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```
exp03(binning)

# Function to partition data into equal-frequency (equal-depth) bins
def partition_into_bins(data, num_bins):
    data.sort()
    # Sort the data
    n = len(data)

    # Calculate how many items should go into each bin
    bin_size = n // num_bins
    remainder = n % num_bins # Remainder to distribute among bins
    bins = []
    start_index = 0

    for i in range(num_bins):
        # Calculate the size of the current bin
        current_bin_size = bin_size + (1 if i < remainder else 0) # Distribute the remainder
        # Append the current bin to the list of bins
        bins.append(data[start_index:start_index + current_bin_size])
        start_index = current_bin_size # Move the start index for the next bin
    return bins

# Function to smooth data by bin means
def smooth_bin_means(bins):
    smoothed_bins = []

    for bin in bins:
        bin_mean = sum(bin) // len(bin) # Calculate bin mean
        smoothed_bin = [bin_mean] * len(bin) # Replace all elements in bin by mean
    return smoothed_bins

# Function to smooth data by bin boundaries
def smooth_by_bin_boundaries(bins):
    smoothed_bins = []

    for bin in bins:
        min_boundary = min(bin) # Minimum value in the bin
        max_boundary = max(bin) # Maximum value in the bin

        # Replace each element with the closest boundary
        smoothed_bin = []
        for value in bin:
            if value - min_boundary < max_boundary - value:
                smoothed_bin.append(min_boundary)
            else:
                smoothed_bin.append(max_boundary)
        smoothed_bins.append(smoothed_bin)
    return smoothed_bins

# Main function to take user input and perform binning
def main():
    # Input data from user (comma-separated values)
    data_input = input("Enter the data (comma-separated values): ")
    data = list(map(int, data_input.split(','))) # Convert to a list of integers

    # Input bin size from user
    num_bins = int(input("Enter the number of bins: "))

    # Partition the data into equal-frequency bins
    bins = partition_into_bins(data, num_bins)

    # Print original bins
    print("\nOriginal Equal-Frequency Bins:")
    for i, bin in enumerate(bins, 1):
        print(f"Bin {i}: {bin}")

    # Perform smoothing by bin means and retain the same bin structure
    smoothed_by_means = smooth_by_bin_means(bins)
    print("\nSmoothing by Bin Means (in bins):")
    for i, bin in enumerate(smoothed_by_means, 1):
        print(f"Bin {i}: {bin}")

    # Perform smoothing by bin boundaries and retain the same bin structure
    smoothed_by_boundaries = smooth_by_bin_boundaries(bins)
    print("\nSmoothing by Bin Boundaries (in bins):")
    for i, bin in enumerate(smoothed_by_boundaries, 1):
        print(f"Bin {i}: {bin}")

# Run the main function
if __name__ == "__main__":
    main()
```

Exp-04 (Naïve Bayes Algorithm)

```
import pandas as pd

def calculate_probability(df, class_label):
    class_count = df['Class'].value_counts().get(class_label, 0)
    total_count = len(df)
    probability = class_count / total_count
    print(f"Probability of '{class_label}': {probability:.4f}")
    return probability

def calculate_conditional_probability(df, feature, value, class_label):
    # Convert boolean to string if necessary
    if isinstance(value, bool):
        value = str(value)

    # Handle case where feature values might be boolean
    if df[feature].dtype == bool:
        value = value.lower() == 'true' # Convert string 'true'/'false' to boolean

    # Calculate conditional probability
    conditional_count = df[(df[feature] == value) & (df['Class'] == class_label)].count()
    conditional_total_count = df[df[feature] == value].count()
    conditional_probability = conditional_count / conditional_total_count
    print(f"Conditional Probability of '{feature}' = '{value}' given '{class_label}': {conditional_probability:.4f}")
    return conditional_probability
```

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```
# Filter rows and calculate probability
matching_row = df[(df[feature] == str_value) & (df['Class'] == class_label)]
matching_count = len(matching_row)
class_count = df['Class'].value_counts().get(class_label, 0)
probability = matching_count / class_count if class_count > 0 else 0
print(f"Conditional probability of '{feature}' = '{value}' given '{class_label}': {probability:.4f}")
return probability

def predict_class(df, outlook, temperature, humidity, windy):
    print("\nCalculating probabilities for prediction...")

    # Overall probabilities
    play_probability = calculate_probability(df, "Play")
    no_play_probability = calculate_probability(df, "No Play")

    # Conditional probabilities for 'Play'
    i1_play_probability = calculate_conditional_probability(df, "outlook", outlook, "Play")
    i2_play_probability = calculate_conditional_probability(df, "temperature", temperature, "Play")
    i3_play_probability = calculate_conditional_probability(df, "humidity", humidity, "Play")
    i4_play_probability = calculate_conditional_probability(df, "windy", windy, "Play")

    # Conditional probabilities for 'No Play'
    i1_no_play_probability = calculate_conditional_probability(df, "outlook", outlook, "No Play")
    i2_no_play_probability = calculate_conditional_probability(df, "temperature", temperature, "No Play")
    i3_no_play_probability = calculate_conditional_probability(df, "humidity", humidity, "No Play")
    i4_no_play_probability = calculate_conditional_probability(df, "windy", windy, "No Play")

    # Final probabilities
    final_play_probability = play_probability * i1_play_probability * i2_play_probability * i3_play_probability * i4_play_probability
    final_no_play_probability = no_play_probability * i1_no_play_probability * i2_no_play_probability * i3_no_play_probability * i4_no_play_probability

    print(f"Final probability of 'Play': {final_play_probability:.4f}")
    print(f"Final probability of 'No Play': {final_no_play_probability:.4f}")

    return "Play" if final_play_probability > final_no_play_probability else "No Play"

def main():
    df_train = pd.read_csv("naive_bayes.csv")
    df_test = pd.read_csv("naive_test.csv")

    correct_predictions = 0

    # Iterate over each row in the test DataFrame
    for index, row in df_test.iterrows():
        outlook = row['outlook']
        temperature = row['temperature']
        humidity = row['humidity']
        windy = row['windy']
        actual_class = row['class']

        # Predict class
        predicted_class = predict_class(df_train, outlook, temperature, humidity, windy)

        # Store predicted class in DataFrame
        df_test.at[index, 'Predicted Class'] = predicted_class

    # Compare and count correct predictions
    if predicted_class == actual_class:
        correct_predictions += 1

    # Calculate accuracy
    accuracy = (correct_predictions / len(df_test)) * 100
    print(f"Accuracy: {accuracy:.2f}%")

    df_test.to_csv("test_with_predictions.csv", index=False)

    if __name__ == "__main__":
        main()
```

Start coding or [continue](#) with AI.

EXP-05 (k-means++)

```
import numpy as np
import pandas as pd
import random
import matplotlib.pyplot as plt

def euclidean_distance(point1, point2):
    """Calculate the Euclidean distance between two points."""
    return np.sqrt((point1[0] - point2[0])**2 + (point1[1] - point2[1])**2)

def k_means_clustering(data, k, max_iterations=100):
    """Perform k-means clustering on 2D data."""
    # Initialize initial indices
    initial_indices = random.sample(range(data.shape[0]), k)
    centers = data[initial_indices].copy()

    print(f"Initial cluster centers (randomly selected): {centers}")

    # Store distances for each iteration
    all_distances = []

    for iteration in range(max_iterations):
        assignments = np.zeros(data.shape[0])
        iteration_distances = [] # Store distances for this iteration

        # (3) Assign each object to the closest cluster
        for i in range(data.shape[0]):
            distances = [euclidean_distance(data[i], center) for center in centers]
            iteration_distances.append(data[i], distances) # Save the point and distance
            assignments[i] = np.argmin(distances)

        all_distances.append(iteration_distances) # Save distances for the iteration

        # (4) Update the cluster means
        new_centers = np.array([data[assignments == i].mean(0) for i in range(k)])

        # Check for convergence
        if np.all_equal(centers, new_centers):
            break
        centers = new_centers

    # Create final clusters
    clusters = [data[assignments == i] for i in range(k)]

    # Print distances for each iteration
    for iter_idx, distances in enumerate(all_distances):
        print(f"Iteration {iter_idx + 1} distances:")
        for point, distance_values in distances:
            print(f"Distances from point {point} to centers: {distance_values}")

    return clusters

def plot_clusters(data, clusters):
    """Visualize the clustering result for 2D data."""
    plt.figure(figsize=(8, 6))
    colors = ['red', 'green', 'blue', 'orange', 'purple', 'cyan']
    for i, cluster in enumerate(clusters):
        plt.scatter(cluster, np.random.randint(1, 6, len(cluster)), color=colors[i % len(colors)], label=f'Cluster {i+1}')
    plt.title('2D k-means Clustering')
    plt.xlabel('Feature 1')
    plt.ylabel('Feature 2')
    plt.grid()
    plt.show()
```

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```
# Check for convergence
if np.all_equal(centers, new_centers):
    break
centers = new_centers

# Create final clusters
clusters = [data[assignments == i] for i in range(k)]

# Print distances for each iteration
for iter_idx, distances in enumerate(all_distances):
    print(f"Iteration {iter_idx + 1} distances:")
    for point, distance_values in distances:
        print(f"Distances from point {point} to centers: {distance_values}")

return clusters

def plot_clusters(data, clusters):
    """Visualize the clustering result for 2D data."""
    plt.figure(figsize=(8, 6))
    colors = ['red', 'green', 'blue', 'orange', 'purple', 'cyan']
    for i, cluster in enumerate(clusters):
        plt.scatter(cluster, np.random.randint(1, 6, len(cluster)), color=colors[i % len(colors)], label=f'Cluster {i+1}')
    plt.title('2D k-means Clustering')
    plt.xlabel('Feature 1')
    plt.ylabel('Feature 2')
    plt.grid()
    plt.show()

# Example usage
if __name__ == "__main__":
    # Load data from a CSV file
    data = pd.read_csv("kmeans_2d.csv").values.flatten() # Ensure data is a 1D array

    k = 3 # Number of clusters
    clusters = k_means_clustering(data, k)

    # Output results
    for i, cluster in enumerate(clusters):
        print(f"Cluster {i+1}: {cluster}")

    # Plot the clusters
    plot_clusters(data, clusters)

EXP-05 (k-means++)

import numpy as np
import pandas as pd
import random
import matplotlib.pyplot as plt

def euclidean_distance(point1, point2):
    """Calculate the Euclidean distance between two points."""
    return np.sqrt((point1[0] - point2[0])**2 + (point1[1] - point2[1])**2)

def k_means_clustering_2d(data, k, max_iterations=100):
    """Perform k-means clustering on 2D data."""
    # Initialize initial indices
    initial_indices = random.sample(range(data.shape[0]), k)
    centers = data[initial_indices].copy()

    print(f"Initial cluster centers (randomly selected): {centers}")

    # Store distances for each iteration
    all_distances = []

    for iteration in range(max_iterations):
        assignments = np.zeros(data.shape[0])
        iteration_distances = [] # Store distances for this iteration

        # (3) Assign each object to the closest cluster
        for i in range(data.shape[0]):
            distances = [euclidean_distance(data[i], center) for center in centers]
            iteration_distances.append(data[i], distances) # Save the point and distance
            assignments[i] = np.argmin(distances)

        all_distances.append(iteration_distances) # Save distances for the iteration

        # (4) Update the cluster means
        new_centers = np.array([data[assignments == i].mean(0) for i in range(k)])

        # Check for convergence
        if np.all_equal(centers, new_centers):
            break
        centers = new_centers

    # Create final clusters
    clusters = [data[assignments == i] for i in range(k)]

    # Print distances for each iteration
    for iter_idx, distances in enumerate(all_distances):
        print(f"Iteration {iter_idx + 1} distances:")
        for point, distance_values in distances:
            print(f"Distances from point {point} to centers: {distance_values}")

    return clusters

def plot_clusters(data, clusters):
    """Visualize the clustering result for 2D data."""
    plt.figure(figsize=(8, 6))
    colors = ['red', 'green', 'blue', 'orange', 'purple', 'cyan']
    for i, cluster in enumerate(clusters):
        plt.scatter(cluster, np.random.randint(1, 6, len(cluster)), color=colors[i % len(colors)], label=f'Cluster {i+1}')
    plt.title('2D k-means Clustering')
    plt.xlabel('Feature 1')
    plt.ylabel('Feature 2')
    plt.grid()
    plt.show()
```

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```
plt.show()

# Example usage
if __name__ == "__main__":
    # Load data from a CSV file
    data = pd.read_csv("kmeans_2d.csv").values # Ensure data is a 2D array

    k = 3 # Number of clusters
    clusters = k_means_clustering_2d(data, k)

    # Output results
    for i, cluster in enumerate(clusters):
        print(f"Cluster {i+1}: {cluster}")

    # Plot the clusters
    plot_clusters(data, clusters)

EXP-07 (AGGLOMERATIVE ALGORITHM)

# Step 1: Read csv file with n features
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
from scipy.cluster.hierarchy import dendrogram, linkage

# Define the points
data = {
    'x': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
    'y': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
}

df = pd.DataFrame(data)
df.to_csv("data.csv", index=False)
print(df)

data = pd.read_csv("agglo_data.csv")
coordinates = data[['x', 'y']].values
print(data)

# Step 2: Find distance between object with every
# other object. You can use euclidean function
def euclidean_distance(a, b):
    return np.sqrt((a[0] - b[0])**2 + (a[1] - b[1])**2)

# Step 3: Find distance matrix using Euclidean formula
# Initialize a distance matrix
n_points = len(coordinates)
distance_matrix = np.zeros((n_points, n_points))

# Compute the distance matrix
for i in range(n_points):
    for j in range(n_points):
        if i < j:
            distance_matrix[i, j] = euclidean_distance(coordinates[i], coordinates[j])

# Display the distance matrix
distance_df = pd.DataFrame(distance_matrix, columns=data['Point'], index=data['Point'])
print("Distance Matrix:", distance_df)

# Step 4: Find Minimum Distance and Involved Objects for All Points
min_distance = float('inf')
min_distance_pair = None

for i in range(n_points):
    for j in range(n_points):
        if i < j and distance_matrix[i, j] < min_distance:
            min_distance = distance_matrix[i, j]
            min_distance_pair = (i, j)

# Display the results
print(f"Minimum distance for all points: {min_distance:.2f} and {min_distance_pair}")

# Step 5: Merge these objects Find P2. Now (P1,P2) is one unit/cluster.
# Initialize clusters
clusters = [[data['Point'][i]] for i in range(len(data))]
print("Initial Clusters:", clusters)
# Merge P1 and P2

if min_distance_pair[0] and min_distance_pair[1]:
    merged_cluster = [min_distance_pair[0], min_distance_pair[1]]

# Update the clusters list
clusters = [c for c in clusters if c[0] not in merged_cluster] # Remove old clusters
clusters.append(merged_cluster) # Add the new cluster

print("Updated Clusters after merging:", clusters)

# Step 6: Reassociate the distances.
def update_cluster_coordinates(clusters, original_coordinates):
    new_coordinates = []
    for cluster in clusters:
        if len(cluster) == 1:
            new_coordinates.append(original_coordinates[data['Point'].tolist().index(cluster[0])])
        else:
            new_coordinates.append(np.mean([original_coordinates[data['Point'].tolist().index(point)] for point in cluster], axis=0))
    return new_coordinates
```

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```
# Calculate new cluster coordinates
updated_coordinates = update_cluster_coordinates(clusters, coordinates)

# Initialize the new distance matrix
new_distance_matrix = len(updated_coordinates)
new_distance_matrix = np.zeros((new_update_points, new_update_points))

# Compute the new distance matrix
for i in range(new_update_points):
    for j in range(new_update_points):
        if i != j:
            new_distance_matrix[i, j] = euclidean_distance(updated_coordinates[i], updated_coordinates[j])

# Create a DataFrame for easier reading
new_distance_df = pd.DataFrame(new_distance_matrix, columns=[str(cluster) for cluster in clusters], index=[str(cluster) for cluster in clusters])
print("New Distance Matrix:\n", new_distance_df)

# Perform hierarchical clustering using Ward's method
Z = linkage(df[['x', 'y']], method='ward')

# Plot the dendrogram
plt.figure(figsize=(8, 6))
dendrogram(Z, labels=df['Point'].values)
plt.title('Dendrogram', fontsize=18, color='red')
plt.xlabel('Points')
plt.ylabel('Distance')
plt.show()

Exp-08 (Apriori Algorithm)

import pandas as pd
from itertools import combinations

# Load CSV file and preprocess the data
def load_data(file_path):
    data = pd.read_csv(file_path)
    transactions = []

    # Iterate through each row in the DataFrame
    for i in range(len(data)):
        transaction = []
        # Check for each item column (item1, item2, item3, item4, item5)
        for j in range(1, len(data.columns)):
            item = data.iloc[i, j]
            if pd.notna(item):
                # Check if the item is not null
                transaction.append(item)
            transaction.append(transaction)

    return transactions

# Calculate the support of items
def calculate_support(transactions, items):
    support = {}
    for itemset in items:
        itemset_count = sum(1 for transaction in transactions if set(itemset).issubset(set(transaction)))
        support[itemset_tuple] = itemset_count / len(transactions)
    return support

# Prune items that do not meet the minimum support
def prune_items(support, min_support):
    return [itemset_tuple for itemset_tuple, support in support.items() if support >= min_support]

# Generate candidate items of size k+1 from frequent items of size k
def generate_candidates(frequent_items, k):
    candidates = set()
    frequent_items = list(frequent_items.keys())

    for i in range(len(frequent_items)):
        for j in range(i+1, len(frequent_items)):
            union_set = set(frequent_items[i]).union(frequent_items[j])
            if len(union_set) == k+1:
                candidates.add(tuple(sorted(union_set)))

    return candidates

# Calculate confidence for association rules
def calculate_confidence(frequent_items, transactions, min_confidence):
    rules = []

    for itemset in frequent_items:
        if len(itemset) > 1:
            subsets = list(combinations(itemset, len(itemset)-1))

            for subset in subsets:
                remaining = tuple(set(itemset) - set(subset))
                subset_support = sum(1 for transaction in transactions if set(subset).issubset(set(transaction))) / len(transactions)
                itemset_support = frequent_items[itemset]

                confidence = itemset_support / subset_support if subset_support > 0 else 0

                # Convert confidence to percentage
                confidence_percentage = confidence * 100

                if confidence >= min_confidence:
                    rules.append((subset, remaining, confidence_percentage))

    return rules

# Apriori algorithm
def apriori(transactions, min_support, min_confidence):
    # Generate 1-itemsets
    items = [item for transaction in transactions for item in transaction]
    items = list(set(x for x in set(tuple(sorted(x)) for x in items)))

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```
# Calculate initial support for 1-itemsets
support = calculate_support(transactions, items)

# Filter out items that do not meet minimum support
frequent_items = prune_items(support, min_support)

all_frequent_items = frequent_items.copy()
k = 1

while frequent_items:
    # Generate candidate items of size k+1
    candidates = generate_candidates(frequent_items, k)

    # Calculate support for candidate items
    support = calculate_support(transactions, candidates)

    # Prune items that do not meet the minimum support
    frequent_items = prune_items(support, min_support)

    # Add frequent items to the global list
    all_frequent_items.update(frequent_items)

    k += 1

# Calculate confidence for association rules
rules = calculate_confidence(all_frequent_items, transactions, min_confidence)

return all_frequent_items, rules

# Main
if __name__ == '__main__':
    file_path = 'apriori.csv' # Ensure this matches your actual file path
    min_support = 0.5
    min_confidence_percentage = 70 # Minimum confidence in percentage

    # Convert percentage to decimal for calculations
    min_confidence = min_confidence_percentage / 100.0

    # Load transactions
    transactions = load_data(file_path)

    # Run Apriori algorithm
    frequent_items, rules = apriori(transactions, min_support, min_confidence)

    # Output frequent items
    print("Frequent Items:")
    for itemset, support in frequent_items.items():
        print(f"{itemset}: {support:.2f}")

    # Output Association Rules with Confidence in Percentage
    print("Association Rules:")
    for rule in rules:
        antecedent, consequent, confidence = rule
        print(f"{antecedent} -> {consequent} Confidence = {confidence:.2f}%")
```

EXP-09 (PAGE RANK ALGORITHM)

```
import numpy as np

def page_rank(graph, num_iterations=100, d=0.85):
    """
    Computes the PageRank of each node in the graph.

    Parameters:
    - graph: dict, a dictionary where keys are node IDs and values are lists of nodes they link to
    - num_iterations: int, number of iterations to perform
    - d: float, damping factor (usually set to 0.85)

    Returns:
    - rank: dict, a dictionary of nodes with their corresponding PageRank scores

    """

    # Number of nodes
    num_nodes = len(graph)

    # Initialize PageRank scores
    rank = {node: 1 / num_nodes for node in graph}

    for iteration in range(num_iterations):
        new_rank = {}
        for node in graph:
            # For node, links in graph.items():
            if len(links) == 0:
                continue # node is dangling node
            for link in links:
                new_rank[link] += d * (rank[node] / len(links))

        rank = new_rank

    # Print the PageRank scores for this iteration
    print(f"Iteration {iteration + 1}: {rank}")

    return rank

# Example graph represented as an adjacency list
graph = {
    'A': ['B', 'C'],
    'B': ['C'],
    'C': ['A'],
    'D': ['A'],
    'E': ['A', 'D']
}

# Compute PageRank with iteration visualization
rank_scores = page_rank(graph, num_iterations=8)
print("Final PageRank scores:", rank_scores)
```

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EXP-10 (HITS ALGORITHM)

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

def hits(graph, num_iterations=100):
    n = len(graph)

    # Initialize hub and authority scores
    hub_scores = np.zeros(n)
    authority_scores = np.zeros(n)

    for _ in range(num_iterations):
        # Update authority scores
        new_authority_scores = np.zeros(n)
        for i in range(n):
            for j in range(n):
                if graph[i][j] == 1: # If there's a link from j to i
                    new_authority_scores[i] = hub_scores[j]

        # Update hub scores
        new_hub_scores = np.zeros(n)
        for i in range(n):
            for j in range(n):
                if graph[i][j] == 1: # If there's a link from i to j
                    new_hub_scores[i] = new_authority_scores[j]

        # Normalize authority scores
        authority_norm = np.linalg.norm(new_authority_scores, 2)
        if authority_norm > 0:
            new_authority_scores /= authority_norm

        # Normalize hub scores
        hub_norm = np.linalg.norm(new_hub_scores, 2)
        if hub_norm > 0:
            new_hub_scores /= hub_norm

        # Check for convergence
        if (np.all(np.abs(new_authority_scores - authority_scores) < 1e-6) and
            np.all(np.abs(new_hub_scores - hub_scores) < 1e-6)):
            break

        authority_scores = new_authority_scores
        hub_scores = new_hub_scores

    return authority_scores, hub_scores

def visualize_graph(graph, authority_scores, hub_scores, pages):
    s = nx.DiGraph()

    # Add edges to the graph
    for i in range(len(graph)):
        for j in range(len(graph)):
            if graph[i][j] == 1:
                s.add_edge(i+1, j+1)

    pos = nx.spring_layout(s) # positions for all nodes
    nx.draw(s, pos, with_labels=True, node_size=3000, node_color='lightblue', font_size=18, font_weight='bold')

    # Display scores on the nodes
    labels = [pages[i] + f"({pages[i]}): {authority_scores[i]:.2f} | {hub_scores[i]:.2f}" for i in range(len(pages))]
    nx.draw_networkx_labels(s, pos, labels=labels)

    plt.title('HITS Algorithm: Authority and Hub Scores')
    plt.show()

# Example usage
pages = ['A', 'B', 'C']
graph = np.array([[0, 1, 1], # A -> B, A -> C
                  [1, 0, 0], # B -> A
                  [0, 1, 0]] # C -> B

authority_scores, hub_scores = hits(graph)
print("Authority Scores:", authority_scores)
print("Hub Scores:", hub_scores)

# Visualize the graph
visualize_graph(graph, authority_scores, hub_scores, pages)
```

https://colab.research.google.com/drive/1vuDb_K8tn3xRv7/60dW6D2h6u0SOaE#scrollTo=vpynNhyC9877&printMode=true

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