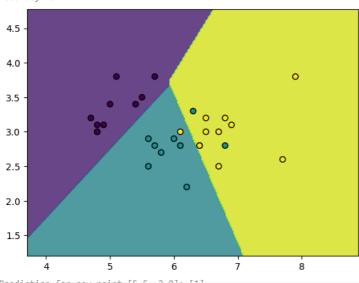
```
#find s
import pandas as pd
def find_s_algorithm(data):
           hypothesis = None
            for _, row in data.iterrows():
                        if row[-1] == 'yes':
                                   if hypothesis is None:
                                               hypothesis = row[:-1].values
                                    else:
                                                for i in range(len(hypothesis)):
                                                             if hypothesis[i] != row[i]:
                                                                       hypothesis[i] = '?'
                        print(hypothesis)
           return hypothesis
data = pd.read_csv('/content/data.csv')
specific_hypothesis = find_s_algorithm(data)
print("Most specific hypothesis:", specific hypothesis)
 ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
['sunny' 'warm' '?' 'strong' 'warm' 'same']
['sunny' 'warm' '?' 'strong' 'warm' 'same']
               ['sunny' warm' '?' 'strong' '?' '?']

Most specific hypothesis: ['sunny' 'warm' '?' 'strong' '?' '?']
               /usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `should run async` will not call `transform of the control of the con
                    and should_run_async(code)
              4
#candidate elimination
import pandas as pd
def candidate_elimination(data):
           S, G = ['0'] * (data.shape[1] - 1), [['?'] * (data.shape[1] - 1)]
            print(f"Initial Specific Boundary S: {S}")
            print(f"Initial General Boundary G: {G}\n")
            for i, row in data.iterrows():
                       x, y = row[:-1], row[-1]
                       print(f"Instance {i+1}: ")
                        if y == 'yes':
                                    S = [xi \text{ if } si == '0' \text{ else } si \text{ if } si == xi \text{ else } '?' \text{ for } si, xi \text{ in } zip(S, x)]
                                    G = [g \text{ for } g \text{ in } G \text{ if all } (g[i] \text{ in } ('?', xi) \text{ for } i, xi \text{ in } enumerate(x))]
                        else:
                                    G_new = []
                                    for g in G:
                                                if all(g[i] in ('?', xi) for i, xi in enumerate(x)):
                                                             for i in range(len(x)):
                                                                        if g[i] == '?':
                                                                                     for val in set(data.iloc[:, i]):
                                                                                                if val != x[i]:
                                                                                                            new g = g[:]
                                                                                                            new_g[i] = val
                                                                                                              if \ any(all(new_g[j] \ in \ ('?', \ ex[j]) \ for \ j \ in \ range(len(new_g))) \ for \ ex \ in \ data[data.iloc[:, \ -1] == \ 'y \ for \ ex \ in \ data[data.iloc[:, \ -1] == \ 'y \ for \ ex \ fo
                                                                                                                        G new.append(new g)
                                                           G_new.append(g)
                                    G = G_new
                        print(f"Updated Specific Boundary S: {S}")
                        print(f"Updated General Boundary G: {G}\n")
            return S, G
data = pd.read_csv('/content/data.csv')
S, G = candidate_elimination(data)
print("Final Specific Boundary:", S)
print("Final General Boundary:", G)
           Initial Specific Boundary S: ['0', '0', '0', '0', '0', '0', '0']
Initial General Boundary G: [['?', '?', '?', '?', '?', '?', '?']]
               Instance 1:
               Updated Specific Boundary S: ['sunny', 'warm', 'normal', 'strong', 'warm', 'same']
Updated General Boundary G: [['?', '?', '?', '?', '?', '?']]
              Updated Specific Boundary S: ['sunny', 'warm', '?', 'strong', 'warm', 'same']
Updated General Boundary G: [['?', '?', '?', '?', '?', '?']]
               Instance 3:
               Updated Specific Boundary S: ['sunny', 'warm', '?', 'strong', 'warm', 'same']
Updated General Boundary G: [['sunny', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?'], ['?', '?', '?'], ['?', '?', '?']
```

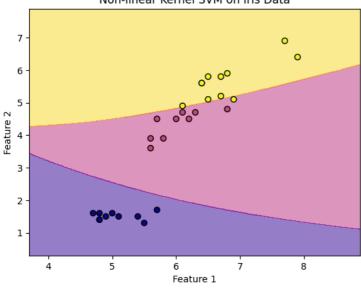
```
Instance 4:
     Updated Specific Boundary S: ['sunny', 'warm', '?', 'strong', '?', '?']
Updated General Boundary G: [['sunny', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?'], ['?', '?', '?', '?', '?', '?', '?']
     Final Specific Boundary: ['sunny', 'warm', '?', 'strong', '?', '?']
Final General Boundary: [['sunny', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?'], ['?', '?', '?', '?', '?']
#linear svm
#!pip install scikit-learn matplotlib
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
import numpy as np
# Load and prepare data
iris = datasets.load_iris()
X = iris.data[:, :2] # Use only the first two features for simplicity
y = iris.target
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
#train svm
svm = SVC(kernel='linear')
svm.fit(X_train, y_train)
# Evaluate
print("Accuracy:", accuracy_score(y_test, svm.predict(X_test)))
# Plot decision boundaries
def plot decision boundaries(X, y, model):
    h = .02
    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, h), np.arange(y_min, y_max, h))
    Z = model.predict(np.c_[xx.ravel(), yy.ravel()]).reshape(xx.shape)
    plt.contourf(xx, yy, Z, alpha=0.8)
    plt.scatter(X[:, 0], X[:, 1], c=y, edgecolor='k')
    plt.show()
plot_decision_boundaries(X_test, y_test, svm)
new_point = svm.predict([[5.5, 2.0]])
print("Prediction for new point [5.5, 2.0]:", new_point)
→ Accuracy: 0.9
       4.5
       4.0
                                                                   0
```



```
#non linear svm
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
iris = load_iris()
X = iris.data[:, [0, 2]]
y = iris.target
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
svm = SVC(kernel='poly')
svm.fit(X_train, y_train)
accuracy=accuracy_score(y_test, svm.predict(X_test))
print("Accuracy is: ", accuracy)
def plot_decision_boundaries(X, y, model):
   h = .02
    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, h), np.arange(y_min, y_max, h))
    Z = model.predict(np.c_[xx.ravel(), yy.ravel()]).reshape(xx.shape)
    plt.contourf(xx, yy, Z, alpha=0.5, cmap='plasma')
    plt.scatter(X[:, 0], X[:, 1], c=y, edgecolors='k', cmap='plasma')
    plt.xlabel('Feature 1')
    plt.ylabel('Feature 2')
    plt.title('Non-linear Kernel SVM on Iris Data')
    plt.show()
plot decision boundaries(X test, y test, svm)
new_point = svm.predict([[5.5, 2.0]])
print("Prediction for new point [5.5, 2.0]:", new_point)
```

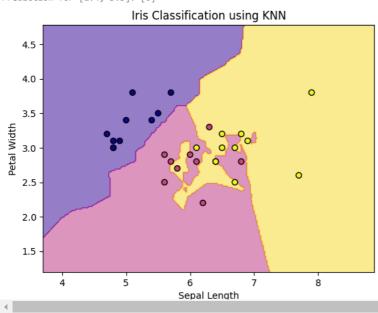
Accuracy is: 0.9666666666666667

Non-linear Kernel SVM on Iris Data

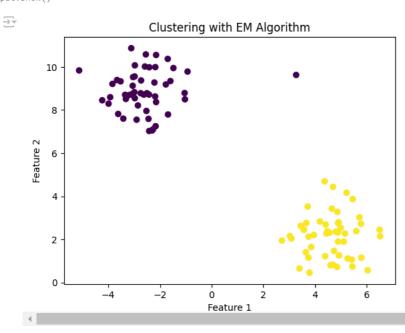


```
#knn
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from \ sklearn.neighbors \ import \ KNeighbors Classifier
from sklearn.model_selection import train_test_split
iris = load_iris()
X, y = iris.data[:, :2], iris.target
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
knn = KNeighborsClassifier(n_neighbors=3)
knn.fit(X_train, y_train)
accuracy = knn.score(X_test, y_test)
print("Accuracy:", accuracy)
print("Prediction for [1.4, 5.3]:", knn.predict([[1.4, 5.3]]))
def plot_decision_boundaries(X, y, model, title='Decision Boundary'):
    h = .02
    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, h), np.arange(y_min, y_max, h))
    Z = model.predict(np.c_[xx.ravel(), yy.ravel()]).reshape(xx.shape)
    plt.contourf(xx, yy, Z, alpha=0.5, cmap='plasma')
    \verb|plt.scatter(X[:, 0], X[:, 1], c=y, edgecolors='k', cmap='plasma')|\\
    plt.xlabel('Sepal Length')
    plt.ylabel('Petal Width')
    plt.title(title)
    plt.show()
\verb|plot_decision_boundaries(X_test, y_test, knn, title='Iris Classification using KNN')| \\
```

Accuracy: 0.8333333333333334
Prediction for [1.4, 5.3]: [0]



```
#em
import numpy as np
import matplotlib.pyplot as plt
from sklearn.mixture import GaussianMixture
from sklearn.datasets import make_blobs
# Generate synthetic data
X, _ = make_blobs(n_samples=100, centers=2, cluster_std=1.0, random_state=42)
# Randomly introduce missing values
X[np.random.choice(X.shape[0], size=1, replace=False), 0] = np.nan
\ensuremath{\text{\#}} Handle missing values by mean imputation
X_imputed = np.nan_to_num(X, nan=np.nanmean(X))
# Apply EM algorithm using Gaussian Mixture Model
gmm = GaussianMixture(n_components=2, random_state=42)
gmm.fit(X_imputed)
labels = gmm.predict(X_imputed)
\verb|plt.scatter(X_imputed[:, 0], X_imputed[:, 1], c=labels, cmap='viridis', marker='o')|\\
plt.title('Clustering with EM Algorithm')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.show()
```



```
#naive bayes
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
from \ sklearn.datasets \ import \ make\_classification
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
 \texttt{X, y} = \texttt{make\_classification} (\texttt{n\_samples=300, n\_features=2, n\_informative=2, n\_redundant=0, n\_clusters\_per\_class=1, random\_state=42) 
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
nb = GaussianNB()
nb.fit(X_train, y_train)
y_pred = nb.predict(X_test)
def plot_decision_boundaries(X, y, model, title='Decision Boundary'):
    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))
    Z = model.predict(np.c_[xx.ravel(), yy.ravel()]).reshape(xx.shape)
    plt.contourf(xx, yy, Z, alpha=0.3, cmap=ListedColormap(('red', 'yellow')))
    for i, color in enumerate(['red', 'green']):
        plt.scatter(X[y == i, 0], X[y == i, 1],
                    c=color, label=f'Class {i}', edgecolors='k')
    plt.title('Naive Bayes Decision Boundary')
    plt.xlabel('Feature 1')
    plt.ylabel('Feature 2')
    plt.legend()
    plt.show()
plot_decision_boundaries(X_train, y_train, nb)
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

$\overline{\Rightarrow}$ Naive Bayes Decision Boundary Class 0 Class 1 3 2 1 Feature 2 0 $^{-1}$ -2 -3 -1 3 -2 Feature 1 [[45 1]

https://colab.research.google.com/drive/11Zx sQncwdtvLG2FubzkiV6VFn9zQhY4#printMode=true

```
#k means
from sklearn.cluster import KMeans
from sklearn.datasets import load_iris
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
dataset = load_iris()
X = pd.DataFrame(dataset.data, columns=['Sepal_Length', 'Sepal_Width', 'Petal_Length', 'Petal_Width'])
initial_centroids = np.array([
   [5.0, 3.5, 1.4, 0.2],
    [6.5, 3.0, 5.5, 2.0],
    [5.5, 2.5, 4.0, 1.3]
1)
n_{clusters} = 3
iterations = 5
for i in range(iterations):
   kmeans = KMeans(n_clusters=n_clusters, init=initial_centroids, n_init=1, max_iter=1, random_state=42)
    kmeans.fit(X)
    print(f"Iteration {i+1}:")
    print(f"Cluster Centers:\n{kmeans.cluster_centers_}\n")
   initial_centroids = kmeans.cluster_centers_
plt.figure(figsize=(7, 5))
plt.scatter(X['Petal_Length'], X['Petal_Width'], c=kmeans.labels_, cmap='viridis', s=40)
plt.title('KMeans Clustering - Final Iteration')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
plt.show()
```

```
→ Iteration 1:
    Cluster Centers:
     [5.006 3.428 1.462 0.246 ]
[6.61129032 2.9983871 5.39032258 1.92258065]
    [[5.006
     [5.69210526 2.66578947 4.11578947 1.27368421]]
    Iteration 2:
    Cluster Centers:
    [[5.006
                 3.428
                            1.462
                                        0.246
     [6.63220339 2.99830508 5.43050847 1.93728814]
     [5.72926829 2.6902439 4.15121951 1.3
    Iteration 3:
    Cluster Centers:
    [[5.006
                3.428
                             1.462
                                        0.246
     [6.66481481 3.00740741 5.5
                                        1.96851852]
     [5.78913043 2.71304348 4.20869565 1.3326087 ]]
    Iteration 4:
    Cluster Centers:
    [[5.006 3.428 1.462 0.246]
     [6.702 3.016 5.556 1.992]
     [5.822 2.728 4.256 1.36 ]]
    Iteration 5:
    Cluster Centers:
    [[5.006
                3.428
                             1.462
                                        0.246
     [6.76956522 3.03695652 5.6
                                        2.008695651
     [5.82962963 2.73148148 4.31481481 1.39259259]]
```

KMeans Clustering - Final Iteration 2.5 2.0 1.0 0.5 0.0 Petal Length

```
#Apriori
import pandas as pd
from mlxtend.frequent_patterns import apriori, association_rules
# Create the dataset
dataset = [
    ['Milk', 'Bread', 'Butter'],
    ['Bread', 'Butter'],
['Beer', 'Cookies', 'Diaper'],
['Milk', 'Diaper', 'Butter', 'Bread'],
    ['Beer', 'Diaper']
# Convert to DataFrame and one-hot encode
df = pd.DataFrame(dataset)
df = df.stack().str.get_dummies().groupby(level=0).sum()
# Apply Apriori algorithm
frequent_itemsets = apriori(df, min_support=0.5, use_colnames=True)
rules = association_rules(frequent_itemsets, metric="confidence", min_threshold=0.7)
# Display results
print("Frequent Itemsets:")
print(frequent_itemsets)
print("\nAssociation Rules:")
print(rules)
```

```
→ Frequent Itemsets:
                            support
                                                                                          itemsets
                                          0.6
                 0
                                                                                             (Bread)
                                           0.6
                                                                                          (Butter)
                                           0.6
                                                                                         (Diaper)
                                           0.6 (Bread, Butter)
                 Association Rules:
                        antecedents consequents antecedent support consequent support \
                 a
                                      (Bread)
                                                                               (Butter)
                                                                                                                                                                                0.6
                                                                                                                                                                                                                                                             0.6
                                                                                                                                                                                                                                                                                               0.6
                                    (Butter)
                                                                                    (Bread)
                                                                                                                                                                                 0.6
                                                                                                                                                                                                                                                             0.6
                                                                                                                                                                                                                                                                                               0.6
                            confidence
                                                                                       lift leverage conviction zhangs_metric
                                                     1.0 1.666667
                                                                                                                              0.24
                                                                                                                                                                            inf
                                                                                                                                                                                                                                        1.0
                                                       1.0 1.666667
                                                                                                                               0.24
                                                                                                                                                                                inf
                                                                                                                                                                                                                                          1.0
                 /usr/local/lib/python 3.10/dist-packages/ipykernel/ipkernel.py: 283: \ Deprecation Warning: `should_run_async` will not call `transform_continuous of the continuous of the 
                        and should_run_async(code)
                 /usr/local/lib/python3.10/dist-packages/mlxtend/frequent_patterns/fpcommon.py:109: DeprecationWarning: DataFrames with non-bool type
                        warnings.warn(
               4
```

```
#pca
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
dataset = load_iris()
X = pd.DataFrame(dataset.data, columns=dataset.feature_names)
y = dataset.target
X_{meaned} = X - np.mean(X, axis=0)
cov_matrix = np.cov(X_meaned, rowvar=False)
eigenvalues, eigenvectors = np.linalg.eigh(cov_matrix)
sorted_indices = np.argsort(eigenvalues)[::-1]
sorted_eigenvectors = eigenvectors[:, sorted_indices]
n_{components} = 2
principal_eigenvectors = sorted_eigenvectors[:, :n_components]
\label{eq:continuous_problem} $$X_{\text{reduced}} = \text{np.dot(principal\_eigenvectors.transpose(), } X_{\text{meaned.transpose()).transpose())}$}
plt.figure(figsize=(8, 6))
for target in np.unique(y):
    plt.scatter(X reduced[y == target, 0], X reduced[y == target, 1], label=dataset.target names[target])
plt.title('PCA of Iris Dataset')
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.legend()
plt.show()
```

- /usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283: DeprecationWarning: `should_run_async` will not call `transform_α