PES Institute of Technology and Management

Department of Computer Science & Design

Laboratory Manual

Semester: VI

Subject: Machine Learning Lab

Subject Code: BCSL606

Compiled By:

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PROGRAM OUTCOMES

PO's	PO Description
PO1	**Engineering knowledge**: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
PO2	**Problem analysis:** Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.
PO3	**Design/development of solutions**: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
PO4	**Conduct investigations of complex problems:** Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
PO5	**Modern tool usage:** Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.
PO6	**The engineer and society:** Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.
PO7	**Environment and sustainability:** Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.
PO8	**Ethics:** Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
PO9	**Individual and team work**: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.
PO10	**Communication:** Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
PO11	**Project management and finance**: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.
PO12	**Life-long learning:** Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

PROGRAM SPECIFIC OUTCOMES

PSO's	PSO Description
PSO1	An ability to design and analyze algorithms by applying theoretical concepts to build complex and computer- based systems in the domain of System Software, Computer Networks & Security, Web technologies, Data Science and Analytics.
PSO2	Be able to develop various software solutions by applying the techniques of Data Base Management, Complex Mathematical Models, Software Engineering practices and Machine Learning with Artificial Intelligence.

	Machine Learning lab	Semester	6
Course Code	BCSL606	CIE Marks	50
Teaching Hours/Week (L:T:P: S)	0:0:2:0	SEE Marks	50
Credits	01	Exam Hours	100
Examination type (SEE)	Practical		

Course objectives:

1. To become familiar with data and visualize univariate, bivariate, and multivariate data using statistical techniques and dimensionality reduction.
2. To understand various machine learning algorithms such as similarity-based learning, regression, decision trees, and clustering.
3. To familiarize with learning theories, probability-based models and developing the skills required for decision-making in dynamic environments.

Sl.NO	Experiments
1	Develop a program to create histograms for all numerical features and analyze the distribution of each feature. Generate box plots for all numerical features and identify any outliers. Use California Housing dataset. **Book 1: Chapter 2**
2	Develop a program to Compute the correlation matrix to understand the relationships between pairs of features. Visualize the correlation matrix using a heatmap to know which variables have strong positive/negative correlations. Create a pair plot to visualize pairwise relationships between features. Use California Housing dataset. **Book 1: Chapter 2**
3	Develop a program to implement Principal Component Analysis (PCA) for reducing the dimensionality of the Iris dataset from 4 features to 2. **Book 1: Chapter 2**
4	For a given set of training data examples stored in a .CSV file, implement and demonstrate the Find-S algorithm to output a description of the set of all hypotheses consistent with the training examples. **Book 1: Chapter 3**
5	Develop a program to implement k-Nearest Neighbour algorithm to classify the randomly generated 100 values of x in the range of [0,1]. Perform the following based on dataset generated. 1. Label the first 50 points *[x1,......,xsoj* aS follows: if (xi s 0.5), then x; e Classi, else x, e Classi 2. Classify the remaining points, *X51,......,xi oo* using KNN. Perform this for *k——1,2,3,4,5,20,30* **Book 2: Chapter -** 2
6	Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs **Book 1: Chapter** — 4
7	Develop a program to demonstrate the working of Linear Regression and Polynomial Regression. Use Boston Housing Dataset for Linear Regression and Auto MPG Dataset (for vehicle fuel efficiency prediction) for Polynomial Regression. **Book 1: Chapter** — 5
8	Develop a program to demonstrate the working of the decision tree algorithm. Use Breast Cancer Data set for building the decision tree and apply this knowledge to classify a new sample. **Book 2: Chapter** — 3

9	Develop a program to implement the Naive Bayesian classifier considering Olivetti Face Data set for training. Compute the accuracy of the classifier, considering a few test data sets. **Book 2: Chapter** — 4
10	Develop a program to implement k-means clustering using Wisconsin Breast Cancer data set and visualize the clustering result. **Book 2: Chapter -** 4

Course outcomes (Course Skill Set):

At the end of the course the student will be able to:

1. Illustrate the principles of multivariate data and apply dimensionality reduction techniques.
2. Demonstrate similarity-based learning methods and perform regression analysis.
3. Develop decision trees for classification and regression problems, and Bayesian models for probabilistic learning.
1. Implement the clustering algorithms to share computing resources.

Assessment Details (both CIE and SEE)

The weightage of Continuous Internal Evaluation (CIE) is 50% and for Semester End Exam (SEE) is 50%. The minimum passing mark for the CIE is 40% of the maximum marks (20 marks out of 50) and for the SEE minimum passing mark is 35% of the maximum marks (18 out of 50 marks). A student shall be deemed to have satisfied the academic requirements and earned the credits allotted to each subject/ course if the student secures a minimum of 40% (40 marks out of 100) in the sum total of the CIE (Continuous Internal Evaluation) and SEE (Semester End Examination) taken together

Continuous Internal Evaluation (CIE):

CIE marks for the practical course are **50 Marks.**

The split-up of CIE marks for record/ journal and test are in the ratio **60:40.**

Each experiment is to be evaluated for conduction with an observation sheet and record write-up. Rubrics for the evaluation of the journal/write-up for hardware/software experiments are designed by the faculty who is handling the laboratory session and are made known to students at the beginning of the practical session.

Record should contain all the specified experiments in the syllabus and each experiment write-up will be evaluated for 10 marks.

Total marks scored by the students are scaled down to **30 marks** (60% of maximum marks).

Weightage to be given for neatness and submission of record/write-up on time.

Department shall conduct a test of 100 marks after the completion of all the experiments listed in the syllabus.

In a test, test write-up, conduction of experiment, acceptable result, and procedural knowledge will carry a weightage of 60% and the rest 40% for viva-voce.

The suitable rubrics can be designed to evaluate each student's performance and learning ability.

The marks scored shall be scaled down to **20 marks** (40% of the maximum marks).

The Sum of scaled-down marks scored in the report write-up/journal and marks of a test is the total CIE marks scored by the student.

Semester End Evaluation (SEE):

1. SEE marks for the practical course are 50 Marks.
2. SEE shall be conducted jointly by the two examiners of the same institute, examiners are appointed by the Head of the Institute.
3. The examination schedule and names of examiners are informed to the university before the conduction of the examination. These practical examinations are to be conducted between the schedule mentioned in the academic calendar of the University.
4. All laboratory experiments are to be included for practical examination.

5. (Rubrics) Breakup of marks and the instructions printed on the cover page of the answer script to be strictly adhered to by the examiners. OR based on the course requirement evaluation rubrics shall be decided jointly by examiners.

6. Students can pick one question (experiment) from the questions lot prepared by the examiners jointly.

7. Evaluation of test write-up/ conduction procedure and result/viva will be conducted jointly by examiners.

General rubrics suggested for SEE are mentioned here, writeup-20%, Conduction procedure and result in -60%, Viva-voce 20% of maximum marks. SEE for practical shall be evaluated for 100 marks and scored marks shall be scaled down to 50 marks (however, based on course type, rubrics shall be decided by the examiners)

Change of experiment is allowed only once and 15% of Marks allotted to the procedure part are to be made zero.

The minimum duration of SEE is 02 hours

Suggested Learning Resources:
Books:

1. S Sridhar and M Vijayalakshmi, "Machine Learning", Oxford University Press, 2021.
2. M N Murty and Ananthanarayana V S, "Machine Learning: Theory and Practice", Universities Press (India) Pvt. Limited, 2024.

Web links and Video Lectures (e-Resources):

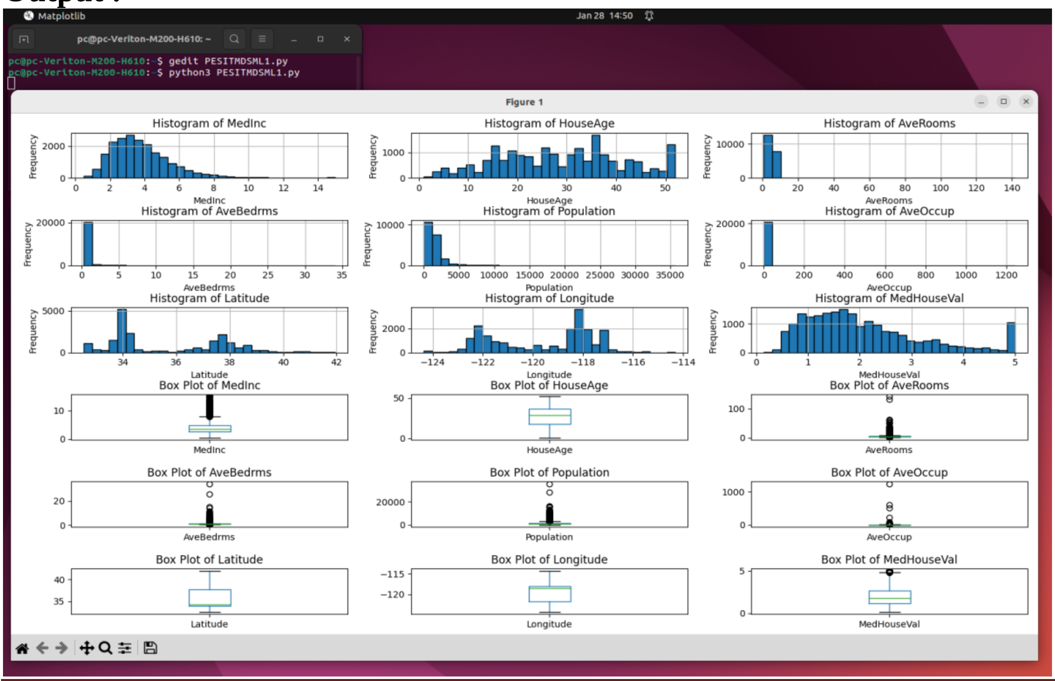
1. https://www.drssridhar.com/?page_id=1053
2. https://www.universitiespress.com/resources?id=9789393330697
3. https://onlinecourses.nptel.ac.in/noc23_cs18/preview

1. Develop a program to create histograms for all numerical features and analyze the distribution of each feature. Generate box plots for all numerical features and identify any outliers. Use California Housing dataset.

Python Code:

```
import matplotlib
matplotlib.use('TkAgg')  # Use TkAgg backend
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import fetch_california_housing
# Load the California Housing Dataset
data = fetch_california_housing(as_frame=True)
df = data.frame
# Set up the grid layout
n_columns = 3
n_rows = (len(df.select_dtypes(include=['float64', 'int64']).columns) * 2 + n_columns - 1) // n_columns
fig, axes = plt.subplots(n_rows, n_columns, figsize=(15, 10))
axes = axes.flatten()
# Create plots
columns = df.select_dtypes(include=['float64', 'int64']).columns
for i, column in enumerate(columns):
    # Histogram
    ax = axes[i]
    df[column].hist(bins=30, edgecolor='black', ax=ax)
    ax.set(title=f"Histogram of {column}", xlabel=column, ylabel="Frequency")
    # Box Plot
    ax = axes[len(columns) + i]
    df.boxplot(column=column, grid=False, ax=ax)
    ax.set(title=f"Box Plot of {column}")
# Adjust layout and display
plt.tight_layout()
plt.savefig("combined_plots.png")
plt.show()
```

Output :

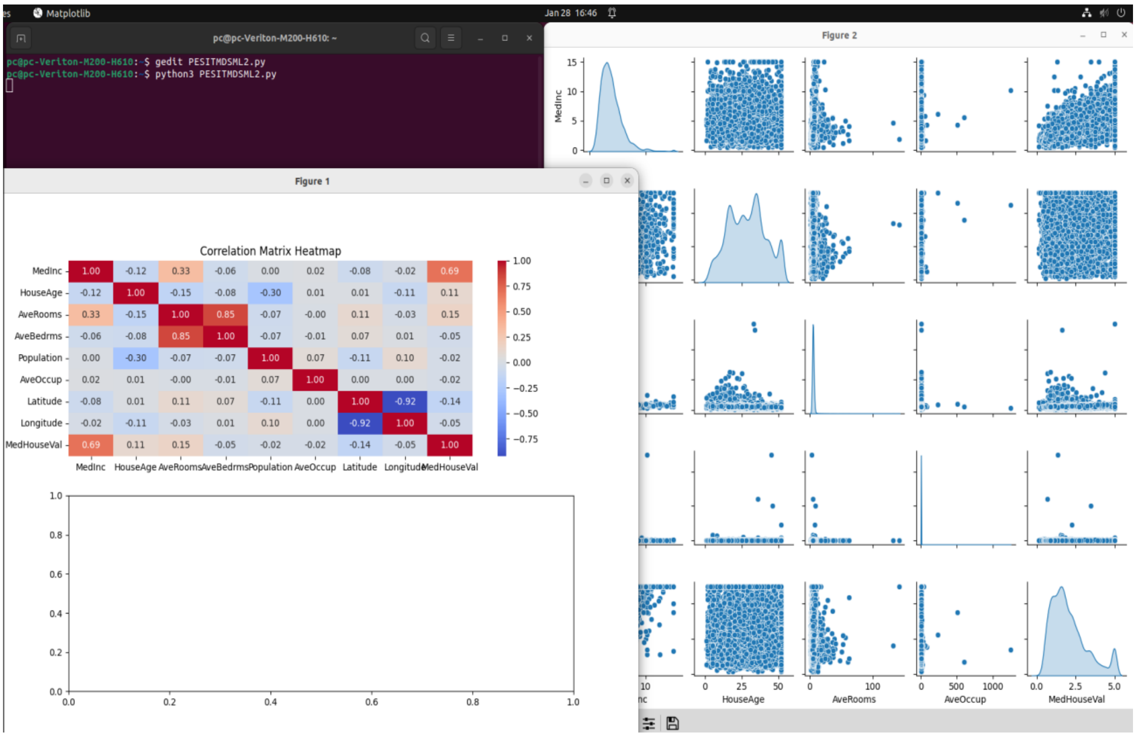


2. Develop a program to Compute the correlation matrix to understand the relationships between pairs of features. Visualize the correlation matrix using a heatmap to know which variables have strong positive/negative correlations. Create a pair plot to visualize pairwise relationships between features. Use California Housing dataset.

Python Code:

```
import matplotlib
matplotlib.use('TkAgg')  # Use TkAgg backend
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.datasets import fetch_california_housing

# Load the dataset
df = fetch_california_housing(as_frame=True).frame

# Set up the grid layout for plots (2 rows, 1 column)
fig, axes = plt.subplots(2, 1, figsize=(12, 12))

# Heatmap of correlation matrix (Top plot)
sns.heatmap(df.corr(), annot=True, fmt=".2f", cmap="coolwarm", cbar=True, ax=axes[0])
axes[0].set_title("Correlation Matrix Heatmap")

# Pair plot for selected features (Bottom plot)
sns.pairplot(df[['MedInc', 'HouseAge', 'AveRooms', 'AveOccup', 'MedHouseVal']], diag_kind="kde")
plt.subplots_adjust(hspace=0.4)  # Adjust space between subplots

# Show the combined figure
plt.show()
```

Output:

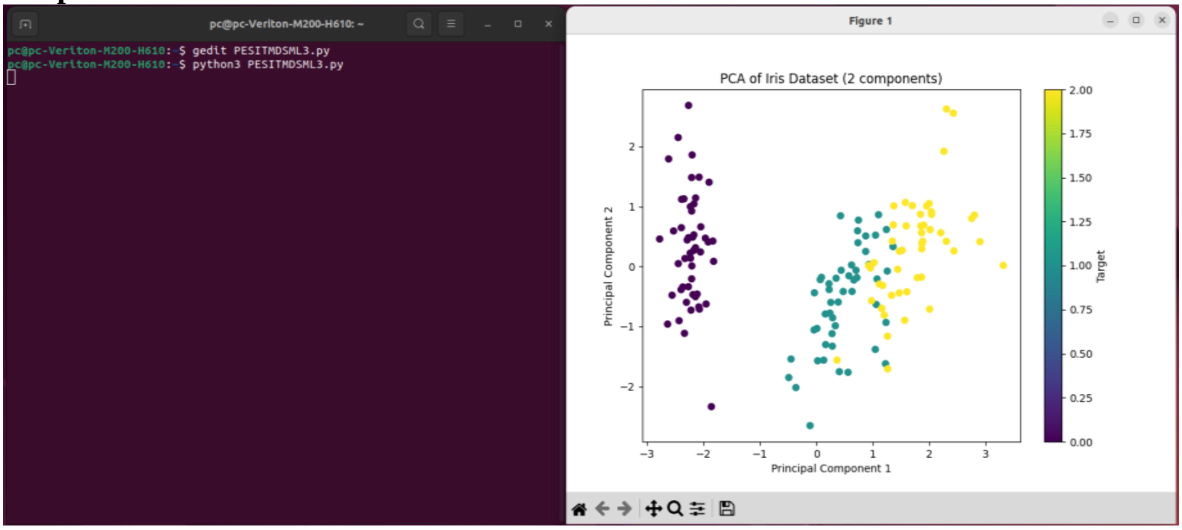


3. Develop a program to implement Principal Component Analysis (PCA) for reducing the dimensionality of the Iris dataset from 4 features to 2.

Python Code:

```
import matplotlib
matplotlib.use('TkAgg')  # Use TkAgg backend
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
from sklearn.datasets import load_iris
from sklearn.preprocessing import StandardScaler

# Load the Iris dataset
iris = load_iris()
df = pd.DataFrame(iris.data, columns=iris.feature_names)

# Standardize the features (important for PCA)
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df)

# Apply PCA to reduce to 2 dimensions
pca = PCA(n_components=2)
pca_result = pca.fit_transform(scaled_data)

# Create a DataFrame for the 2 principal components
pca_df = pd.DataFrame(pca_result, columns=['PC1', 'PC2'])

# Visualize the result
plt.figure(figsize=(8, 6))
plt.scatter(pca_df['PC1'], pca_df['PC2'], c=iris.target, cmap='viridis')
plt.title("PCA of Iris Dataset (2 components)")
plt.xlabel("Principal Component 1")
plt.ylabel("Principal Component 2")
plt.colorbar(label='Target')
plt.show()
```

Output:



4. For a given set of training data examples stored in a .CSV file, implement and demonstrate the Find-S algorithm to output a description of the set of all hypotheses consistent with the training examples.

Python Code:

```
import pandas as pd

# Load the dataset
df = pd.read_csv('training_data.csv')

# Assume the last column is the class (target variable)
X = df.iloc[:, :-1]  # Features (all columns except the last)
y = df.iloc[:, -1]   # Class (the last column)

# Find-S algorithm
def find_s_algorithm(X, y):
    # Initialize the hypothesis to the most general hypothesis (all attributes can be anything)
    hypothesis = ['?' for _ in range(X.shape[1])]

    # Loop through all examples in the dataset
    for i in range(len(X)):
        if y[i] == 'Yes':  # If the example is a positive example
            for j in range(len(X.columns)):
                # If the hypothesis is still general or the feature matches the example, keep it
                if hypothesis[j] == '?' or hypothesis[j] == X.iloc[i, j]:
                    hypothesis[j] = X.iloc[i, j]
                # If the feature doesn't match, make it specific to the example
                else:
                    hypothesis[j] = '?'
    return hypothesis

# Get the most specific hypothesis
hypothesis = find_s_algorithm(X, y)

# Output the hypothesis
print("Hypothesis consistent with the positive examples:", hypothesis)
```

Output:

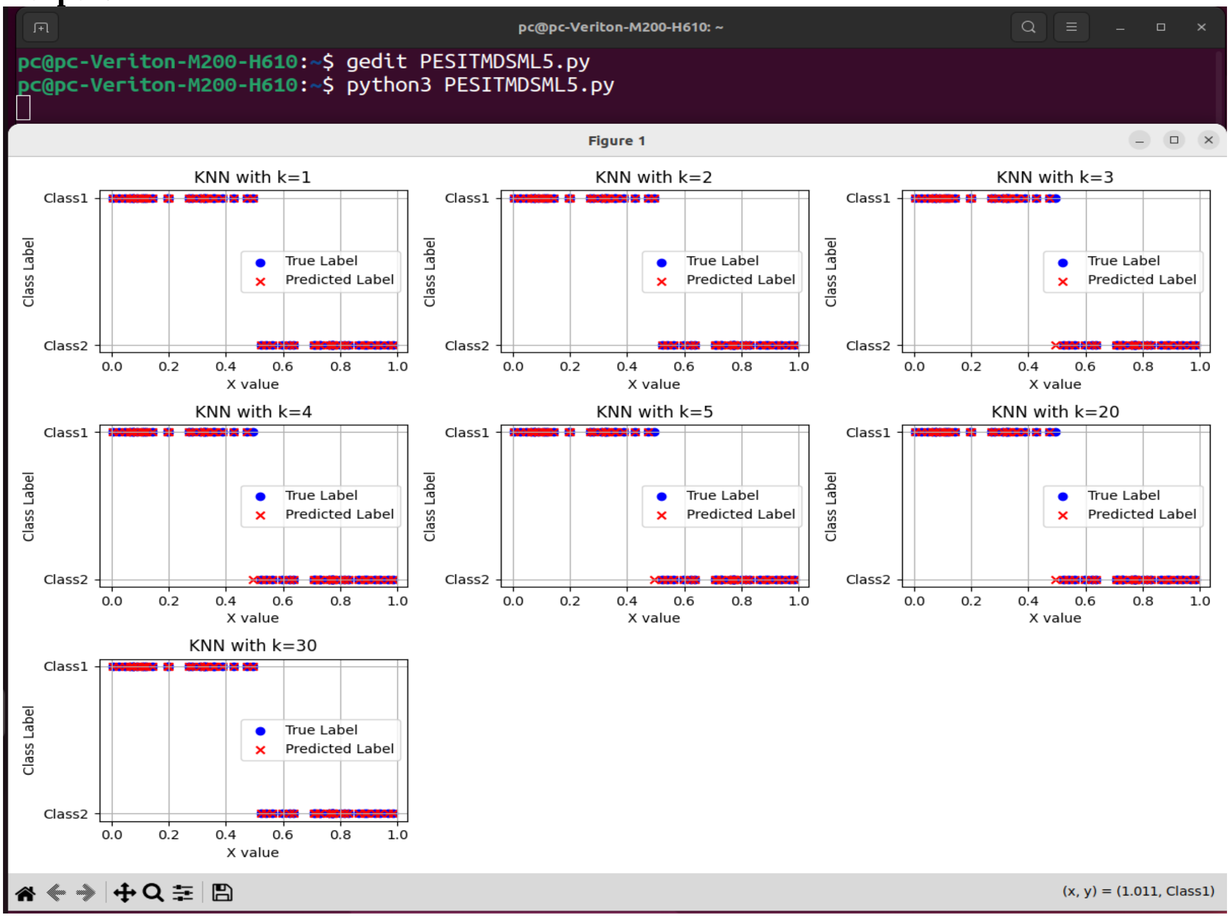
5. Develop a program to implement k-Nearest Neighbour algorithm to classify the randomly generated 100 values of x in the range of [0,1]. Perform the following based on dataset generated.
1.Label the first 50 points [x1,. ,xsoj aS follows: if (xi s 0.5), then x; e Classi, else x, e Classi
2.Classify the remaining points, X51,......,xi oo using KNN. Perform this for k——1,2,3,4,5,20,30

Python Code:

```
import matplotlib
matplotlib.use('TkAgg')  # Use the TkAgg backend for stable display

import numpy as np
import matplotlib.pyplot as plt
from sklearn.neighbors import KNeighborsClassifier

# Step 1: Generate 100 random values of x in the range [0, 1]
np.random.seed(42)  # For reproducibility
x_values = np.random.rand(100, 1)  # 100 random values in the range [0,1]

# Step 2: Label the first 50 points as Class1 and the rest as Class2
y_labels = np.array(['Class1' if x <= 0.5 else 'Class2' for x in x_values.flatten()])

# Split into training and testing sets
X_train = x_values[:50]  # First 50 points
y_train = y_labels[:50]  # First 50 labels
X_test = x_values[50:]   # Remaining 50 points
y_test = y_labels[50:]   # Remaining 50 labels

# Step 3: Classify using KNN for different k values
k_values = [1, 2, 3, 4, 5, 20, 30]
plt.figure(figsize=(12, 8))

for i, k in enumerate(k_values, 1):
    # Initialize the k-NN classifier with the current k value
    knn = KNeighborsClassifier(n_neighbors=k)

    # Fit the model on the training data
    knn.fit(X_train, y_train)

    # Predict the labels for the test set
    y_pred = knn.predict(X_test)

    # Plot the decision boundary and the points
    plt.subplot(3, 3, i)
    plt.scatter(X_test, y_test, color='blue', label='True Label')
    plt.scatter(X_test, y_pred, color='red', marker='x', label='Predicted Label')

    plt.title(f"KNN with k={k}")
    plt.xlabel("X value")
    plt.ylabel("Class Label")
    plt.legend(loc='best')
    plt.grid(True)

# Display the plots
```

```
plt.tight_layout()
plt.show()

# Step 4: Evaluate classification accuracy for each k value
for k in k_values:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
    accuracy = knn.score(X_test, y_test)
    print(f"Accuracy for k={k}: {accuracy:.2f}")
```

Output:



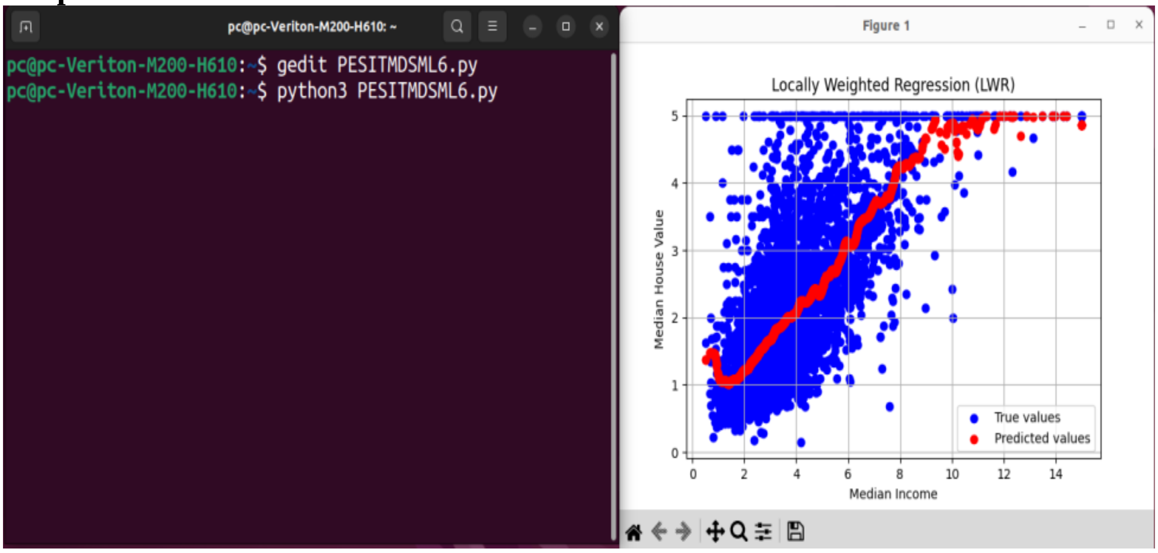

```
pc@pc-Veriton-M200-H610: ~
pc@pc-Veriton-M200-H610:~$ gedit PESITMDSML5.py
pc@pc-Veriton-M200-H610:~$ python3 PESITMDSML5.py
Accuracy for k=1: 1.00
Accuracy for k=2: 1.00
Accuracy for k=3: 0.98
Accuracy for k=4: 0.98
Accuracy for k=5: 0.98
Accuracy for k=20: 0.98
Accuracy for k=30: 1.00
pc@pc-Veriton-M200-H610:~$
```

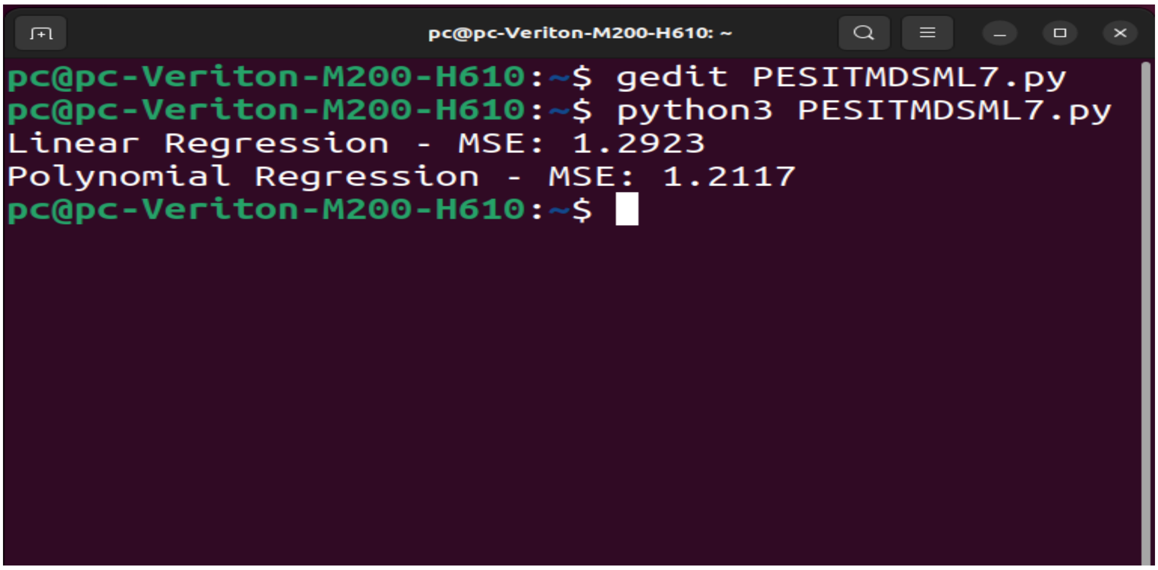
6. Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.

Python Code:

```
import matplotlib
matplotlib.use('TkAgg')  # Use TkAgg backend for interactive plotting
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split

# Load the dataset and select a feature
data = fetch_california_housing(as_frame=True)
df = data.frame
X = df['MedInc'].values.reshape(-1, 1)
y = df['MedHouseVal'].values

# Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Locally Weighted Regression (LWR)
def locally_weighted_regression(X_train, y_train, X_test, tau=0.1):
    predictions = []
    for x in X_test:
        weights = np.exp(-np.sum((X_train - x) ** 2, axis=1) / (2 * tau ** 2))
        X_train_b = np.c_[np.ones((X_train.shape[0], 1)), X_train]

        # Solve the weighted least squares problem using np.linalg.lstsq for efficiency
        theta, _, _, _ = np.linalg.lstsq(X_train_b * weights[:, np.newaxis], y_train * weights, rcond=None)

        # Make prediction for the current test point
        X_test_b = np.c_[1, x]  # Add bias term
        predictions.append(X_test_b @ theta)
    return np.array(predictions)

# Predict values for the test set
y_pred = locally_weighted_regression(X_train, y_train, X_test, tau=0.1)

# Plot results
plt.scatter(X_test, y_test, color='blue', label='True values')
plt.scatter(X_test, y_pred, color='red', label='Predicted values')
plt.xlabel('Median Income')
plt.ylabel('Median House Value')
plt.title('Locally Weighted Regression (LWR)')
plt.legend()
plt.grid(True)

# Show plot (interactive window)
plt.show()
# Evaluate performance
mse = np.mean((y_pred - y_test) ** 2)
print(f"Mean Squared Error: {mse:.4f}")
```

Output:





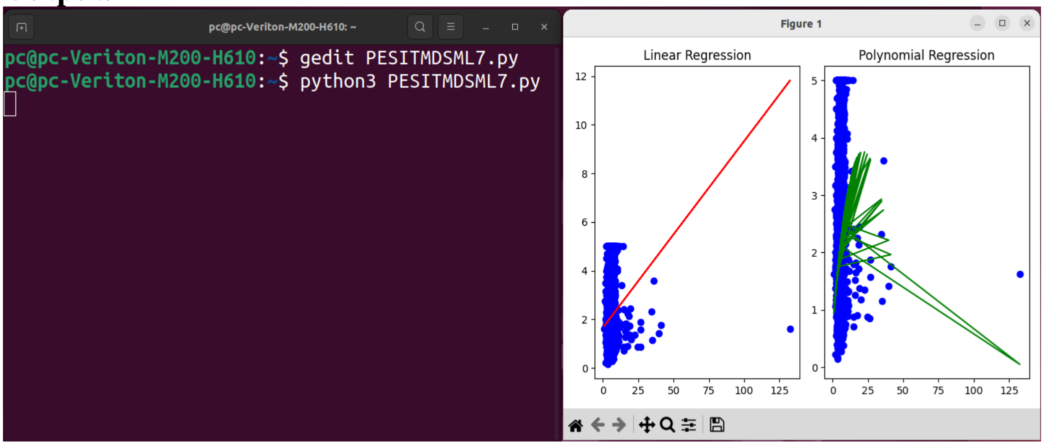
7. Develop a program to demonstrate the working of Linear Regression and Polynomial Regression. Use Boston Housing Dataset for Linear Regression and Auto MPG Dataset (for vehicle fuel efficiency prediction) for Polynomial Regression.

Python Code:

```
import numpy as np
import pandas as pd
import matplotlib
matplotlib.use('TkAgg')  # Use TkAgg backend
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.datasets import fetch_california_housing
# Load California Housing dataset for Linear Regression
data = fetch_california_housing(as_frame=True)
X = data.data[['AveRooms']]
```

```
y = data.target
# Split dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
# Linear Regression
linear_reg = LinearRegression()
linear_reg.fit(X_train, y_train)
y_pred = linear_reg.predict(X_test)
# Polynomial Regression
poly = PolynomialFeatures(degree=3)
X_poly = poly.fit_transform(X_train)
poly_reg = LinearRegression()
poly_reg.fit(X_poly, y_train)
y_pred_poly = poly_reg.predict(poly.fit_transform(X_test))
# Plotting results
plt.subplot(1, 2, 1)
plt.scatter(X_test, y_test, color='blue')
plt.plot(X_test, y_pred, color='red')
plt.title('Linear Regression')
plt.subplot(1, 2, 2)
plt.scatter(X_test, y_test, color='blue')
plt.plot(X_test, y_pred_poly, color='green')
plt.title('Polynomial Regression')
plt.tight_layout()
plt.show()
# Output MSE
print(f"Linear Regression - MSE: {mean_squared_error(y_test, y_pred):.4f}")
print(f"Polynomial Regression - MSE: {mean_squared_error(y_test, y_pred_poly):.4f}")
```

Output:



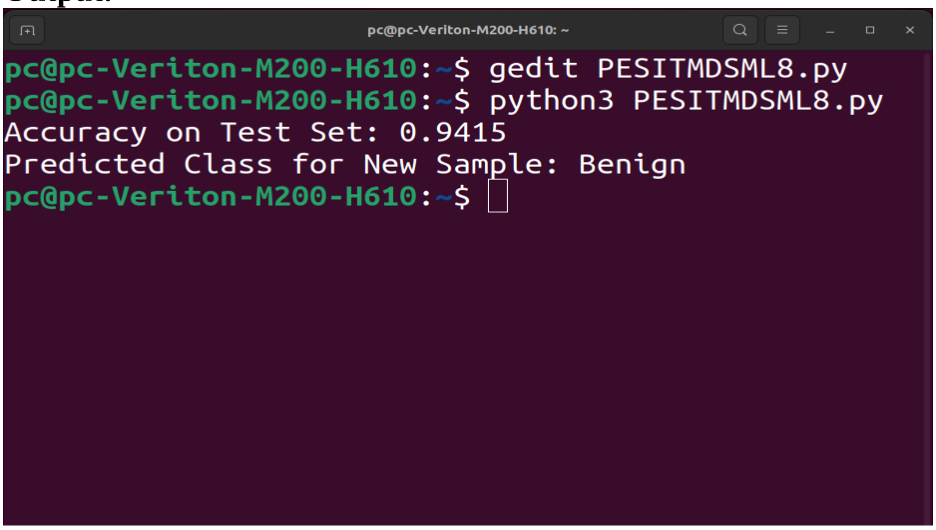

```
pc@pc-Veriton-M200-H610: ~
pc@pc-Veriton-M200-H610:~$ gedit PESITMDSML7.py
pc@pc-Veriton-M200-H610:~$ python3 PESITMDSML7.py
Linear Regression - MSE: 1.2923
Polynomial Regression - MSE: 1.2117
pc@pc-Veriton-M200-H610:~$
```

8. Develop a program to demonstrate the working of the decision tree algorithm. Use Breast Cancer Data set for building the decision tree and apply this knowledge to classify a new sample.

Python Code:

```
# Import necessary libraries
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
import numpy as np

# Load the Breast Cancer dataset
data = load_breast_cancer()
X = data.data
y = data.target

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# Create a DecisionTreeClassifier instance and train it
clf = DecisionTreeClassifier(random_state=42)
clf.fit(X_train, y_train)

# Predict the test set results
y_pred = clf.predict(X_test)

# Evaluate the classifier performance
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy on Test Set: {accuracy:.4f}')

# Classify a new sample (randomly selected from the test set for demonstration)
new_sample = X_test[0].reshape(1, -1)  # Take the first sample from the test set
predicted_class = clf.predict(new_sample)

# Output the predicted class (0: malignant, 1: benign)
print(f'Predicted Class for New Sample: {"Benign" if predicted_class == 1 else "Malignant"}')
```

Output:

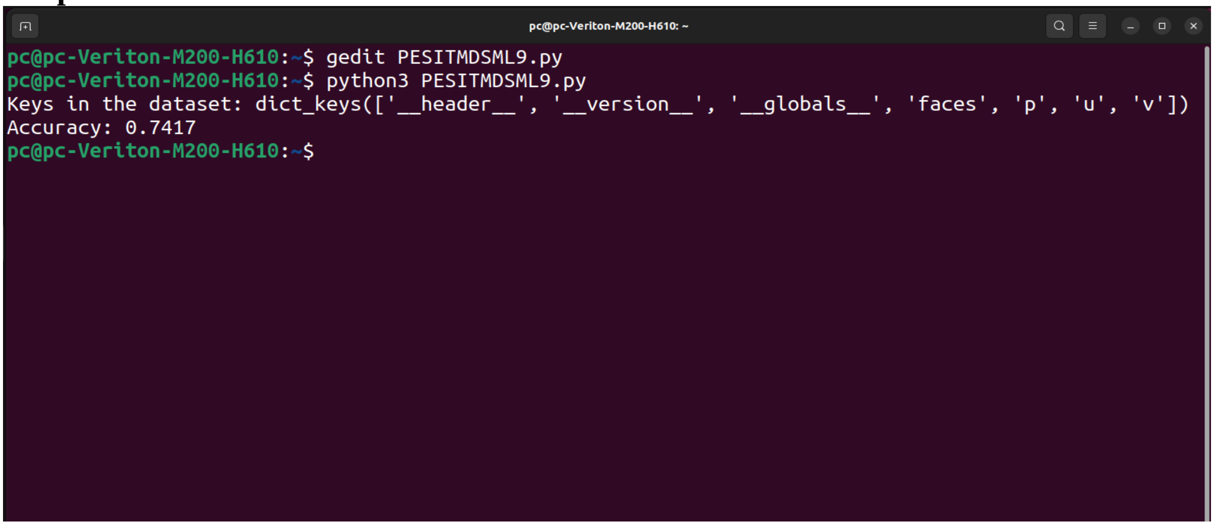


9. Develop a program to implement the Naive Bayesian classifier considering Olivetti Face Data set for training. Compute the accuracy of the classifier, considering a few test data sets.

Python Code:

```
import numpy as np
from scipy.io import loadmat
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# Load the olivettifaces.mat file (ensure it's in the same directory or update the path)
data = loadmat('olivettifaces.mat')

# Inspect the keys in the dataset
print("Keys in the dataset:", data.keys())

# Use 'faces' as the feature matrix
X = data['faces']  # Features (faces), this is the matrix of images

# Assuming labels are the index of faces (0-40 for 40 individuals, 10 images per individual)
y = np.repeat(np.arange(40), 10)  # 40 classes (individuals), 10 images per class

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X.T, y, test_size=0.3, random_state=42)  # Transpose
for correct shape

# Create and train the Naive Bayes classifier
model = GaussianNB()
model.fit(X_train, y_train)

# Make predictions
y_pred = model.predict(X_test)

# Calculate accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy:.4f}")
```

Output:

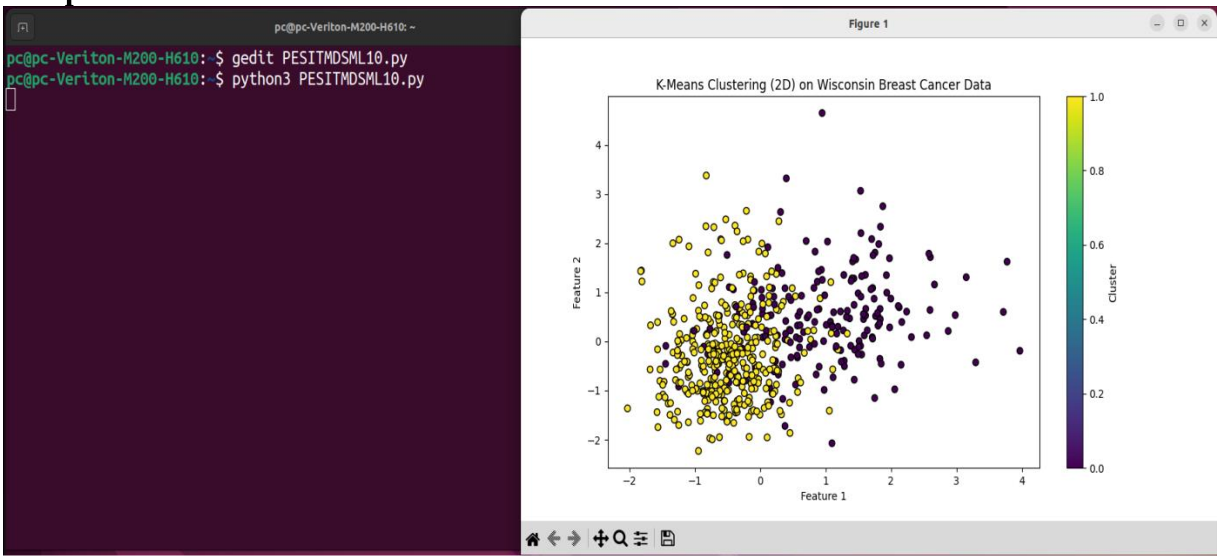


10. Develop a program to implement k-means clustering using Wisconsin Breast Cancer data set and visualize the clustering result.

Python Code:

```
import matplotlib
matplotlib.use('TkAgg')  # Use the TkAgg backend for interactive GUI rendering
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.datasets import load_breast_cancer
from sklearn.preprocessing import StandardScaler
# Load the breast cancer dataset
data = load_breast_cancer()
X = data.data
y = data.target
# Standardize the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Apply KMeans clustering
kmeans = KMeans(n_clusters=2, random_state=42)
y_kmeans = kmeans.fit_predict(X_scaled)

# Visualize the clustering result
plt.figure(figsize=(10, 6))
plt.scatter(X_scaled[:, 0], X_scaled[:, 1], c=y_kmeans, cmap='viridis', edgecolors='k')
plt.title('K-Means Clustering (2D) on Wisconsin Breast Cancer Data')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.colorbar(label='Cluster')
# Show the plot interactively using TkAgg
plt.show()
# Optionally, print cluster centers
print("Cluster centers:\n", kmeans.cluster_centers_)
```

Output:



```
pc@pc-Veriton-M200-H610:~$ gedit PESITMDSML10.py
pc@pc-Veriton-M200-H610:~$ python3 PESITMDSML10.py
Cluster centers:
 [[ 0.98649786  0.49202131  1.01866689  0.97479724  0.5871176   1.014073
   1.14492245  1.17028266  0.60339021  0.22927434  0.86311672  0.04416341
   0.86446528  0.8137762   0.01228944  0.69281919  0.63976499  0.77166695
   0.13798752  0.40384985  1.05221312  0.51705679  1.07769473  1.01391704
   0.59804381  0.95285513  1.05144274  1.15328841  0.5994129   0.61362004]
 [-0.48677585 -0.24278217 -0.50264928 -0.48100231 -0.28970632 -0.50038248
  -0.56494861 -0.57746231 -0.29773585 -0.11313275 -0.42589487 -0.02179192
  -0.4265603  -0.40154836 -0.00606408 -0.34186354 -0.31568456 -0.38077004
  -0.06808833 -0.19927499 -0.51920227 -0.25513563 -0.53177588 -0.50030552
  -0.29509774 -0.47017523 -0.51882214 -0.56907669 -0.29577329 -0.30278364]]
pc@pc-Veriton-M200-H610:~$
```