```
Start coding or generate with AI.
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Task

Implement K-Nearest Neighbors (KNN) from scratch, including functions for Euclidean, Manhattan, Minkowski, Cosine, and Hamming distance metrics. Experiment with different K values and distance metrics, evaluate the model's performance using testing accuracy, confusion matrix, recall, and precision, visualize the results to show the impact of different distance metrics and K values on accuracy, and provide insights into the findings.

Implement Distance Metrics

Subtask:

Write Python functions from scratch for Euclidean, Manhattan, Minkowski, Cosine, and Hamming distances.

```
import math
import numpy as np

def euclidean_distance(point1, point2):
    if len(point1) != len(point2):
        raise ValueError("Points must have the same dimension")

    sum_sq_diff = 0
    for i in range(len(point1)):
        sum_sq_diff += (point1[i] - point2[i])**2
    return math.sqrt(sum_sq_diff)

def manhattan_distance(point1, point2):
    if len(point1) != len(point2):
        raise ValueError("Points must have the same dimension")

    sum_abs_diff = 0
    for i in range(len(point1)):
        sum_abs_diff += abs(point1[i] - point2[i])
    return sum_abs_diff

def minkowski_distance(point1, point2, p):
    if len(point1) != len(point2):
        raise ValueError("Points must have the same dimension")
    if p < 1:
        raise ValueError("Order 'p' must be a positive integer.")

    sum_p_diff = 0
    for i in range(len(point1)):
        sum_p_diff += abs(point1[i] - point2[i])**p
    return sum_p_diff**(1/p)

def cosine_distance(point1, point2):
    if len(point1) != len(point2):
        raise ValueError("Points must have the same dimension")

    vec1 = np.array(point1)
    vec2 = np.array(point2)

    dot_product = np.dot(vec1, vec2);
    norm_vec1 = np.linalg.norm(vec1)
    norm_vec2 = np.linalg.norm(vec2)

    if norm_vec1 == 0 or norm_vec2 == 0:
        return 1.0

    similarity = dot_product / (norm_vec1 * norm_vec2)
    return 1 - similarity

def hamming_distance(point1, point2):
    if len(point1) != len(point2):
        raise ValueError("Points must have the same length")
```

```
        distance = 0
        for i in range(len(point1)):
            if point1[i] != point2[i]:
                distance += 1
        return distance

    print("Distance functions (euclidean_distance, manhattan_distance, minkowski_distance, cosine_distance, hamming_distance) defir
```

```
    Distance functions (euclidean_distance, manhattan_distance, minkowski_distance, cosine_distance, hamming_distance) defined succe
```

Implement KNN Classifier

Subtask:

Develop a K-Nearest Neighbors classifier from scratch, including functions for training (fitting) and prediction.

```
import numpy as np
from collections import Counter

class KNNClassifier:
    def __init__(self, n_neighbors=5, distance_metric=euclidean_distance):
        self.n_neighbors = n_neighbors
        self.distance_metric = distance_metric
        self.X_train = None
        self.y_train = None

    def fit(self, X_train, y_train):
        self.X_train = np.array(X_train)
        self.y_train = np.array(y_train)
        print("KNNClassifier fitted successfully. Training data and labels stored.")

    def _get_neighbors(self, X_test_point):
        distances = []
        for i, x_train_point in enumerate(self.X_train):
            dist = self.distance_metric(X_test_point, x_train_point)
            distances.append((dist, self.y_train[i]))

        distances.sort(key=lambda x: x[0])
        neighbors = distances[:self.n_neighbors]
        return neighbors

    def predict(self, X_test):
        X_test = np.array(X_test)
        predictions = []

        for x_test_point in X_test:
            neighbors = self._get_neighbors(x_test_point)

            neighbor_labels = [label for dist, label in neighbors]

            if not neighbor_labels:
                predictions.append(None)
                continue

            most_common = Counter(neighbor_labels).most_common(1)
            predicted_label = most_common[0][0]
            predictions.append(predicted_label)

        print(f"Predictions generated for {len(X_test)} test points.")
        return predictions

print("KNNClassifier class defined successfully.")
```

```
KNNClassifier class defined successfully.
```

Experiment and Evaluate

Subtask:

Iterate through different values of K and each implemented distance metric, train the KNN model, and evaluate its testing accuracy.

```
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import pandas as pd

X, y = make_classification(n_samples=1000, n_features=10, n_informative=5, n_redundant=5, n_classes=2, random_state=42)
print("Synthetic dataset generated: X shape", X.shape, "y shape", y.shape)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
print("Dataset split into training and testing sets.")
print(f"X_train shape: {X_train.shape}, y_train shape: {y_train.shape}")
print(f"X_test shape: {X_test.shape}, y_test shape: {y_test.shape}")

k_values = [1, 3, 5, 7, 9, 11, 13, 15]
print("K values defined:", k_values)

distance_metrics = {
    'Euclidean': euclidean_distance,
    'Manhattan': manhattan_distance,
    'Minkowski (p=3)': lambda p1, p2: minkowski_distance(p1, p2, p=3),
    'Cosine': cosine_distance,
    'Hamming': hamming_distance
}
print("Distance metrics defined:", list(distance_metrics.keys()))

results = []

print("Starting KNN model training and evaluation...")
for metric_name, metric_func in distance_metrics.items():
    for k in k_values:
        knn_model = KNNClassifier(n_neighbors=k, distance_metric=metric_func)

        knn_model.fit(X_train, y_train)

        y_pred = knn_model.predict(X_test)

        accuracy = accuracy_score(y_test, y_pred)

        results.append({
            'Distance Metric': metric_name,
            'K': k,
            'Accuracy': accuracy
        })
        print(f"  Evaluated: Metric={metric_name}, K={k}, Accuracy={accuracy:.4f}")

results_df = pd.DataFrame(results)
print("\n--- Experiment Results ---")
print(results_df.to_string())
```

```
Predictions generated for 300 test points.
```

```
  Evaluated: Metric=Hamming, K=15, Accuracy=0.4800

--- Experiment Results ---
    Distance Metric   K  Accuracy
0         Euclidean   1  0.930000
1         Euclidean   3  0.953333
2         Euclidean   5  0.950000
3         Euclidean   7  0.940000
4         Euclidean   9  0.943333
5         Euclidean  11  0.936667
6         Euclidean  13  0.933333
7         Euclidean  15  0.930000
8         Manhattan   1  0.923333
9         Manhattan   3  0.946667
10        Manhattan   5  0.933333
11        Manhattan   7  0.943333
12        Manhattan   9  0.936667
13        Manhattan  11  0.933333
14        Manhattan  13  0.930000
15        Manhattan  15  0.926667
16  Minkowski (p=3)   1  0.923333
17  Minkowski (p=3)   3  0.946667
18  Minkowski (p=3)   5  0.950000
19  Minkowski (p=3)   7  0.943333
20  Minkowski (p=3)   9  0.936667
21  Minkowski (p=3)  11  0.933333
22  Minkowski (p=3)  13  0.933333
```

Identify Best Model and Metrics

Subtask:

Determine the optimal K value and distance metric based on the highest testing accuracy.

```
best_result = results_df.loc[results_df['Accuracy'].idxmax()]

optimal_k = int(best_result['K'])
best_metric = best_result['Distance Metric']
highest_accuracy = best_result['Accuracy']

print(f"Optimal K value: {optimal_k}")
print(f"Best Distance Metric: {best_metric}")
print(f"Highest Testing Accuracy: {highest_accuracy:.4f}")
```

```
Optimal K value: 3
Best Distance Metric: Euclidean
Highest Testing Accuracy: 0.9533
```

Calculate Detailed Performance

Subtask:

For the best performing model, calculate and print the confusion matrix, recall, and precision.

```
from sklearn.metrics import confusion_matrix, recall_score, precision_score

best_knn_model = KNNClassifier(n_neighbors=optimal_k, distance_metric=distance_metrics[best_metric])

best_knn_model.fit(X_train, y_train)

y_pred_best = best_knn_model.predict(X_test);

conf_matrix = confusion_matrix(y_test, y_pred_best)

recall = recall_score(y_test, y_pred_best)

precision = precision_score(y_test, y_pred_best)

print(f"\n--- Detailed Performance for Best Model (K={optimal_k}, Metric={best_metric}) ---")
print("Confusion Matrix:")
print(conf_matrix)
print(f"Recall Score: {recall:.4f}")
print(f"Precision Score: {precision:.4f}")
```

```
KNNClassifier fitted successfully. Training data and labels stored.
Predictions generated for 300 test points.

--- Detailed Performance for Best Model (K=3, Metric=Euclidean) ---
Confusion Matrix:
[[140   4]
 [ 10 146]]
Recall Score: 0.9359
Precision Score: 0.9733
```

Visualize Results

Subtask:

Create plots to visualize how different distance metrics affect accuracy across varying K values.

```python
import matplotlib.pyplot as plt
import seaborn as sns

sns.set_style("whitegrid")

plt.figure(figsize=(12, 7))
sns.lineplot(data=results_df, x='K', y='Accuracy', hue='Distance Metric', marker='o')

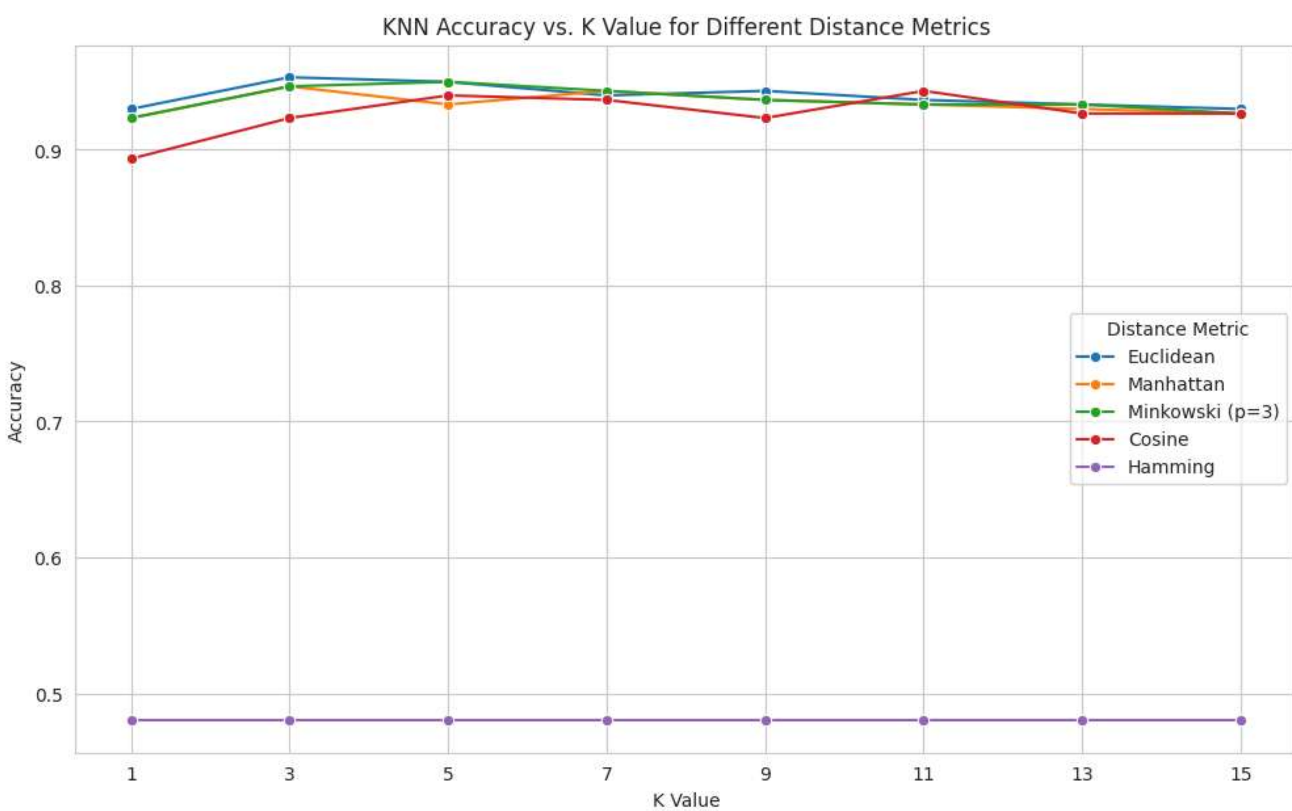
plt.title('KNN Accuracy vs. K Value for Different Distance Metrics')
plt.xlabel('K Value')
plt.ylabel('Accuracy')

plt.legend(title='Distance Metric')

plt.xticks(k_values)

plt.show()

print("Plot of KNN accuracy for different K values and distance metrics generated successfully.")
```




```
Plot of KNN accuracy for different K values and distance metrics generated successfully.
```

```
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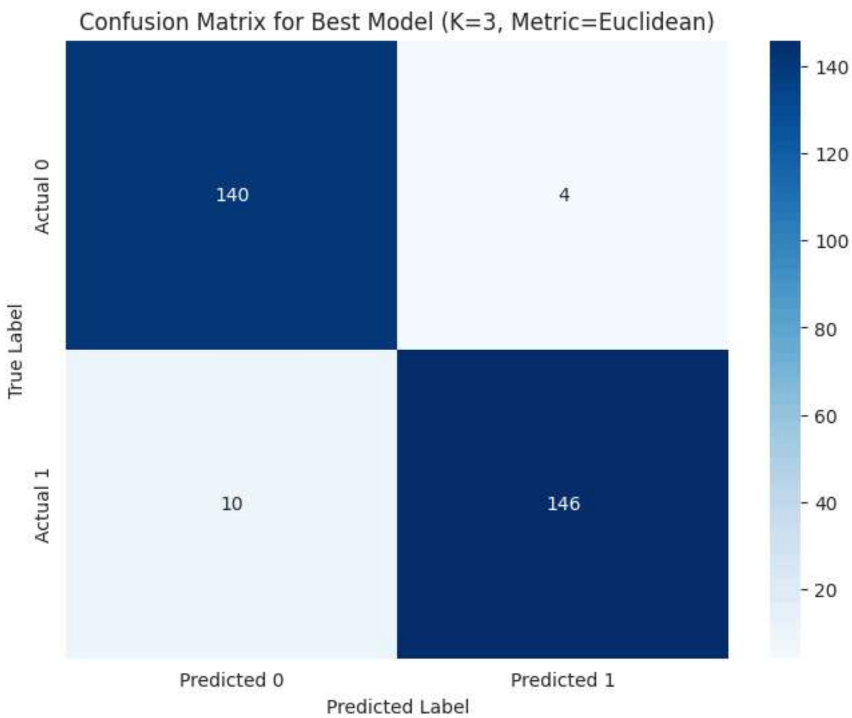
```
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
            xticklabels=['Predicted 0', 'Predicted 1'],
            yticklabels=['Actual 0', 'Actual 1'])
plt.title(f'Confusion Matrix for Best Model (K={optimal_k}, Metric={best_metric})')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()

print("Confusion Matrix plot generated successfully.")
```




```
Confusion Matrix plot generated successfully.
```

Task

Iterate through all the entries in the `results_df` dataframe, and for each combination of 'Distance Metric' and 'K' value, create a `KNNClassifier` with the corresponding parameters. Then, fit each classifier on `X_train` and `y_train`, make predictions on `X_test`, calculate the confusion matrix using `sklearn.metrics.confusion_matrix`, and visualize each confusion matrix using `seaborn.heatmap`, with titles indicating the K value and distance metric. Finally, summarize the findings from the multiple confusion matrices, highlighting differences or patterns observed across different K values and distance metrics, and discuss the overall performance of the KNN models.

Iterate and Plot Confusion Matrices

Subtask:

Loop through all the entries in the `results_df`. For each combination of 'Distance Metric' and 'K' value, re-instantiate the `KNNClassifier` with the corresponding parameters. Fit the model on `X_train` and `y_train`, make predictions on `X_test`, calculate the confusion matrix using `confusion_matrix` from `sklearn.metrics`, and then visualize each confusion matrix using `seaborn.heatmap`. Each plot will have a title indicating the K value and distance metric used.

Reasoning: The subtask requires iterating through all the entries in `results_df` to re-evaluate the KNN model for each combination of K and distance metric, calculate their confusion matrices, and then visualize each one using a heatmap. This step systematically creates and plots all confusion matrices.

```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

print("Generating confusion matrices for all K values and distance metrics...")

for index, row in results_df.iterrows():
    metric_name = row['Distance Metric']
    k_value = int(row['K'])

    if metric_name == 'Minkowski (p=3)':
        metric_func = lambda p1, p2: minkowski_distance(p1, p2, p=3)
    else:
        metric_func = globals()[metric_name.split(' ')[0].lower() + '_distance']

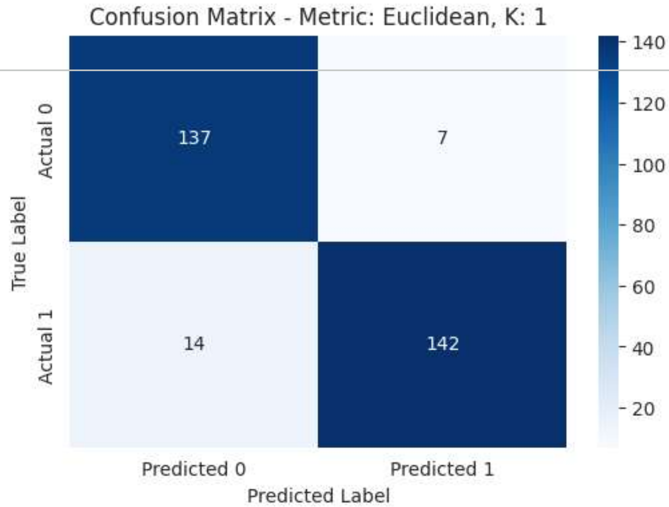
    knn_model = KNNClassifier(n_neighbors=k_value, distance_metric=metric_func)
    knn_model.fit(X_train, y_train)
    y_pred = knn_model.predict(X_test)

    conf_matrix_current = confusion_matrix(y_test, y_pred)

    plt.figure(figsize=(6, 4))
    sns.heatmap(conf_matrix_current, annot=True, fmt='d', cmap='Blues',
                xticklabels=['Predicted 0', 'Predicted 1'],
                yticklabels=['Actual 0', 'Actual 1'])
    plt.title(f'Confusion Matrix - Metric: {metric_name}, K: {k_value}')
    plt.xlabel('Predicted Label')
    plt.ylabel('True Label')
    plt.show()

print("All confusion matrix plots generated successfully.")
```

```
Generating confusion matrices for all K values and distance metrics...
KNNClassifier fitted successfully. Training data and labels stored.
Predictions generated for 300 test points.
```




```
KNNClassifier fitted successfully. Training data and labels stored.
```