Experiment 6

Assuming a set of documents that need to be classified, use the naïve Bayesian Classifier model to perform this task. Built-in Java classes/API can be used to write the program. Calculate the accuracy, precision, and recall for your data set.

```
# Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from bs4 import BeautifulSoup
from wordcloud import WordCloud
import re
import string
#from textblob import TextBlob
import nltk
from nltk.corpus import stopwords
#import emoji
nltk.download('punkt')
nltk.download('wordnet')
from sklearn.preprocessing import LabelEncoder
import re
from nltk.stem import PorterStemmer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import MultinomialNB, GaussianNB
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
from sklearn.metrics import *
from sklearn.model_selection import train_test_split
# ignore warnings
import warnings
warnings.filterwarnings('ignore')
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data...
```

```
pip install xgboost
```

```
Requirement already satisfied: xgboost in /usr/local/lib/python3.11/dist-packages (2.1.4)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (from xgboost) (2.0.2)
Requirement already satisfied: nvidia-nccl-cu12 in /usr/local/lib/python3.11/dist-packages (from xgboost) (2.21.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from xgboost) (1.14.1)
```

Spam DataSet From Github Repo

```
url = 'https://raw.githubusercontent.com/aayushsh2003/ML/main/Experiment/Experiment%206/spam.csv'
df = pd.read_csv(url, encoding='latin-1')
```

```
df.head()
```

	Category	Message
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

Next steps: Generate code with df | View recommended plots | New interactive sheet

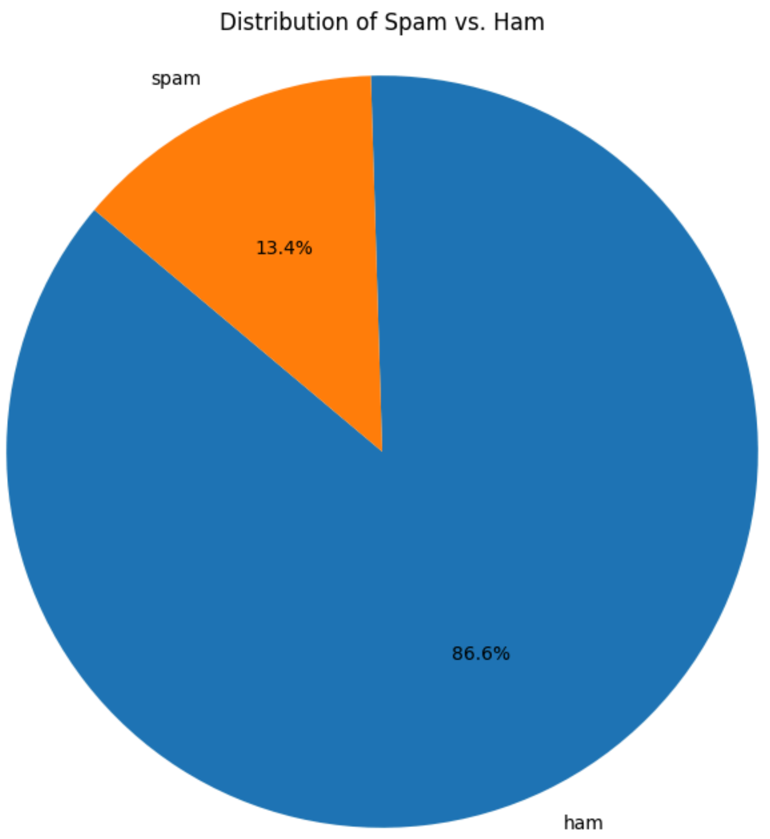
```
pip install emoji --upgrade
```

```
Collecting emoji
  Downloading emoji-2.14.1-py3-none-any.whl.metadata (5.7 kB)
```

```
Downloading emoji-2.14.1-py3-none-any.whl (590 kB)
   ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 590.6/590.6 kB 6.9 MB/s eta 0:00:00
Installing collected packages: emoji
Successfully installed emoji-2.14.1
```

```
# Calculate the count of each label
category_counts = df['Category'].value_counts()

# Plotting the pie chart
plt.figure(figsize=(8, 8))
plt.pie(category_counts, labels=category_counts.index, autopct='%1.1f%%', startangle=140)
plt.title('Distribution of Spam vs. Ham')
plt.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.
plt.show()
```




```
# Iterate through unique categories
for category in df['Category'].unique():
    # Filter the DataFrame for the current category
    filtered_df = df[df['Category'] == category]

    # Concatenate all text data for the current category
    text = ' '.join(filtered_df['Message'])

    # Generate word cloud
    wordcloud = WordCloud(width=800, height=400, background_color='white').generate(text)

    # Plot the word cloud
    plt.figure(figsize=(10, 5))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title(f'Word Cloud for Category: {category}')
    plt.axis('off')
    plt.show()
```

Word Cloud for Category: ham

Word Cloud for Category: spam


```
# Encode Category column
le = LabelEncoder()
df['Category']=le.fit_transform(df['Category'])
df.head()
```

	Category	Message
0	0	Go until jurong point, crazy.. Available only ...
1	0	Ok lar... Joking wif u oni...
2	1	Free entry in 2 a wkly comp to win FA Cup fina...
3	0	U dun say so early hor... U c already then say...
4	0	Nah I don't think he goes to usf, he lives aro...

Next steps: Generate code with df View recommended plots New interactive sheet

```
# Convert 'Text' column to lowercase
df['Message'] = df['Message'].str.lower()
df.head()
```

	Category	Message
0	0	go until jurong point, crazy.. available only ...
1	0	ok lar... joking wif u oni...
2	1	free entry in 2 a wkly comp to win fa cup fina...
3	0	u dun say so early hor... u c already then say...
4	0	nah i don't think he goes to usf, he lives aro...

Next steps: Generate code with df View recommended plots New interactive sheet

```
# Remove extra white spaces from the 'Text' column
df['Message'] = df['Message'].str.strip()
df.head()
```

	Category	Message
0	0	go until jurong point, crazy.. available only ...
1	0	ok lar... joking wif u oni...
2	1	free entry in 2 a wkly comp to win fa cup fina...
3	0	u dun say so early hor... u c already then say...
4	0	nah i don't think he goes to usf, he lives aro...

Next steps: Generate code with df View recommended plots New interactive sheet

```
# Function to remove HTML tags from text
def remove_html_tags(text):
    soup = BeautifulSoup(text, 'html.parser')
    return soup.get_text()

# Remove HTML tags from 'Text' column
df['Message'] = df['Message'].apply(remove_html_tags)
```

```
# Define a function to remove URLs using regular expressions
def remove_urls(text):
    return re.sub(r'http\S+|www\S+', '', text)

# Apply the function to the 'Text' column
df['Message'] = df['Message'].apply(remove_urls)
```

```
string.punctuation

# Define the punctuation characters to remove
punctuation = string.punctuation
# Function to remove punctuation from text
def remove_punctuation(text):
    return text.translate(str.maketrans('', '', punctuation))

# Apply remove_punctuation function to 'Text' column
df['Message'] = df['Message'].apply(remove_punctuation)
```

```
def remove_special_characters(text):
    # Define the pattern to match special characters
    pattern = r'[^a-zA-Z0-9\s]'  # Matches any character that is not alphanumeric or whitespace

    # Replace special characters with an empty string
    clean_text = re.sub(pattern, '', text)

    return clean_text

# Apply the function to the 'Message' column
df['Message'] = df['Message'].apply(remove_special_characters)
```

```
# Define a function to remove non-alphanumeric characters
def remove_non_alphanumeric(text):
    return re.sub(r'[^a-zA-Z0-9\s]', '', text)

# Apply the function to the "Message" column
df['Message'] = df['Message'].apply(remove_non_alphanumeric)
```

```
# Define a dictionary of chat word mappings
chat_words = {
    "AFAIK": "As Far As I Know",
    "AFK": "Away From Keyboard",
    "ASAP": "As Soon As Possible",
    "ATK": "At The Keyboard",
    "ATM": "At The Moment",
```

```
    "A3": "Anytime, Anywhere, Anyplace",
    "BAK": "Back At Keyboard",
    "BBL": "Be Back Later",
    "BBS": "Be Back Soon",
    "BFN": "Bye For Now",
    "B4N": "Bye For Now",
    "BRB": "Be Right Back",
    "BRT": "Be Right There",
    "BTW": "By The Way",
    "B4": "Before",
    "B4N": "Bye For Now",
    "CU": "See You",
    "CUL8R": "See You Later",
    "CYA": "See You",
    "FAQ": "Frequently Asked Questions",
    "FC": "Fingers Crossed",
    "FWIW": "For What It's Worth",
    "FYI": "For Your Information",
    "GAL": "Get A Life",
    "GG": "Good Game",
    "GN": "Good Night",
    "GMTA": "Great Minds Think Alike",
    "GR8": "Great!",
    "G9": "Genius",
    "IC": "I See",
    "ICQ": "I Seek you (also a chat program)",
    "ILU": "ILU: I Love You",
    "IMHO": "In My Honest/Humble Opinion",
    "IMO": "In My Opinion",
    "IOW": "In Other Words",
    "IRL": "In Real Life",
    "KISS": "Keep It Simple, Stupid",
    "LDR": "Long Distance Relationship",
    "LMAO": "Laugh My A.. Off",
    "LOL": "Laughing Out Loud",
    "LTNS": "Long Time No See",
    "L8R": "Later",
    "MTE": "My Thoughts Exactly",
    "M8": "Mate",
    "NRN": "No Reply Necessary",
    "OIC": "Oh I See",
    "PITA": "Pain In The A..",
    "PRT": "Party",
    "PRW": "Parents Are Watching",
    "QPSA?": "Que Pasa?",
    "ROFL": "Rolling On The Floor Laughing",
    "ROFLOL": "Rolling On The Floor Laughing Out Loud",
    "ROTFLMAO": "Rolling On The Floor Laughing My A.. Off",
    "SK8": "Skate",
    "STATS": "Your sex and age",
    "ASL": "Age, Sex, Location",
    "THX": "Thank You",
    "TTFN": "Ta-Ta For Now!",
    "TTYL": "Talk To You Later",
    "U": "You",
    "U2": "You Too",
    "U4E": "Yours For Ever",
    "WB": "Welcome Back",
    "WTF": "What The F...",
    "WTG": "Way To Go!",
    "WUF": "Where Are You From?",
    "W8": "Wait...",
    "7K": "Sick:-D Laugher",
    "TFW": "That feeling when",
    "MFW": "My face when",
    "MRW": "My reaction when",
    "IFYP": "I feel your pain",
    "TNTL": "Trying not to laugh",
    "JK": "Just kidding",
    "IDC": "I don't care",
    "ILY": "I love you",
    "IMU": "I miss you",
    "ADIH": "Another day in hell",
    "ZZZ": "Sleeping, bored, tired",
```

```
    "WYWH": "Wish you were here",
    "TIME": "Tears in my eyes",
    "BAE": "Before anyone else",
    "FIMH": "Forever in my heart",
    "BSAAW": "Big smile and a wink",
    "BWL": "Bursting with laughter",
    "BFF": "Best friends forever",
    "CSL": "Can't stop laughing"
}
```

```
# Function to replace chat words with their full forms
def replace_chat_words(text):
    words = text.split()
    for i, word in enumerate(words):
        if word.lower() in chat_words:
            words[i] = chat_words[word.lower()]
    return ' '.join(words)

# Apply replace_chat_words function to 'Text' column
df['Message'] = df['Message'].apply(replace_chat_words)
```

```
# Download NLTK stopwords corpus
nltk.download('stopwords')

# Get English stopwords from NLTK
stop_words = set(stopwords.words('english'))

# Function to remove stop words from text
def remove_stopwords(text):
    words = text.split()
    filtered_words = [word for word in words if word.lower() not in stop_words]
    return ' '.join(filtered_words)

# Apply remove_stopwords function to 'Text' column
df['Message'] = df['Message'].apply(remove_stopwords)
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
```

```
!pip install emoji --upgrade
import emoji

# Function to remove emojis from text
def remove_emojis(text):
    return emoji.demojize(text)

# Apply remove_emojis function to 'Text' column
df['Message'] = df['Message'].apply(remove_emojis)
```

```
Requirement already satisfied: emoji in /usr/local/lib/python3.11/dist-packages (2.14.1)
```

```
# Initialize the Porter Stemmer
porter_stemmer = PorterStemmer()

# Apply stemming
df['Message_stemmed'] = df['Message'].apply(lambda x: ' '.join([porter_stemmer.stem(word) for word in x.split()]))
```

```
# Intlize CountVectorizer
cv = CountVectorizer()

# Fitting CountVectorizer on X
X = cv.fit_transform(df['Message_stemmed']).toarray()
y = df['Category']
```

```
# Train Test Split
X_train, X_test , y_train, y_test = train_test_split(X,y,test_size = 0.2, random_state = 42)
```

```
# Gaussian Naive Bayes
gnb_model = GaussianNB()
gnb_model.fit(X_train, y_train)
gnb_pred = gnb_model.predict(X_test)
```

```
gnb_accuracy = accuracy_score(y_test, gnb_pred)
gnb_precision = precision_score(y_test, gnb_pred, average='weighted')
gnb_recall = recall_score(y_test, gnb_pred, average='weighted')
gnb_conf_matrix = confusion_matrix(y_test, gnb_pred)
```

```
# Multinomial Naive Bayes with tuned parameters
mnb_model = MultinomialNB(alpha=0.1)
mnb_model.fit(X_train, y_train)
mnb_pred = mnb_model.predict(X_test)
```

```
mnb_accuracy = accuracy_score(y_test, mnb_pred)
mnb_precision = precision_score(y_test, mnb_pred, average='weighted')
mnb_recall = recall_score(y_test, mnb_pred, average='weighted')
mnb_conf_matrix = confusion_matrix(y_test, mnb_pred)
```

```
print("Multinomial Naive Bayes:")
print(f"The accuracy score of MultinomialNB is {mnb_accuracy}, The Precision Score is {mnb_precision},The Recall Score
print(f"The Confusion matrix is \n{mnb_conf_matrix}")
print("\n")

print("Gaussian Naive Bayes:")
print(f"The accuracy score of GaussianNB is {gnb_accuracy}, The Precision Score is {gnb_precision},The Recall Score is
print(f"The Confusion matrix is \n{gnb_conf_matrix}")
print("\n")
```

```
Multinomial Naive Bayes:
The accuracy score of MultinomialNB is 0.9721973094170404, The Precision Score is 0.9728833837324558,The Recall Score is 0.97219730
The Confusion matrix is
[[947  19]
 [ 12 137]]


Gaussian Naive Bayes:
The accuracy score of GaussianNB is 0.863677130044843, The Precision Score is 0.9180444492929181,The Recall Score is 0.86367713004
The Confusion matrix is
[[828 138]
 [ 14 135]]
```

Experiment 7

Write a program to construct aBayesian network considering medical data. Use this model to demonstrate the diagnosis of heart patients using the standard Heart Disease Data Set. You can use Java/Python ML library classes/API.

```
!pip install pgmpy
```

Show hidden output

+ Code + Text

```
!pip install --upgrade pgmpy
```

Show hidden output

```
!pip install --upgrade pgmpy  # Ensure pgmpy is up-to-date
from pgmpy.models import DiscreteBayesianNetwork # Import DiscreteBayesianNetwork instead of BayesianNetwork or Bayesian

cancer_model = DiscreteBayesianNetwork([('Pollution', 'Cancer'),
                              ('Smoker', 'Cancer'),
                              ('Cancer', 'Xray'),
                              ('Cancer', 'Dyspnoea')])
print(cancer_model)
```

Show hidden output

```
print(cancer_model)
```

```
DiscreteBayesianNetwork with 5 nodes and 4 edges
```

```
cancer_model.nodes()   #to print nodes
```

```
NodeView(('Pollution', 'Cancer', 'Smoker', 'Xray', 'Dyspnoea'))
```

```
cancer_model.edges() # to print edges
```

```
OutEdgeView([('Pollution', 'Cancer'), ('Cancer', 'Xray'), ('Cancer', 'Dyspnoea'), ('Smoker', 'Cancer')])
```

Conditional Probability Distribution

```
cancer_model.get_cpds()   # to show conditional probability Distribution
```

```
[]
```

Creation of Conditional Probability Table

```
from pgmpy.factors.discrete import TabularCPD
```

```
cpd_poll = TabularCPD(variable='Pollution', variable_card=2,
                      values=[[0.9],[0.1]])
cpd_smoke = TabularCPD(variable='Smoker', variable_card=2,
                      values=[[0.3],[0.7]])
cpd_cancer = TabularCPD(variable='Cancer', variable_card=2,
                      values=[[0.03, 0.05, 0.001, 0.02],
                      [0.97, 0.95, 0.999, 0.98]],
                      evidence=['Smoker', 'Pollution'],
                      evidence_card=[2, 2])
cpd_xray = TabularCPD(variable='Xray', variable_card=2,
                      values=[[0.9, 0.2],[0.1, 0.8]],
                      evidence=['Cancer'], evidence_card=[2])
cpd_dysp = TabularCPD(variable='Dyspnoea', variable_card=2,
                      values=[[0.65, 0.3],[0.35, 0.7]],
                      evidence=['Cancer'], evidence_card=[2])
```

Double-click (or enter) to edit

```
# associating the parameters with the model structure
cancer_model.add_cpds(cpd_poll, cpd_smoke, cpd_cancer, cpd_xray, cpd_dysp)

#checking if the cpds are valid for the model
```

```
cancer_model.get_cpds()
cancer_model.check_model()
```

```
True
```

```
#If you want to stick with DiscreteBayesianNetwork and identify active trails.
#This approach identifies all nodes on the active trail, including the start and end nodes.
active_trail = cancer_model.active_trail_nodes('Pollution', observed=['Cancer'])
# Check if 'Smoker' is in the active trail
is_active = 'Smoker' in active_trail['Pollution']
print(f"Is there an active trail between Pollution and Smoker given Cancer? {is_active}")
```

```
Is there an active trail between Pollution and Smoker given Cancer? True
```

```
cancer_model.local_independencies('Xray')     #Xray and Dyspnoea are Independent
```

```
(Xray ⊥ Dyspnoea, Smoker, Pollution | Cancer)
```

```
cancer_model.local_independencies('Pollution')
```

```
(Pollution ⊥ Smoker)
```

```
cancer_model.local_independencies('Smoker')
```

```
(Smoker ⊥ Pollution)
```

```
cancer_model.local_independencies('Dyspnoea')
```

```
(Dyspnoea ⊥ Smoker, Pollution, Xray | Cancer)
```

```
cancer_model.local_independencies('Cancer')
```

```
cancer_model.local_independencies('Dyspnoea')
```

```
(Dyspnoea ⊥ Smoker, Pollution, Xray | Cancer)
```

```
cancer_model.local_independencies('Pollution')
```

```
(Pollution ⊥ Smoker)
```

```
cancer_model.get_independencies()
```

```
(Pollution ⊥ Dyspnoea | Cancer)
(Smoker ⊥ Dyspnoea | Cancer)
(Pollution ⊥ Smoker)
(Dyspnoea ⊥ Xray | Cancer)
(Smoker ⊥ Xray | Cancer)
(Pollution ⊥ Xray | Cancer)
```

```
cancer_model.get_cpds()
print(cancer_model.get_cpds('Pollution'))
```

```
+--------------+-----+
| Pollution(0) | 0.9 |
+--------------+-----+
| Pollution(1) | 0.1 |
+--------------+-----+
```

```
cancer_model.get_cpds()
print(cancer_model.get_cpds('Cancer'))
```

```
+-----------+--------------+--------------+--------------+--------------+
| Smoker    | Smoker(0)    | Smoker(0)    | Smoker(1)    | Smoker(1)    |
+-----------+--------------+--------------+--------------+--------------+
| Pollution | Pollution(0) | Pollution(1) | Pollution(0) | Pollution(1) |
+-----------+--------------+--------------+--------------+--------------+
| Cancer(0) | 0.03         | 0.05         | 0.001        | 0.02         |
+-----------+--------------+--------------+--------------+--------------+
| Cancer(1) | 0.97         | 0.95         | 0.999        | 0.98         |
+-----------+--------------+--------------+--------------+--------------+
```

```
cancer_model.get_cpds()
#conditional probabilities
```

```
[<TabularCPD representing P(Pollution:2) at 0x797c11002310>,
 <TabularCPD representing P(Smoker:2) at 0x797c102a7190>,
 <TabularCPD representing P(Cancer:2 | Smoker:2, Pollution:2) at 0x797c110197d0>,
 <TabularCPD representing P(Xray:2 | Cancer:2) at 0x797c11018110>,
 <TabularCPD representing P(Dyspnoea:2 | Cancer:2) at 0x797c1101bf90>]
```

Inferencing with Bayesian Network with Variable Elimination

```
from pgmpy.inference import VariableElimination
cancer_infer = VariableElimination(cancer_model)

q=cancer_infer.query(variables=['Cancer'], evidence={'Smoker': 1})
print(q)
```

```
+-----------+---------------+
| Cancer    |   phi(Cancer) |
+===========+===============+
| Cancer(0) |        0.0029 |
+-----------+---------------+
| Cancer(1) |        0.9971 |
+-----------+---------------+
```

```
r=cancer_infer.query(variables=['Cancer'], evidence={'Smoker': 1, 'Pollution':1})
print(r)
```

```
+-----------+---------------+
| Cancer    |   phi(Cancer) |
+===========+===============+
| Cancer(0) |        0.0200 |
+-----------+---------------+
| Cancer(1) |        0.9800 |
+-----------+---------------+
```

```
s=cancer_infer.query(variables=['Cancer'], evidence={'Pollution':1})
print(r)
```

```
+-----------+---------------+
| Cancer    |   phi(Cancer) |
+===========+===============+
| Cancer(0) |        0.0200 |
+-----------+---------------+
| Cancer(1) |        0.9800 |
+-----------+---------------+
```

```
r=cancer_infer.query(variables=['Smoker'], evidence={'Cancer': 1})
print(r)
```

```
+-----------+---------------+
| Smoker    |   phi(Smoker) |
+===========+===============+
| Smoker(0) |        0.2938 |
+-----------+---------------+
| Smoker(1) |        0.7062 |
+-----------+---------------+
```

Start coding or generate with AI.

Experiment 8

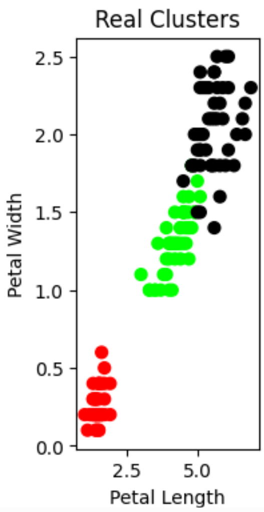
Apply EM algorithm to cluster a set of data stored in a .CSV file. Use the same data set for clustering using k-Means algorithm. Compare the results of these two algorithms and comment on the quality of clustering. You can add Java/Python ML library classes/API in the program.

```
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
from sklearn import preprocessing
from sklearn.mixture import GaussianMixture
import pandas as pd
import numpy as np
```

```
iris = datasets.load_iris()
X = pd.DataFrame(iris.data)
X.columns = ['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width']
y = pd.DataFrame(iris.target)
y.columns = ['Targets']
```

```
model = KMeans(n_clusters=3)
model.fit(X)
plt.figure(figsize=(6,4))
colormap = np.array(['red', 'lime', 'black'])
plt.subplot(1, 3, 1)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y.Targets], s=40)
plt.title('Real Clusters')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
```

```
Text(0, 0.5, 'Petal Width')
```



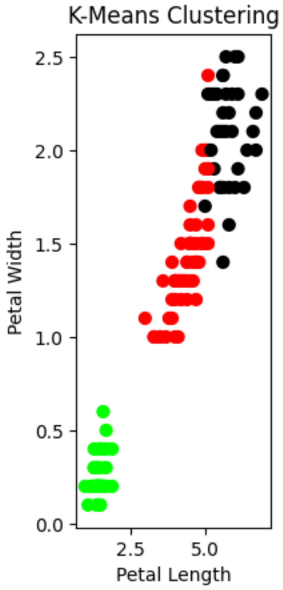

```
Start coding or generate with AI.
```

Double-click (or enter) to edit

```
Start coding or generate with AI.
```

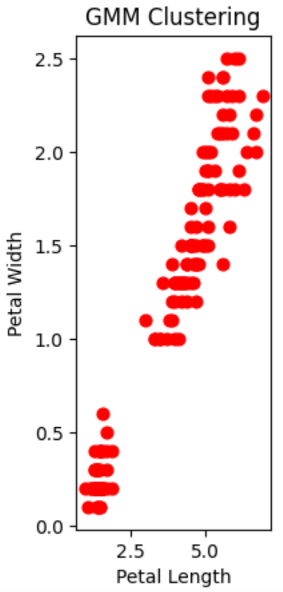
```
plt.subplot(1, 3, 2)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[model.labels_], s=40)
plt.title('K-Means Clustering')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
```

```
Text(0, 0.5, 'Petal Width')
```




```
scaler = preprocessing.StandardScaler()
scaler.fit(X)
xsa = scaler.transform(X)
xs = pd.DataFrame(xsa, columns = X.columns)
gmm = GaussianMixture(n_components=40)
gmm.fit(xs)
plt.subplot(1, 3, 3)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[0], s=40)
plt.title('GMM Clustering')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
```

```
Text(0, 0.5, 'Petal Width')
```




```
print('Observation: The GMM using EM algorithm based clustering matched the true labels more closely than the Kmeans.')
```

```
Observation: The GMM using EM algorithm based clustering matched the true labels more closely than the Kmeans.
```

Experiment 9

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

LWR is a non-parametric regression algorithm that fits a local linear model around each query point using a weighted least squares method, where nearby points have more influence (higher weight) than far ones.

τ (tau): Bandwidth parameter controlling how "local" the regression is.

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

# Generate synthetic dataset
def generate_data():
    X = np.linspace(-3, 3, 100)
    y = np.sin(X) + 0.1 * np.random.randn(100)
    return X.reshape(-1, 1), y

# Add intercept term
def add_bias(X):
    return np.hstack([np.ones((X.shape[0], 1)), X])

# Weight matrix for a given query point x_query
def get_weights(X, x_query, tau):
    m = X.shape[0]
    weights = np.exp(-np.square(X - x_query).flatten() / (2 * tau**2))
    return np.diag(weights)

# Locally Weighted Regression
def locally_weighted_regression(X, y, tau, X_query):
    X_bias = add_bias(X)
    y_pred = []

    for x in X_query:
        W = get_weights(X, x, tau)
        theta = np.linalg.pinv(X_bias.T @ W @ X_bias) @ X_bias.T @ W @ y
        x_bias = np.array([1, x[0]])
        y_hat = x_bias @ theta
        y_pred.append(y_hat)

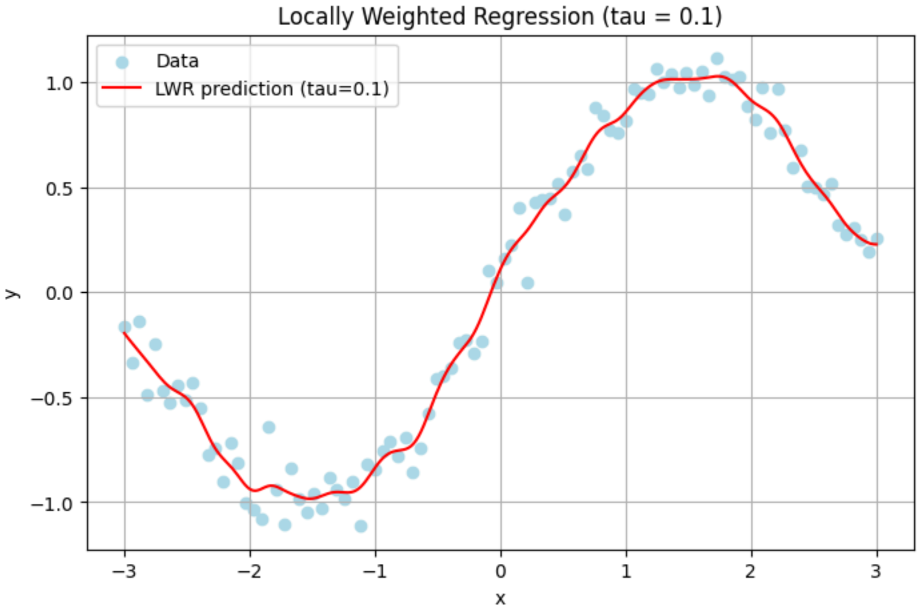
    return np.array(y_pred)

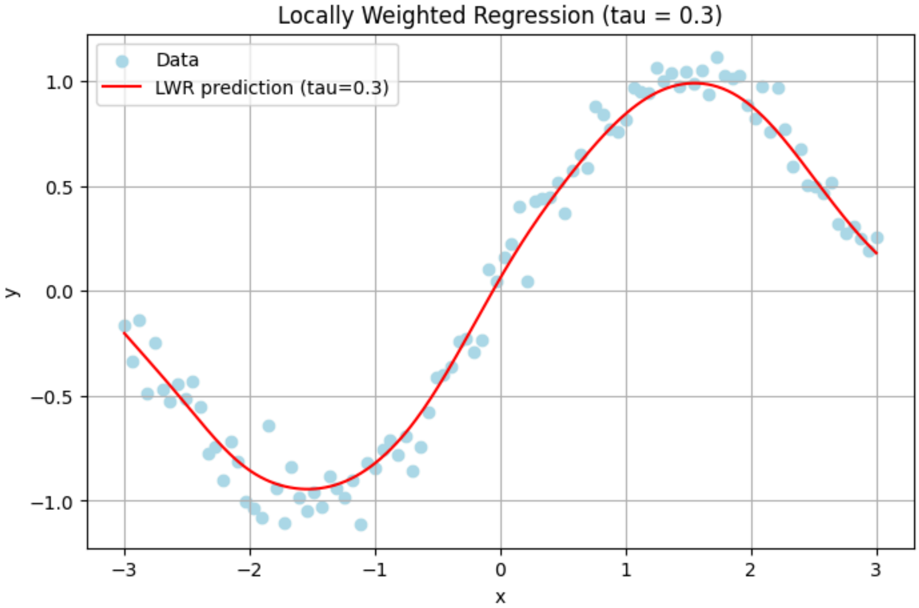
# Main function
def main():
    X, y = generate_data()
    X_query = np.linspace(-3, 3, 300).reshape(-1, 1)

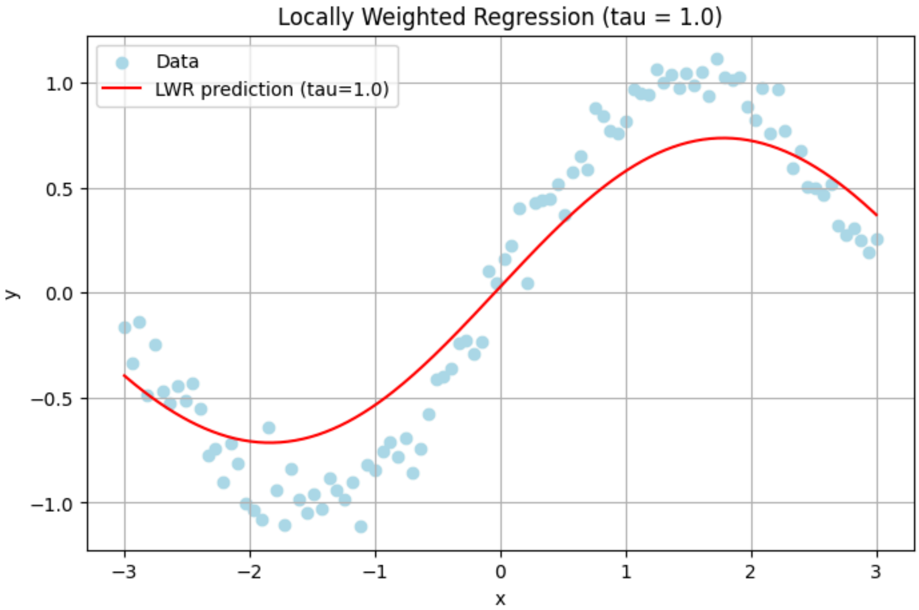
    for tau in [0.1, 0.3, 1.0]:
        y_pred = locally_weighted_regression(X, y, tau, X_query)

        plt.figure(figsize=(8, 5))
        plt.scatter(X, y, label="Data", color="lightblue")
        plt.plot(X_query, y_pred, label=f"LWR prediction (tau={tau})", color="red")
        plt.title(f"Locally Weighted Regression (tau = {tau})")
        plt.xlabel("x")
        plt.ylabel("y")
        plt.legend()
        plt.grid(True)
        plt.show()

main()
```








```
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
from sklearn import preprocessing
from sklearn.mixture import GaussianMixture
```

```
import pandas as pd
import numpy as np
```

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```

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import datasets

# Add intercept to X
def add_bias(X):
    return np.hstack([np.ones((X.shape[0], 1)), X])

# Gaussian weights
def get_weights(X, x_query, tau):
    weights = np.exp(-np.square(X - x_query).flatten() / (2 * tau**2))
    return np.diag(weights)

# Locally Weighted Regression
def locally_weighted_regression(X, y, tau, X_query):
    X_bias = add_bias(X)
    y_pred = []

    for x in X_query:
        W = get_weights(X, x, tau)
        theta = np.linalg.pinv(X_bias.T @ W @ X_bias) @ X_bias.T @ W @ y
        x_bias = np.array([1, x[0]])
        y_hat = x_bias @ theta
        y_pred.append(y_hat)

    return np.array(y_pred)

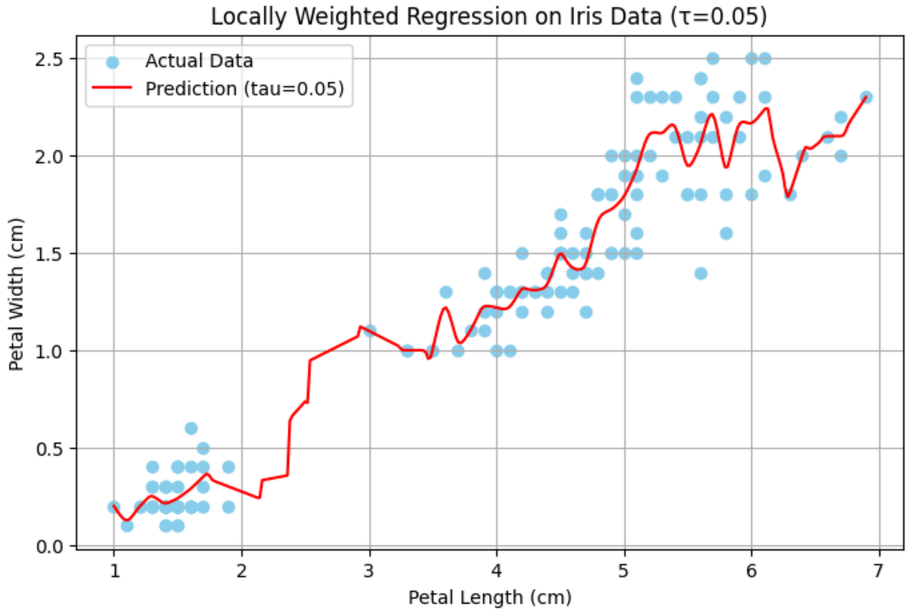
# Load Iris dataset
def load_iris_data():
    iris = datasets.load_iris()
    X = iris.data[:, 2].reshape(-1, 1)  # Petal length
    y = iris.data[:, 3]                 # Petal width
    return X, y

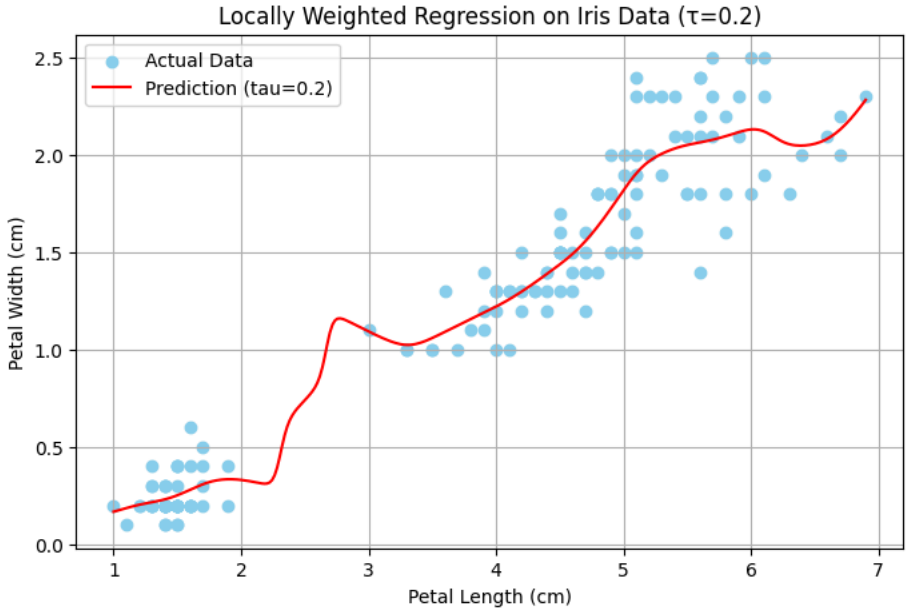
# Main
def main():
    X, y = load_iris_data()
    X_query = np.linspace(X.min(), X.max(), 300).reshape(-1, 1)

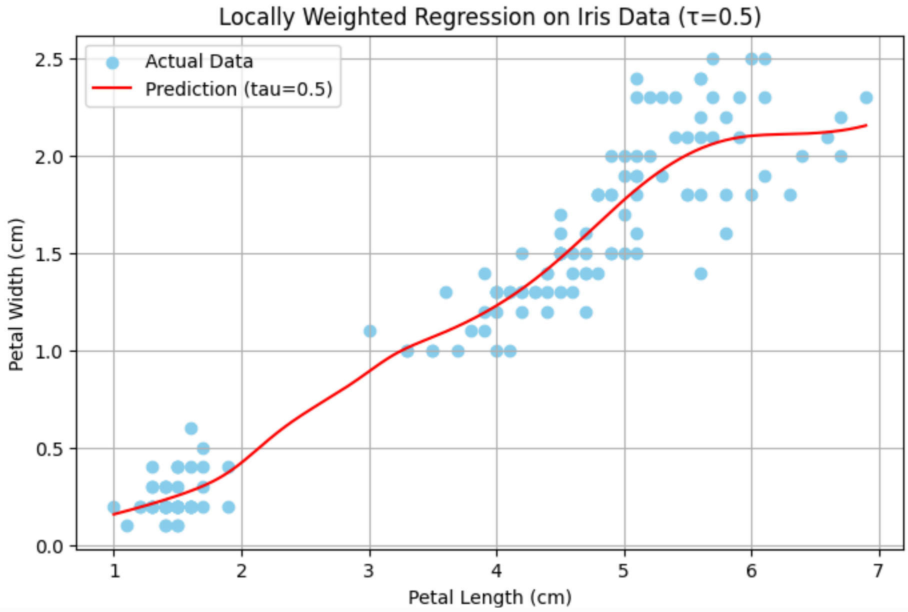
    for tau in [0.05, 0.2, 0.5]:
        y_pred = locally_weighted_regression(X, y, tau, X_query)

        plt.figure(figsize=(8, 5))
        plt.scatter(X, y, label="Actual Data", color="skyblue")
        plt.plot(X_query, y_pred, label=f"Prediction (tau={tau})", color="red")
        plt.title(f"Locally Weighted Regression on Iris Data (τ={tau})")
        plt.xlabel("Petal Length (cm)")
        plt.ylabel("Petal Width (cm)")
        plt.legend()
        plt.grid(True)
        plt.show()

main()
```


Locally Weighted Regression on Iris Data (τ=0.05)
Actual Data
Prediction (tau=0.05)
Petal Width (cm)
Petal Length (cm)
0.0
0.5
1.0
1.5
2.0
2.5
1
2
3
4
5
6
7


Locally Weighted Regression on Iris Data (τ=0.2)
Actual Data
Prediction (tau=0.2)
Petal Width (cm)
Petal Length (cm)
0.0
0.5
1.0
1.5
2.0
2.5
1
2
3
4
5
6
7


Locally Weighted Regression on Iris Data (τ=0.5)
Actual Data
Prediction (tau=0.5)
Petal Width (cm)
Petal Length (cm)
0.0
0.5
1.0
1.5
2.0
2.5
1
2
3
4
5
6
7

Experiment 10

Write a program to implement k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions. Java/Python ML library classes can be used for this problem.

KNN Algorithm implementation on Iris dataset

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
```

```
# Load the Iris dataset
iris = load_iris()
X = iris.data  # Features
y = iris.target  # Target labels
```

```
# Print the details of the iris dataset
print("Iris data keys:", iris.keys())
print("\nFeature names:", iris.feature_names)
print("\nTarget names:", iris.target_names)

print("\nFirst 5 data points:\n", iris.data[:5])
print("\nTarget values:\n", iris.target)
```

```
Iris data keys: dict_keys(['data', 'target', 'frame', 'target_names', 'DESCR', 'feature_names', 'filename', 'data_module'])

Feature names: ['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']

Target names: ['setosa' 'versicolor' 'virginica']

First 5 data points:
 [[5.1 3.5 1.4 0.2]
 [4.9 3.  1.4 0.2]
 [4.7 3.2 1.3 0.2]
 [4.6 3.1 1.5 0.2]
 [5.  3.6 1.4 0.2]]

Target values:
 [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0 0 0 0 0 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2]
```

```
# Split the dataset into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Standardize the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
# Function to find the best k using cross-validation
def find_best_k(X_train, y_train, k_range):
    mean_accuracies = []
    for k in k_range:
        knn = KNeighborsClassifier(n_neighbors=k)
        scores = cross_val_score(knn, X_train, y_train, cv=5)  # 5-fold cross-validation
        mean_accuracies.append(scores.mean())
    return mean_accuracies

# Determine the best k
k_values = range(1, 21)
mean_accuracies = find_best_k(X_train, y_train, k_values)
best_k = k_values[np.argmax(mean_accuracies)]
best_accuracy = np.max(mean_accuracies)
```

```
# Print the best k and its accuracy
print(f"The best value of k is {best_k} with cross-validated accuracy {best_accuracy:.2f}")

# Train the KNN model with the best k
knn_best = KNeighborsClassifier(n_neighbors=best_k)
knn_best.fit(X_train, y_train)
```

```
The best value of k is 3 with cross-validated accuracy 0.95
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=3)
```

The best value of k is 3 with cross-validated accuracy 0.95

```
# Make predictions on the test data
y_pred = knn_best.predict(X_test)
```

```
# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"\nAccuracy of KNN with k={best_k}: {accuracy:.2f}")
```

```

Accuracy of KNN with k=3: 1.00
```

```
# Print classification report and confusion matrix
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

```

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        10
           1       1.00      1.00      1.00         9
           2       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30

Confusion Matrix:
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
```

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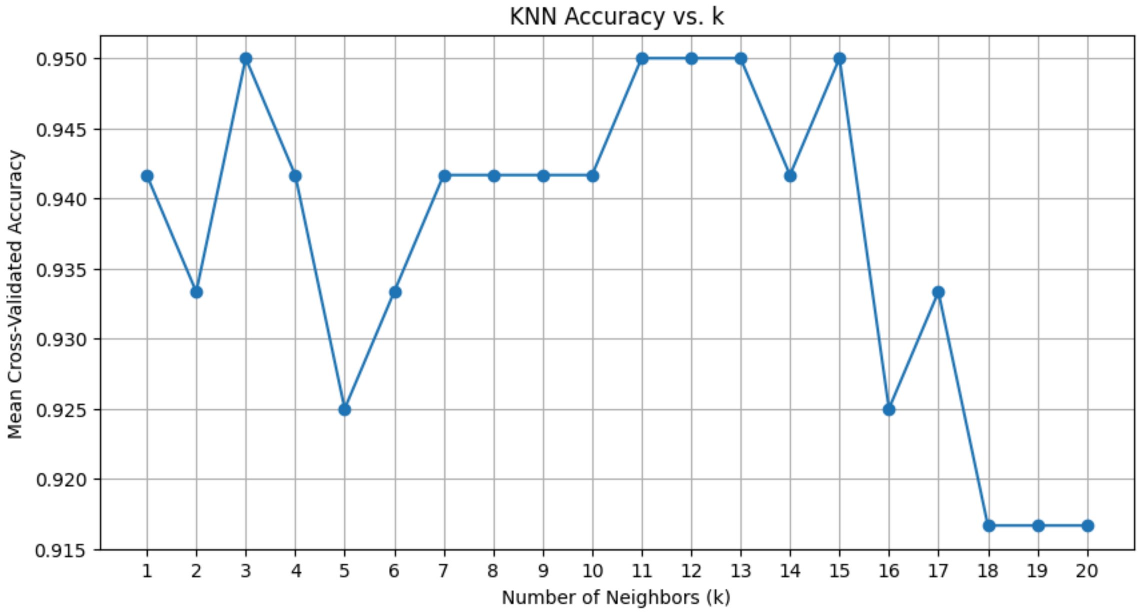
```
# Visualize the accuracy for different values of k
plt.figure(figsize=(10, 5))
plt.plot(k_values, mean_accuracies, marker='o')
plt.title('KNN Accuracy vs. k')
plt.xlabel('Number of Neighbors (k)')
plt.ylabel('Mean Cross-Validated Accuracy')
plt.xticks(k_values)
plt.grid()
plt.show()
```



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+ Code + Text

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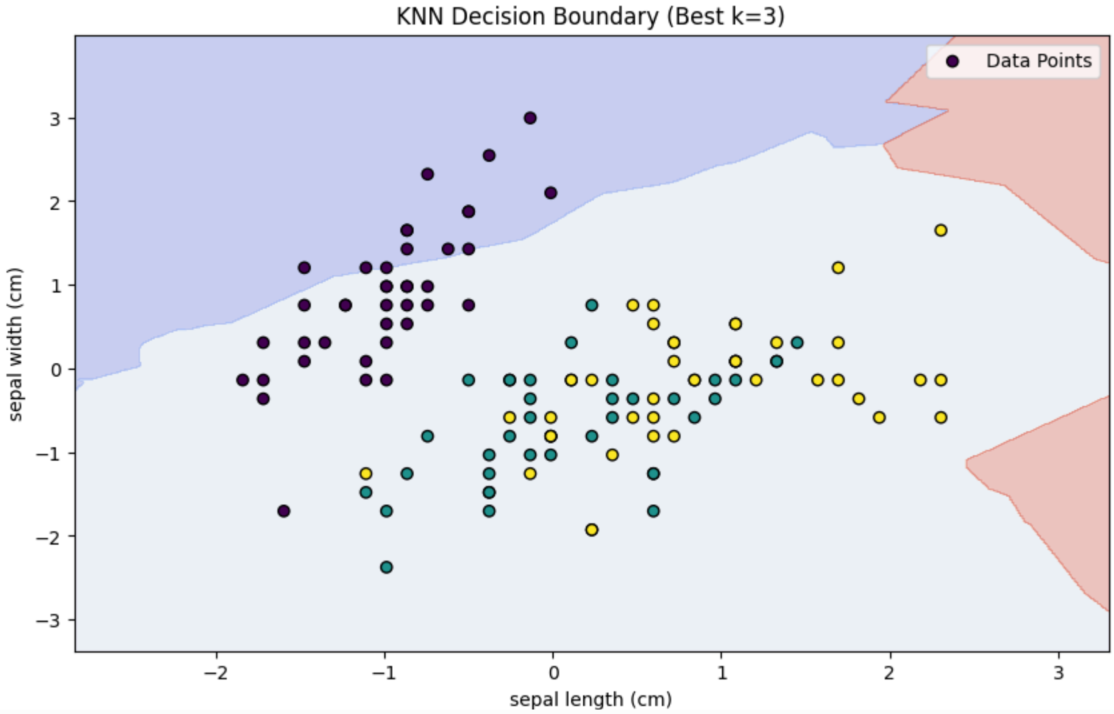
```
# Optional: Visualize the decision boundary (for the first two features)
def plot_decision_boundary(X, y, model):
    x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
    y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01),
                         np.arange(y_min, y_max, 0.01))

    # Predict the class for each point in the mesh
    Z = model.predict(np.c_[xx.ravel(), yy.ravel(), np.zeros_like(xx.ravel()), np.zeros_like(xx.ravel())])
    Z = Z.reshape(xx.shape)

    # Plot the decision boundary
    plt.figure(figsize=(10, 6))
    plt.contourf(xx, yy, Z, alpha=0.3, cmap=plt.cm.coolwarm)
    plt.scatter(X[:, 0], X[:, 1], c=y, edgecolor='k', marker='o', label='Data Points')
    plt.xlabel(iris.feature_names[0])
    plt.ylabel(iris.feature_names[1])
    plt.title(f"KNN Decision Boundary (Best k={best_k})")
    plt.legend()
    plt.show()

# Plot the decision boundary using the first two features
plot_decision_boundary(X_train[:, :2], y_train, knn_best)
```


KNN Decision Boundary (Best k=3)
Data Points
sepal width (cm)
sepal length (cm)
3
2
1
0
−1
−2
−3
−2
−1
0
1
2
3