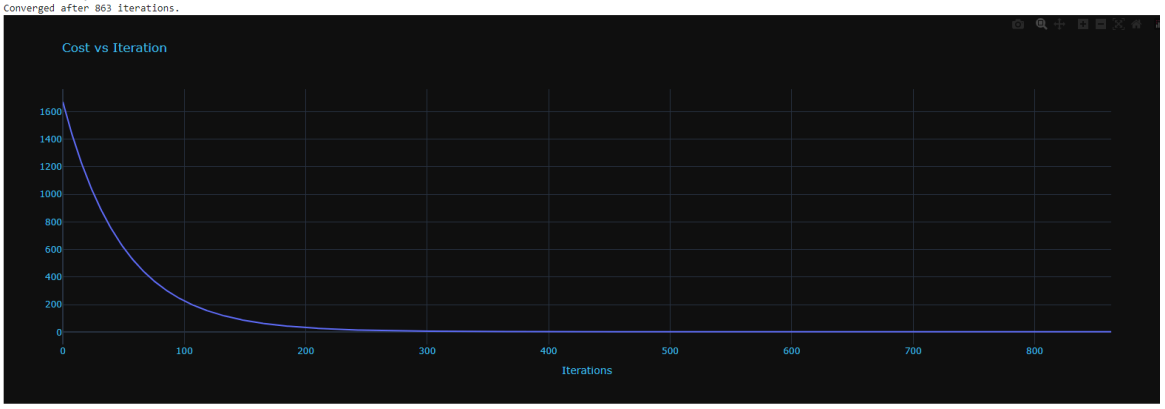
```
            fig.show()
    def predict(self, X):
        """
        Predict target values for new input data.

        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.
```

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
```

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
```

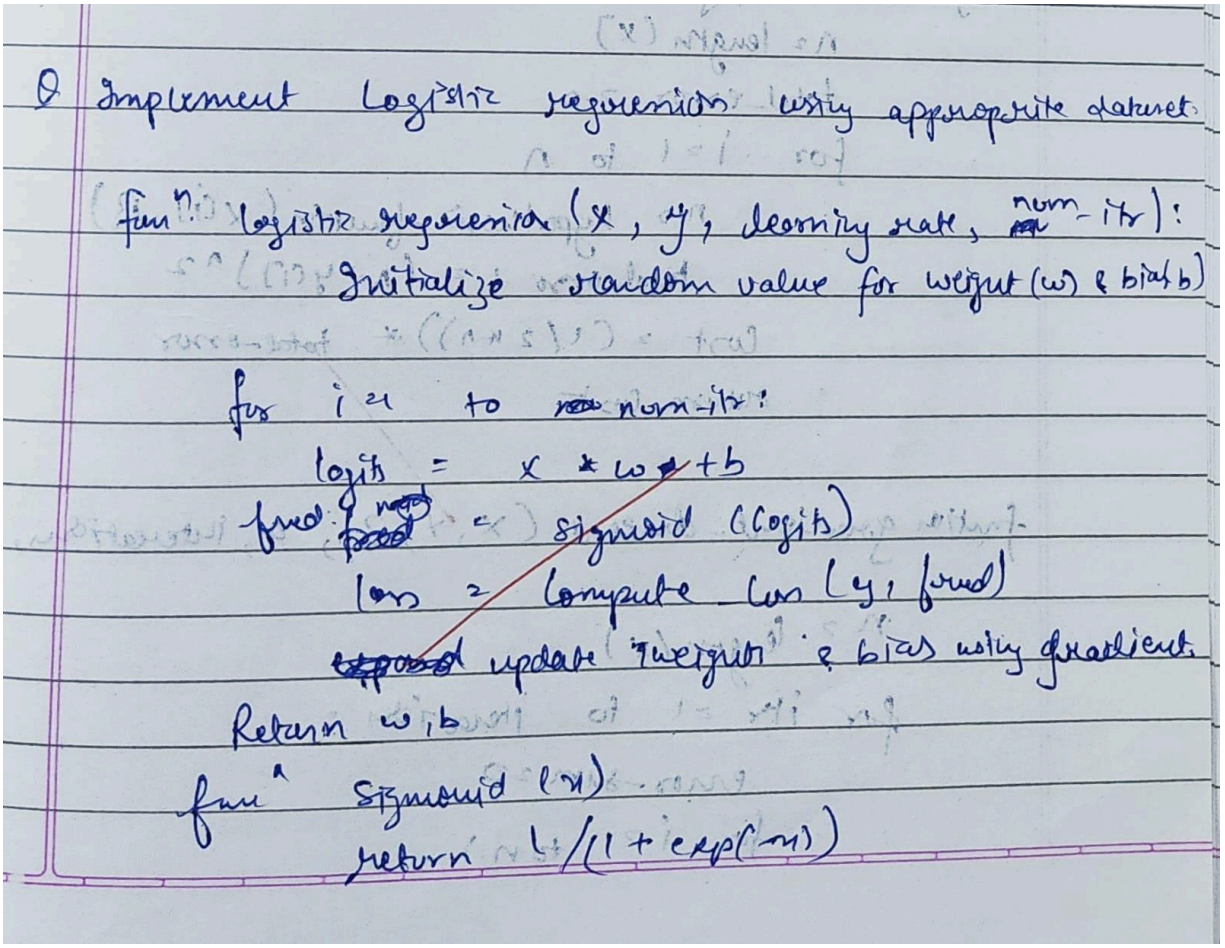
```
model.predict([[2]])
```

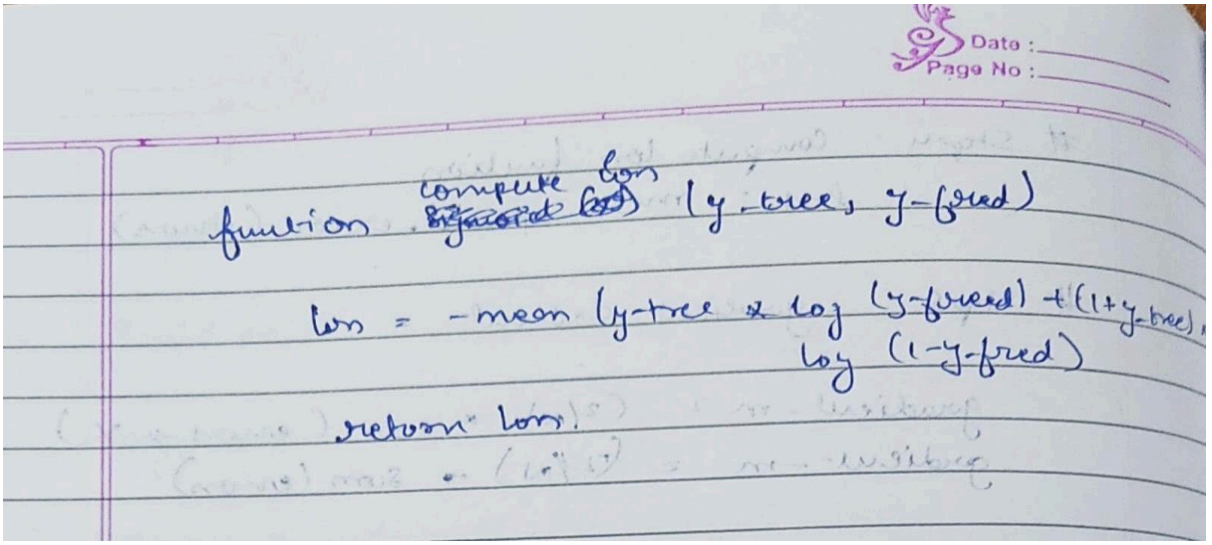
```
array([107.82727115])
```

19.04.2024

Implement logistic regression using appropriate dataset:

Snapshot:





Code:

```
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
```

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

```
[5] 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	

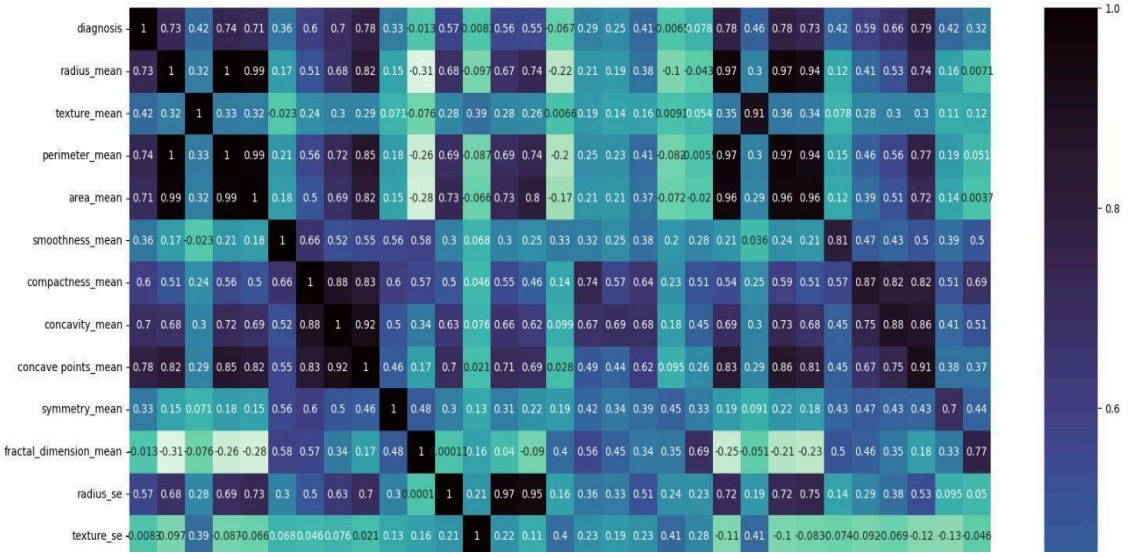
5 rows × 32 columns

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

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

```
[8] 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)
```

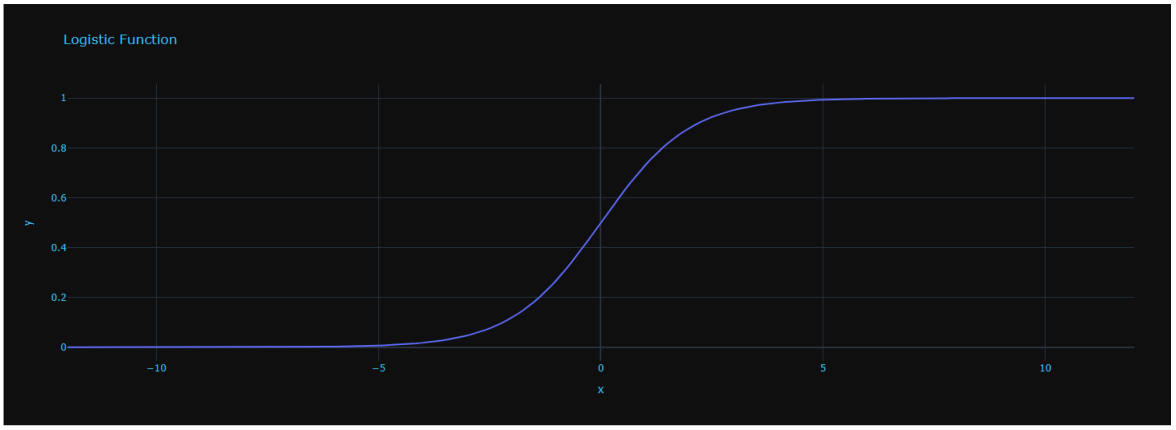
```
[16] def standardize_data(X_train, X_test):
        """
        Standardizes the input data using mean and standard deviation.

        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
```

0s completed at 3:13 PM

```
        """
        # 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
```

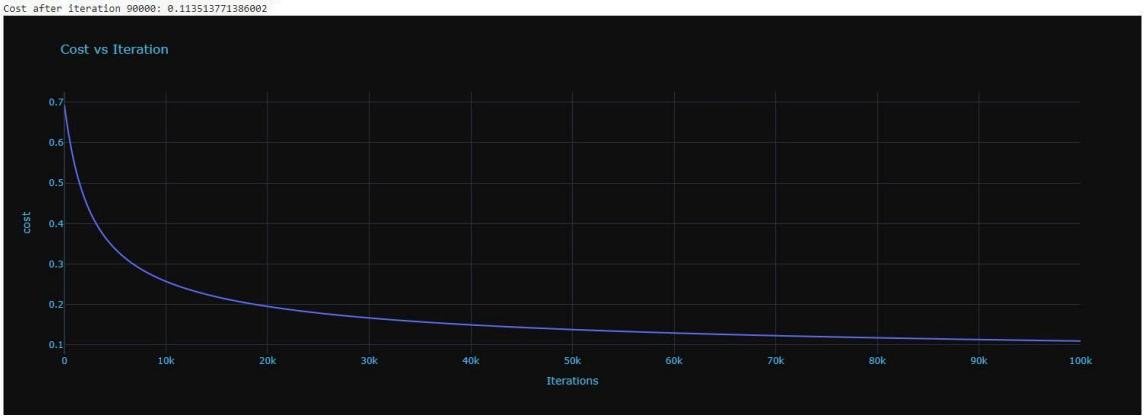
[19]
```
            float: cost of the model.
        """
        m = self.X.shape[0]  # number of training examples
        # compute the cost
        cost = np.sum((-np.log(predictions + 1e-8) * self.y) + (-np.log(1 - predictions + 1e-8)) * (
                1 - self.y))  # we are adding small value 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
```

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

[23]
```
lg = LogisticRegression()
lg.fit(X_train, y_train,100000)
```

```
Cost after iteration 0: 0.6931471605599454
Cost after iteration 10000: 0.257077837055824 6
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: 0.1296814121248933
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")
```

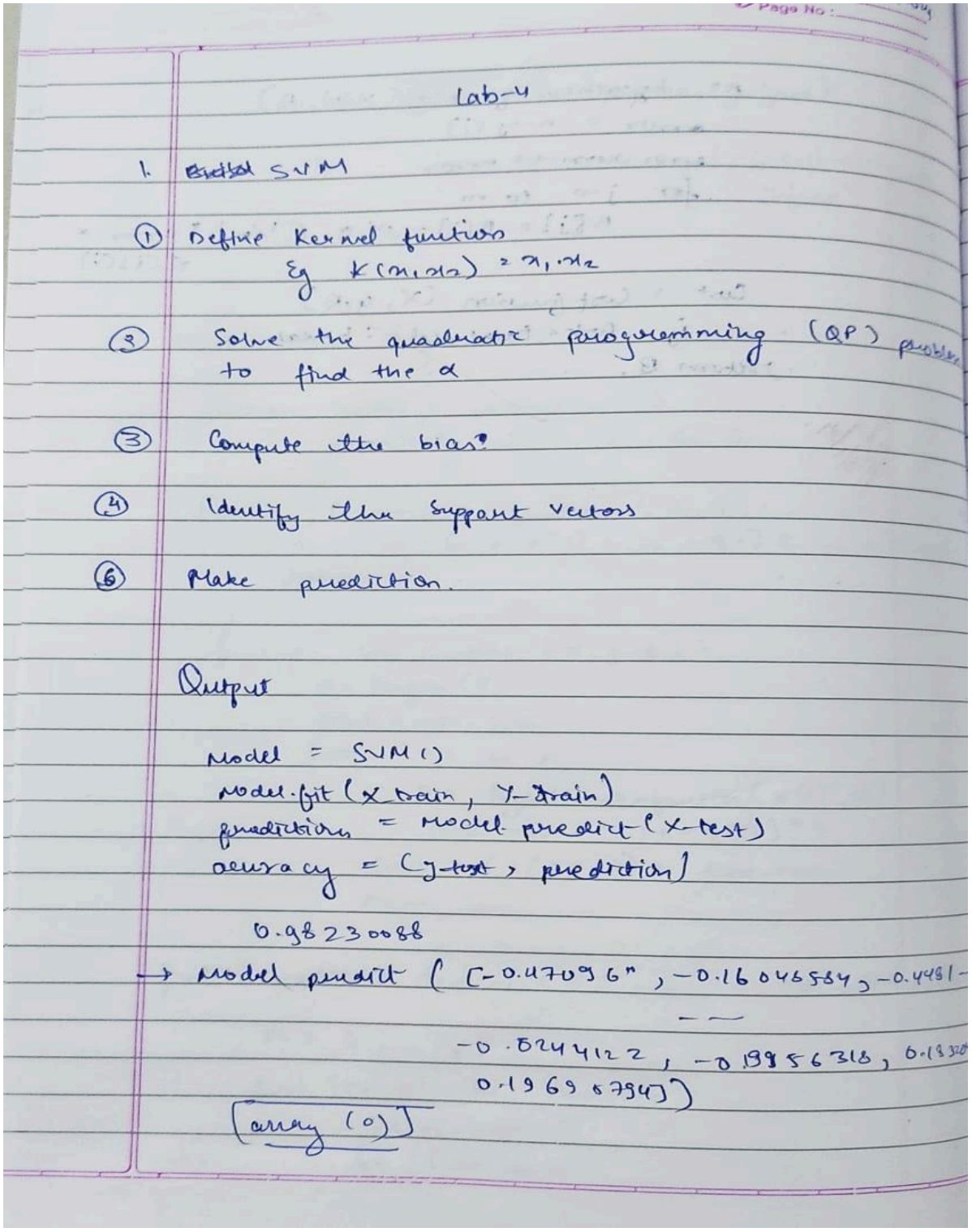
```
[25] y_pred = model.predict(X_test)
     accuracy = ClassificationMetrics.accuracy(y_test, y_pred)
     precision = ClassificationMetrics.precision(y_test, y_pred)
     recall = ClassificationMetrics.recall(y_test, y_pred)
     f1_score = ClassificationMetrics.f1_score(y_test, y_pred)

     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%
```

24.05.2024

Build support vector machine for the dataset:

Snapshot:



Lab-4

1. Build SVM

① Define 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 bias

④ Identify the support vectors

⑥ Make prediction.

Output

```
Model = SVM()
Model.fit(X_train, Y_train)
predictions = Model.predict(X_test)
accuracy = (y_test, prediction)

0.98230088
→ Model predict ( [-0.47096", -0.16046584, -0.4481-
                  --
                  -0.52441122, -0.19856318, 0.1330
                  0.19695794])
[array (0)]
```

Code:

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

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

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

```
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	...	rac
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

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

```
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)
```

24.05.2024

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

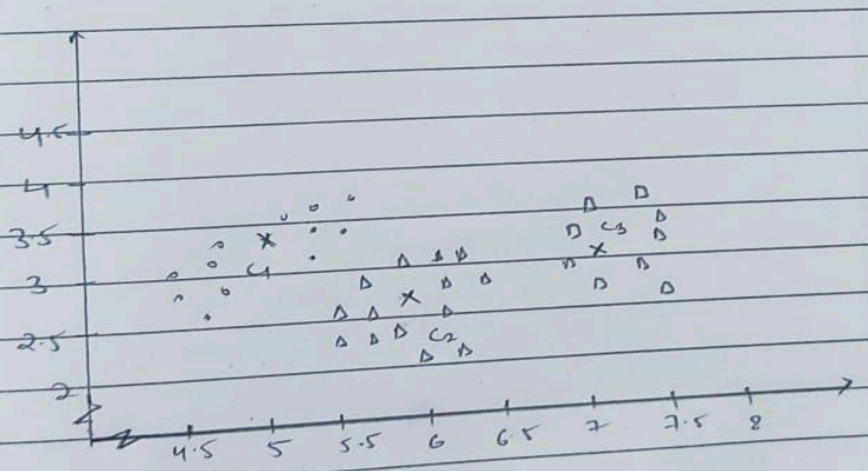
Snapshot:

Date :
Page No :

2. K-means clustering Algorithm:-

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

Output:-



Code:

```
[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
```

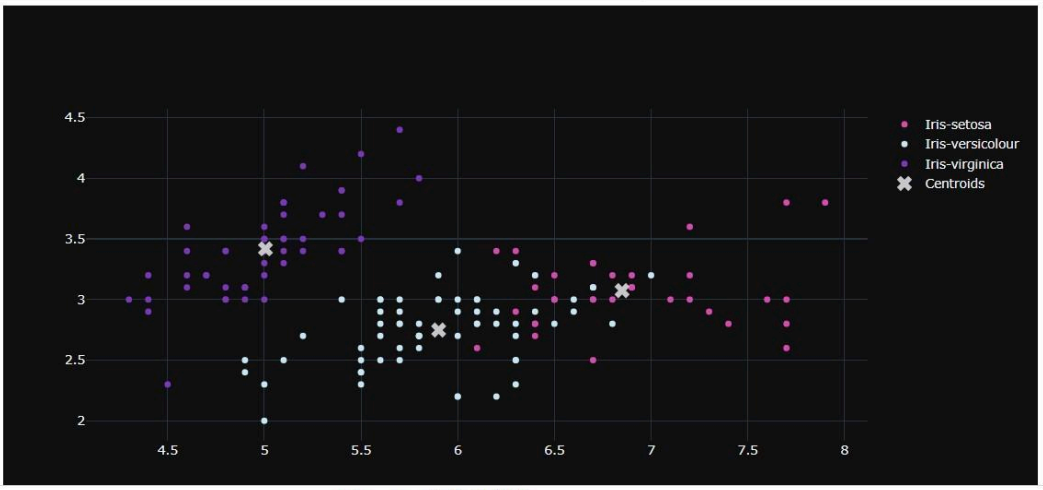
```
[6]  X = X.values
```

```
[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]

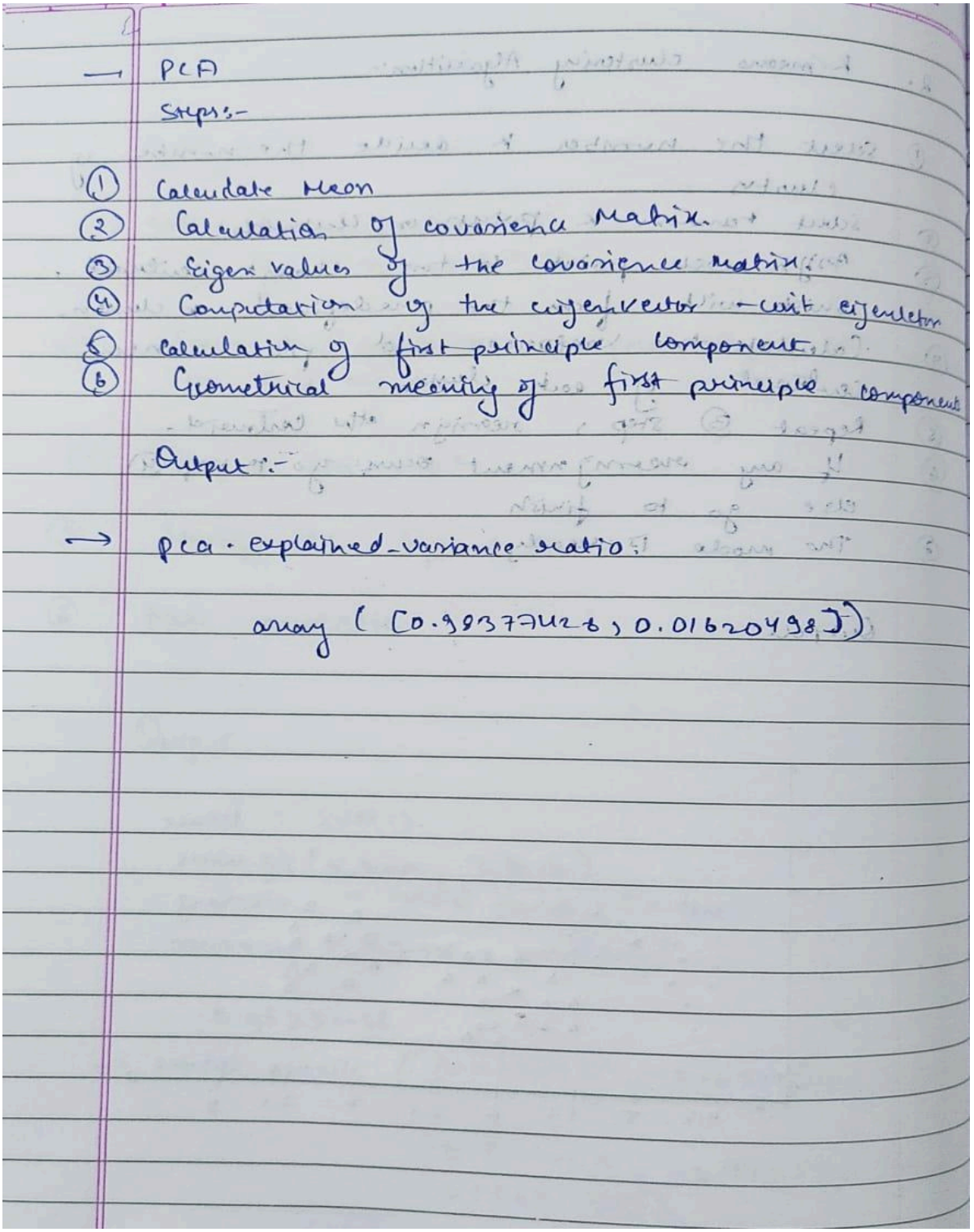
```
    ))

    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,)
```



24.05.2024

Implement dimensionality reduction using principle component analysis (PCA).

Snapshot:



Code:

+ 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_
```

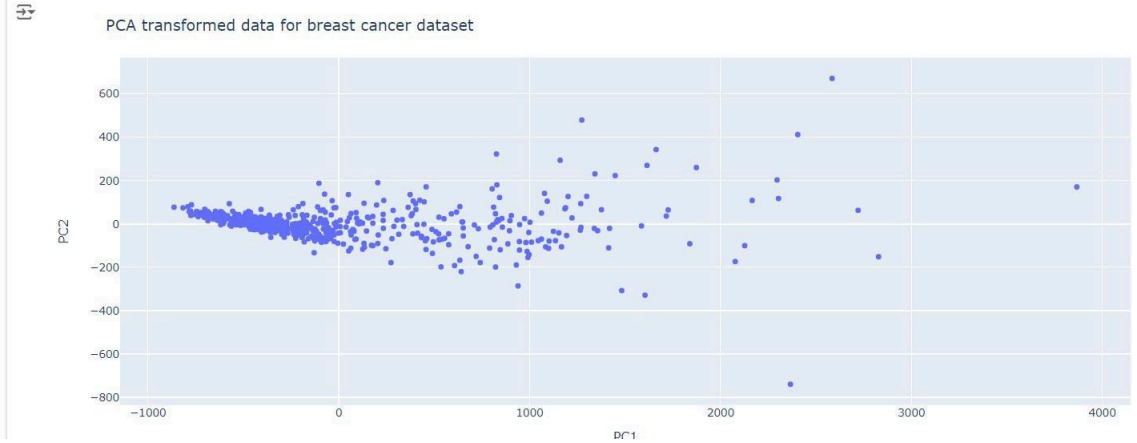
```
array([0.98377428, 0.01620498])
```

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

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

```
(569,)
```

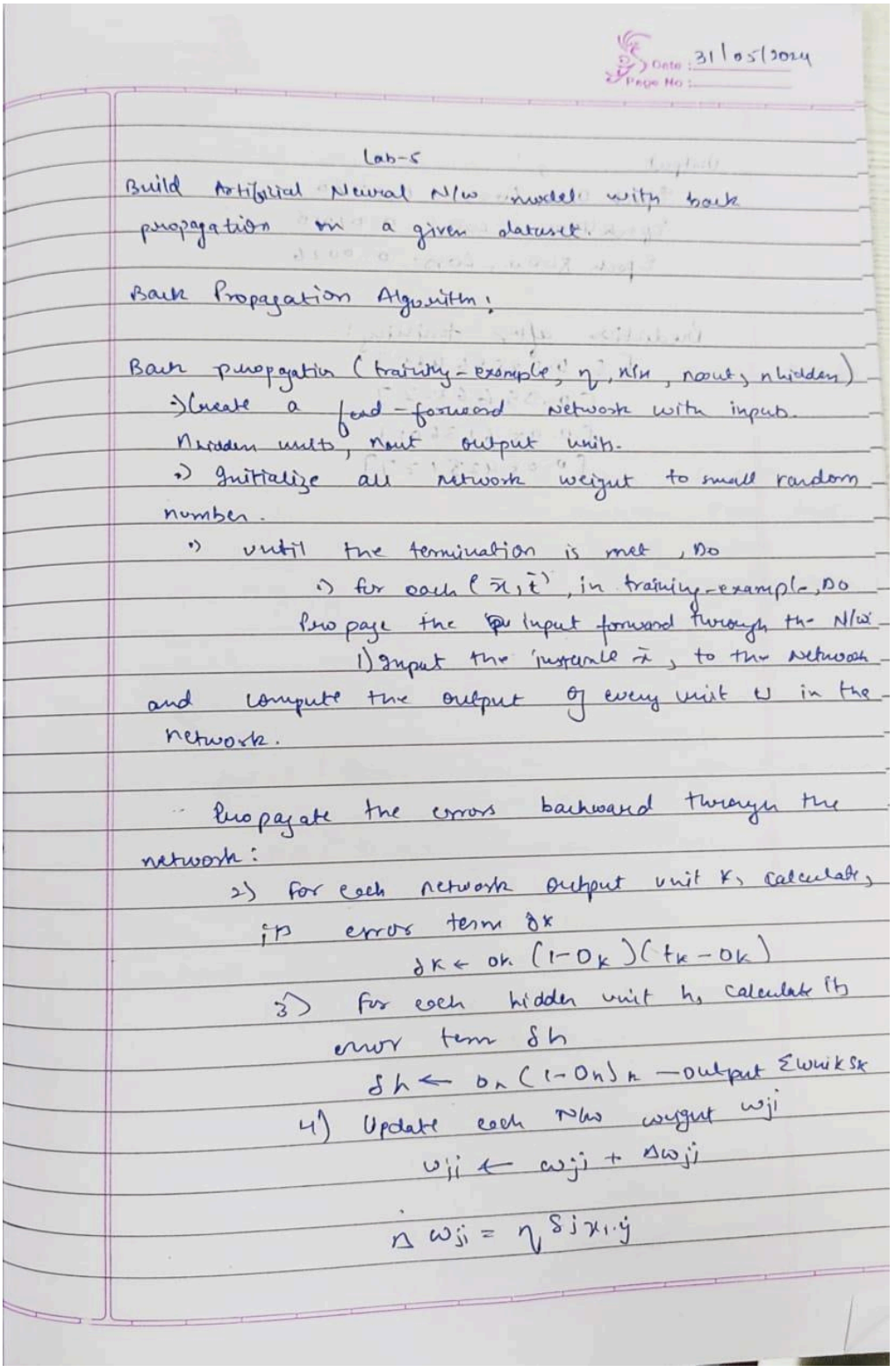
```
fig = px.scatter(x=X_transformed[:,0], y=X_transformed[:,1])
fig.update_layout(
    title="PCA transformed data for breast cancer dataset",
    xaxis_title="PC1",
    yaxis_title="PC2"
)
fig.show()
```



31.05.2024

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

Snapshot:



Date: 31/05/2024
Page No:

Lab-5

Build Artificial Neural N/w model with back propagation on a given dataset.

Back Propagation Algorithm:

Back propagation (training_example, η, n_{in}, n_{out}, n_{hidden})

=> Create a feed-forward network with input. n_{hidden} units, n_{out} output units.

=> Initialize all network weight to small random number.

=> until the termination is met, Do

=> for each $(\vec{x}, \vec{t})$, in training_example, Do

Propagate the input forward through the N/w

1) Input the instance $\vec{x}$, to the network and compute the output o_u of every unit u in the network.

Propagate the errors backward through the network:

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

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

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

$$\delta_h \leftarrow o_h(1-o_h)\sum_k w_{kh}\delta_k$$ — output

4) Update each N/w weight w_{ji}

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

$$\Delta w_{ji} = \eta \delta_j x_{i,j}$$

Output:

Epoch 0, Loss: 0.2780

Epoch 4000, Loss: 0.01056

Epoch 8000, Loss: 0.0026.

Prediction after training:-

[[0.0025864 85]

[0.95663227]

[0.95.61.3605],

[0.05425127]]

Code:

```
import numpy as np

class NeuralNetwork:
  def __init__(self, input_size, hidden_size, output_size):
    self.input_size = input_size
    self.hidden_size = hidden_size
    self.output_size = output_size

    # Initialize weights
    self.weights_input_hidden = np.random.randn(self.input_size, self.hidden_size)
    self.weights_hidden_output = np.random.randn(self.hidden_size, self.output_size)

    # Initialize the biases
    self.bias_hidden = np.zeros((1, self.hidden_size))
    self.bias_output = np.zeros((1, self.output_size))

  def sigmoid(self, x):
    return 1 / (1 + np.exp(-x))

  def sigmoid_derivative(self, x):
    return x * (1 - x)

  def feedforward(self, X):
    # Input to hidden
    self.hidden_activation = np.dot(X, self.weights_input_hidden) + self.bias_hidden
    self.hidden_output = self.sigmoid(self.hidden_activation)

    # Hidden to output
    self.output_activation = np.dot(self.hidden_output, self.weights_hidden_output) + self.bias_output
    self.predicted_output = self.sigmoid(self.output_activation)

    return self.predicted_output

  def backward(self, X, y, learning_rate):
    # Compute the output layer error
    output_error = y - self.predicted_output
    output_delta = output_error * self.sigmoid_derivative(self.predicted_output)

    # Compute the hidden layer error
    hidden_error = np.dot(output_delta, self.weights_hidden_output.T)
    hidden_delta = hidden_error * self.sigmoid_derivative(self.hidden_output)
```

```
    # Update weights and biases
    self.weights_hidden_output += np.dot(self.hidden_output.T, output_delta) * learning_rate
    self.bias_output += np.sum(output_delta, axis=0, keepdims=True) * learning_rate
    self.weights_input_hidden += np.dot(X.T, hidden_delta) * learning_rate
    self.bias_hidden += np.sum(hidden_delta, axis=0, keepdims=True) * learning_rate

  def train(self, X, y, epochs, learning_rate):
    for epoch in ran
      output = self.feedforward(X)
      self.backward(X, y, learning_rate)
      if epoch % 4000 == 0:
        loss = np.mean(np.square(y - output))
        print(f"Epoch {epoch}, Loss:{loss}")

X = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
y = np.array([[0], [1], [1], [0]])

nn = NeuralNetwork(input_size=2, hidden_size=4, output_size=1)
nn.train(X, y, epochs=10000, learning_rate=0.1)

# Test the trained model
output = nn.feedforward(X)
print("Predictions after training:")
print(output)
```

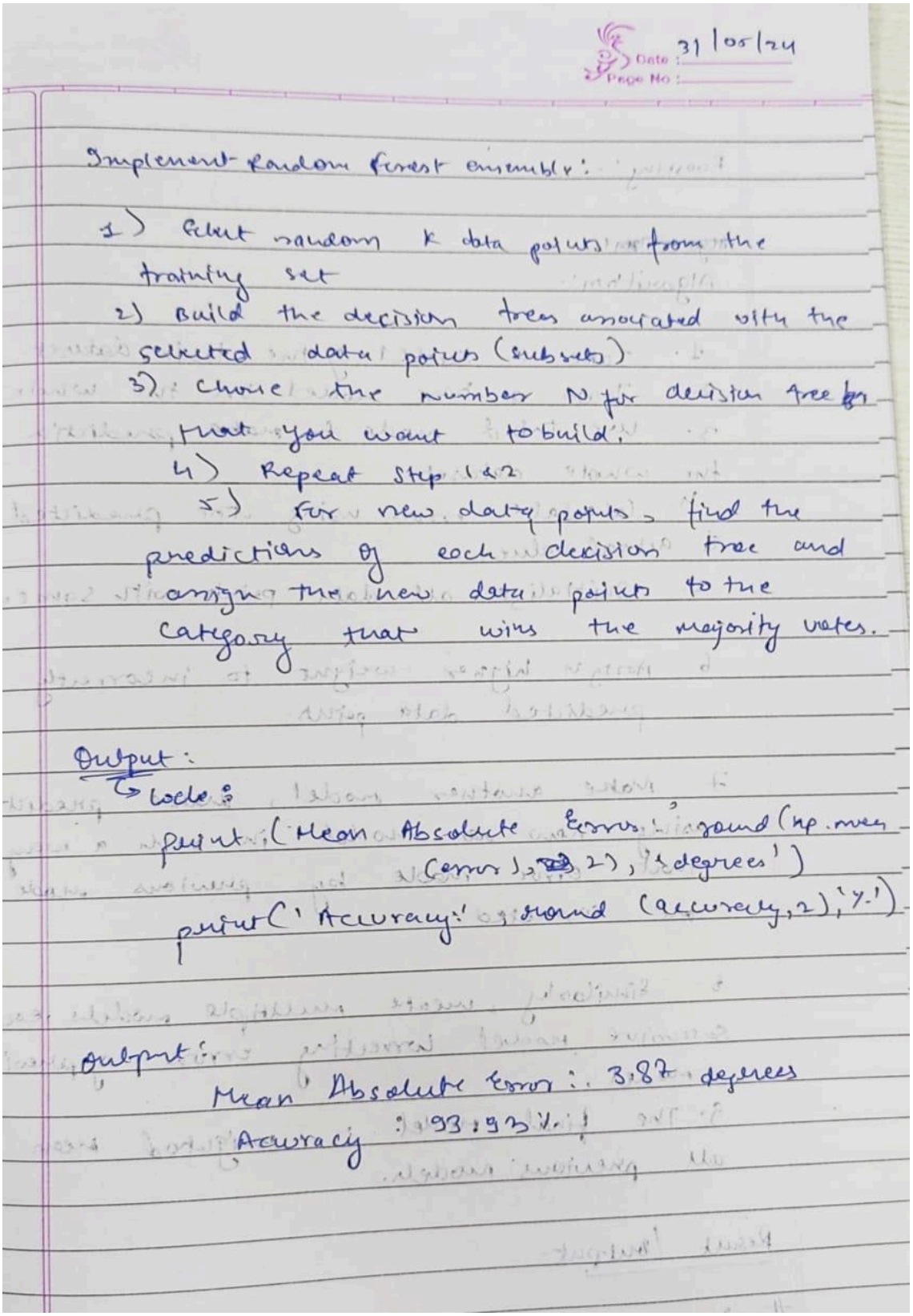
(method) feedforward: (X: Any) -> Any

```
Epoch 0, Loss:0.27464677774699536
Epoch 4000, Loss:0.007581868337942686
Epoch 8000, Loss:0.002423001703124975
Predictions after training:
[[0.03880939]
 [0.95944268]
 [0.95465187]
 [0.04336319]]
```

31.05.2024

2.a) Implement Random Forest ensemble method on a given dataset.

Screenshot:



Code:

+ Code + Text

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

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

Next steps: View recommended plots

```
[3] print('The shape of our features is:', features.shape)
    # The shape of our features is: (348, 9)
```

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

```
[4] # Descriptive statistics for each column
    features.describe()
```

	year	month	day	temp_2	temp_1	average	actual	forecast_noaa	forecast_acc	forecast_under	friend
count	348.0	348.000000	348.000000	348.000000	348.000000	348.000000	348.000000	348.000000	348.000000	348.000000	348.000000
mean	2016.0	6.477011	15.514368	62.652299	62.701149	59.760632	62.543103	57.238506	62.373563	59.772989	60.034483
std	0.0	3.498380	8.772982	12.165398	12.120542	10.527306	11.794146	10.605746	10.549381	10.705256	15.626179
min	2016.0	1.000000	1.000000	35.000000	35.000000	45.100000	35.000000	41.000000	46.000000	44.000000	28.000000
25%	2016.0	3.000000	8.000000	54.000000	54.000000	49.975000	54.000000	48.000000	53.000000	50.000000	47.750000
50%	2016.0	6.000000	15.000000	62.500000	62.500000	58.200000	62.500000	56.000000	61.000000	58.000000	60.000000
75%	2016.0	10.000000	23.000000	71.000000	71.000000	69.025000	71.000000	66.000000	72.000000	69.000000	71.000000
max	2016.0	12.000000	31.000000	117.000000	117.000000	77.400000	92.000000	77.000000	82.000000	79.000000	95.000000

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+ Code + Text

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

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

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

```
[7] # Using Skicit-learn to split data into training and testing sets
    from sklearn.model_selection import train_test_split
    # Split the data into training and testing sets
    train_features, test_features, train_labels, test_labels = train_test_split(features, labels, test_size = 0.25, random_state = 42)
```

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

+ Code + Text

[9]
```
Training Features Shape: (261, 17)
Training Labels Shape: (261,)
Testing Features Shape: (87, 17)
Testing Labels Shape: (87,)
```

[11]
```
# The baseline predictions are the historical averages
baseline_preds = test_features[:, feature_list.index('average')]
# Baseline errors, and display average baseline error
baseline_errors = abs(baseline_preds - test_labels)
print('Average baseline error: ', round(np.mean(baseline_errors), 2))
```

```
Average baseline error:  5.06
```

[12]
```
# Import the model we are using
from sklearn.ensemble import RandomForestRegressor
# Instantiate model with 1000 decision trees
rf = RandomForestRegressor(n_estimators = 1000, random_state = 42)
# Train the model on training data
rf.fit(train_features, train_labels);
```

[14]
```
# Use the forest's predict method on the test data
predictions = rf.predict(test_features)
# Calculate the absolute errors
errors = abs(predictions - test_labels)
# Print out the mean absolute error (mae)
print('Mean Absolute Error:', round(np.mean(errors), 2), 'degrees.')
```

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

[15]
```
# Calculate mean absolute percentage error (MAPE)
mape = 100 * (errors / test_labels)
# Calculate and display accuracy
accuracy = 100 - np.mean(mape)
print('Accuracy:', round(accuracy, 2), '%.')
```

```
Accuracy: 93.93 %.
```

+ Code + Text

5s [16]
```
# Import tools needed for visualization
from sklearn.tree import export_graphviz
import pydot
# Pull out one tree from the forest
tree = rf.estimators_[5]
# Import tools needed for visualization
from sklearn.tree import export_graphviz
import pydot
# Pull out one tree from the forest
tree = rf.estimators_[5]
# Export the image to a dot file
export_graphviz(tree, out_file = 'tree.dot', feature_names = feature_list, rounded = True, precision = 1)
# Use dot file to create a graph
(graph, ) = pydot.graph_from_dot_file('tree.dot')
# Write graph to a png file
graph.write_png('tree.png')
```

1s [17]
```
# Limit depth of tree to 3 levels
rf_small = RandomForestRegressor(n_estimators=10, max_depth = 3)
rf_small.fit(train_features, train_labels)
# Extract the small tree
tree_small = rf_small.estimators_[5]
# Save the tree as a png image
export_graphviz(tree_small, out_file = 'small_tree.dot', feature_names = feature_list, rounded = True, precision = 1)
(graph, ) = pydot.graph_from_dot_file('small_tree.dot')
graph.write_png('small_tree.png');
```

0s [18]
```
# Get numerical feature importances
importances = list(rf.feature_importances_)
# List of tuples with variable and importance
feature_importances = [(feature, round(importance, 2)) for feature, importance in zip(feature_list, importances)]
# Sort the feature importances by most important first
feature_importances = sorted(feature_importances, key = lambda x: x[1], reverse = True)
# Print out the feature and importances
[print('Variable: {:20} Importance: {}'.format(*pair)) for pair in feature_importances];
```

```
Variable: temp_1              Importance: 0.66
Variable: average             Importance: 0.15
Variable: forecast_noaa       Importance: 0.05
Variable: forecast_acc        Importance: 0.03
Variable: day                 Importance: 0.02
```

+ Code + Text

[18]
```
Variable: temp_1               Importance: 0.66
Variable: average              Importance: 0.15
Variable: forecast_noaa        Importance: 0.05
Variable: forecast_acc         Importance: 0.03
Variable: day                  Importance: 0.02
Variable: temp_2               Importance: 0.02
Variable: forecast_under       Importance: 0.02
Variable: friend               Importance: 0.02
Variable: month                Importance: 0.01
Variable: year                 Importance: 0.0
Variable: week_Fri             Importance: 0.0
Variable: week_Mon             Importance: 0.0
Variable: week_Sat             Importance: 0.0
Variable: week_Sun             Importance: 0.0
Variable: week_Thurs           Importance: 0.0
Variable: week_Tues            Importance: 0.0
Variable: week_Wed             Importance: 0.0
```

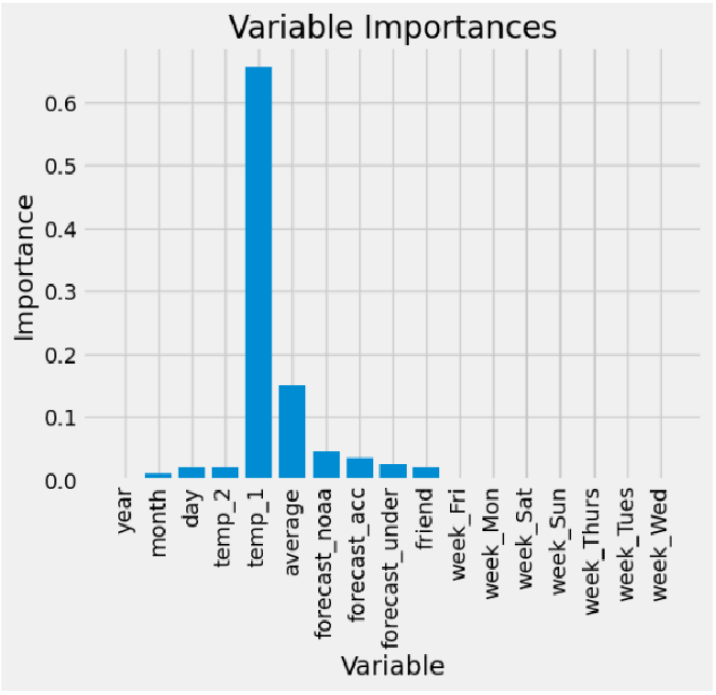
```
# New random forest with only the two most important variables
rf_most_important = RandomForestRegressor(n_estimators= 1000, random_state=42)
# Extract the two most important features
important_indices = [feature_list.index('temp_1'), feature_list.index('average')]
train_important = train_features[:,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

```
Mean Absolute Error: 3.92 degrees.
Accuracy: 93.76 %.
```

[20]
```
# Import matplotlib for plotting and use magic command for Jupyter Notebooks
import matplotlib.pyplot as plt
%matplotlib inline
# Set the style
```

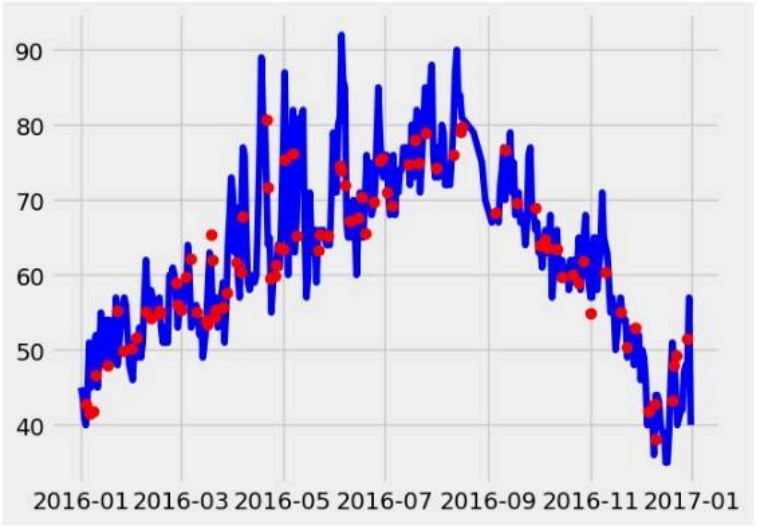
+ Code + Text

```
# Import matplotlib for plotting and use magic command for Jupyter Notebooks
import matplotlib.pyplot as plt
%matplotlib inline
# Set the style
plt.style.use('fivethirtyeight')
# list of x locations for plotting
x_values = list(range(len(importances)))
# Make a bar chart
plt.bar(x_values, importances, orientation = 'vertical')
# Tick labels for x axis
plt.xticks(x_values, feature_list, rotation='vertical')
# Axis labels and title
plt.ylabel('Importance'); plt.xlabel('Variable'); plt.title('Variable Importances');
```



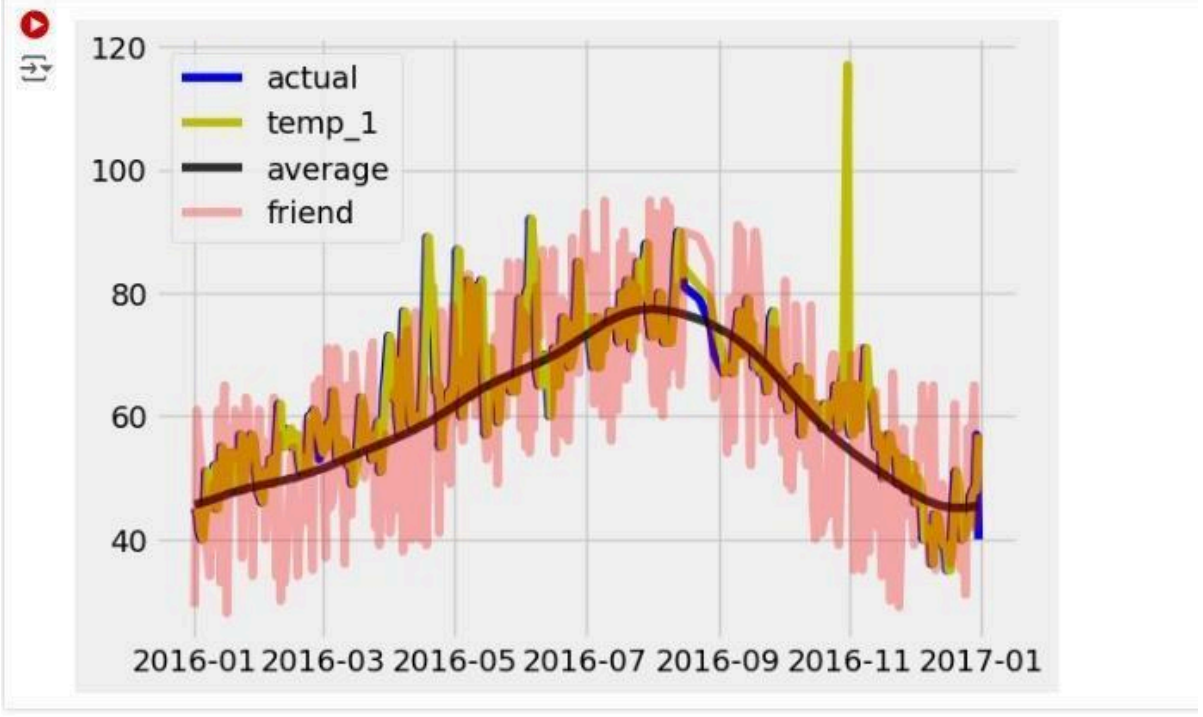
+ Code + Text

```
# Use datetime for creating date objects for plotting
import datetime
# Dates of training values
months = features[:, feature_list.index('month')]
days = features[:, feature_list.index('day')]
years = features[:, feature_list.index('year')]
# List and then convert to datetime object
dates = [str(int(year)) + '-' + str(int(month)) + '-' + str(int(day)) for year, month, day in zip(years, months, days)]
dates = [datetime.datetime.strptime(date, '%Y-%m-%d') for date in dates]
# Dataframe with true values and dates
true_data = pd.DataFrame(data = {'date': dates, 'actual': labels})
# Dates of predictions
months = test_features[:, feature_list.index('month')]
days = test_features[:, feature_list.index('day')]
years = test_features[:, feature_list.index('year')]
# Column of dates
test_dates = [str(int(year)) + '-' + str(int(month)) + '-' + str(int(day)) for year, month, day in zip(years, months, days)]
# Convert to datetime objects
test_dates = [datetime.datetime.strptime(date, '%Y-%m-%d') for date in test_dates]
# Dataframe with predictions and dates
predictions_data = pd.DataFrame(data = {'date': test_dates, 'prediction': predictions})
# Plot the actual values
plt.plot(true_data['date'], true_data['actual'], 'b-', label = 'actual')
# Plot the predicted values
plt.plot(predictions_data['date'], predictions_data['prediction'], 'ro', label = 'prediction')
plt.xticks(rotation = '60');
plt.legend()
# Graph labels
plt.xlabel('Date'); plt.ylabel('Maximum Temperature (F)'); plt.title('Actual and Predicted Values');
```




```
# Make the data accessible for plotting
true_data['temp_1'] = features[:, feature_list.index('temp_1')]
true_data['average'] = features[:, feature_list.index('average')]
true_data['friend'] = features[:, feature_list.index('friend')]
# Plot all the data as lines
plt.plot(true_data['date'], true_data['actual'], 'b-', label  = 'actual', alpha = 1.0)
plt.plot(true_data['date'], true_data['temp_1'], 'y-', label  = 'temp_1', alpha = 1.0)
plt.plot(true_data['date'], true_data['average'], 'k-', label = 'average', alpha = 0.8)
plt.plot(true_data['date'], true_data['friend'], 'r-', label = 'friend', alpha = 0.3)
# Formatting plot
plt.legend()
plt.xticks(rotation = '60')
# Lables and title
plt.xlabel('Date'); plt.ylabel('Maximum Temperature (F)'); plt.title('Actual Max Temp and Variables');
```

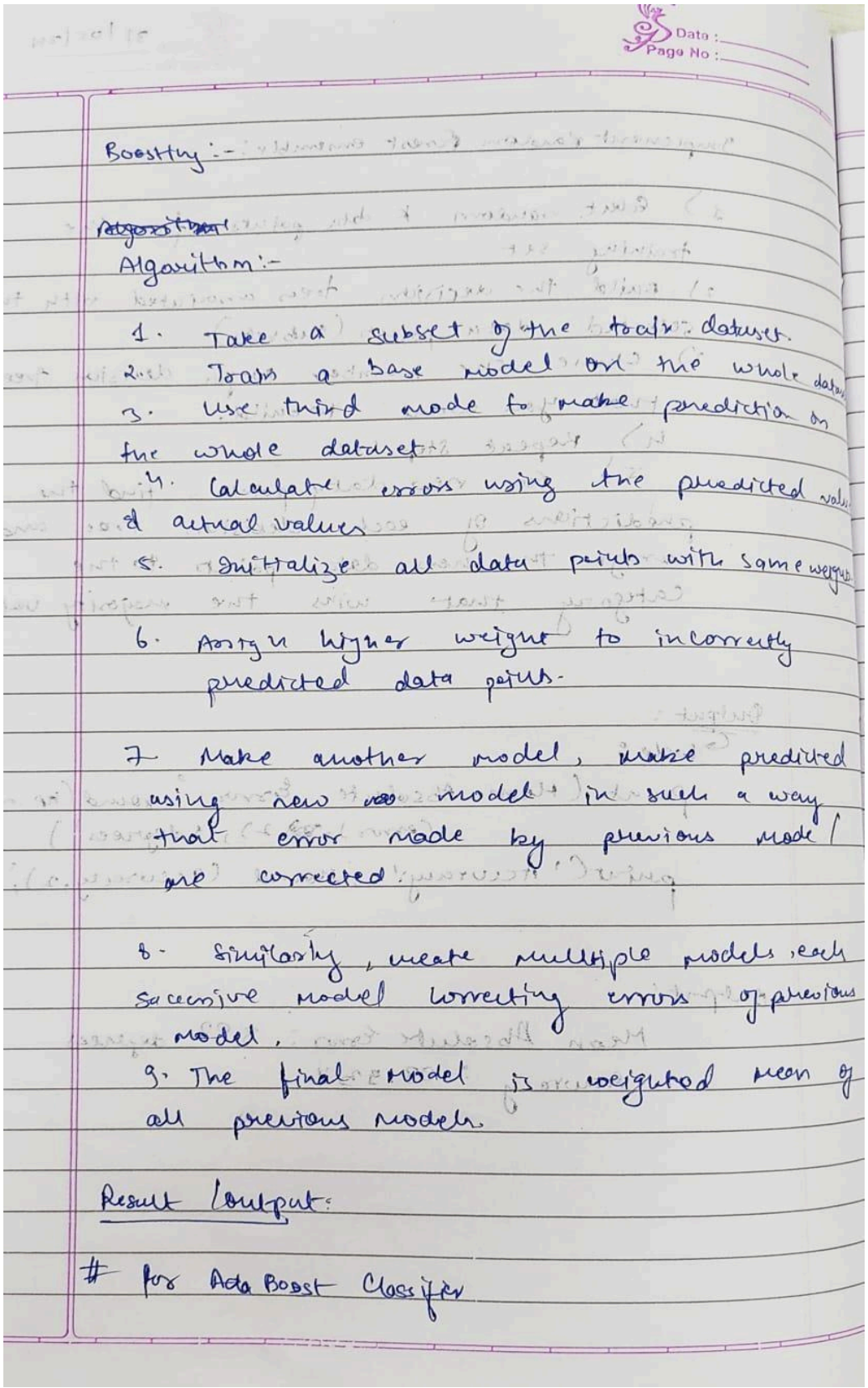
+ Code + Text


120
100
80
60
40
actual
temp_1
average
friend
2016-01
2016-03
2016-05
2016-07
2016-09
2016-11
2017-01

31.05.2024

b) Implement Boosting ensemble method on a given dataset

Screenshot:



Boosting :-

Algorithm :-

1. Take a subset of the train dataset.
2. Train a base model on the whole dataset.
3. Use trained model to make prediction on the whole dataset.
4. Calculate errors using the predicted values and actual values.
5. Initialize all data points with same weights.
6. Assign higher weight to incorrectly predicted data points.
7. Make another model, make predicted using new model in such a way that error made by previous model are corrected.
8. Similarly, create multiple models, each successive model correcting errors of previous model.
9. The final model is weighted mean of all previous models.

Result / output :

for Ada Boost Classifier

Date :
Page No :

Training Result

Confusion Matrix

[[310, 39 -
51, 137]]

Accuracy Score : 0.8324

Testing results :

Confusion Matrix

([[123 28
27 53])

Accuracy score : 0.7619

For Gradient Boosting Classifier :-

Training Result :

Confusion Matrix

[[[342 7
19 169]])

Accuracy Score : 0.9516

Training Result :

Confusion Matrix

[[116 35
26 54]]

Accuracy Score : 0.735

Code:

+ Code + Text

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

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

```
[3] df = pd.read_csv("diabetes.csv")
df.head()
```

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

Next steps: View recommended plots

```
[4] df.info()
```

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

```
[5] df.isnull().sum()
```

```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

```
[5] df.isnull().sum()
```

```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

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

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

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

```
[8] df.columns
```

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

[9]
```
# How many missing zeros are mising in each feature
feature_columns = [
    'Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness',
    'Insulin', 'BMI', 'DiabetesPedigreeFunction', 'Age'
]

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

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

[10]
```
from sklearn.impute import SimpleImputer


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

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

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

+ Code + Text

[11]
```
from sklearn.model_selection import train_test_split


X = df[feature_columns]
y = df.Outcome

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

[12]
```
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report


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

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

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

```
# AdaBoostClassifier
from sklearn.ensemble import AdaBoostClassifier

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

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

+ Code + Text

```
                0     1  accuracy  macro avg  weighted avg
precision    0.82  0.65      0.76       0.74          0.76
recall       0.81  0.66      0.76       0.74          0.76
f1-score     0.82  0.66      0.76       0.74          0.76
support    151.00 80.00      0.76     231.00        231.00
```

```
# Gradient Boosting Classifier
from sklearn.ensemble import GradientBoostingClassifier

grad_boost_clf = GradientBoostingClassifier(n_estimators=100, random_state=42)
grad_boost_clf.fit(X_train, y_train)
evaluate(grad_boost_clf, X_train, X_test, y_train, y_test)
```

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