

```
In [40]: import pandas  
import numpy as np
```

```
In [41]: ODAQ_results = pandas.read_csv('./ODAQ/ODAQ_listening_test/ODAQ_results.csv')  
ODAQ_results_BSU1 = pandas.read_csv('./ODAQ_v1_BSU/Cohort_B1_results.csv')  
ODAQ_results_BSU2 = pandas.read_csv('./ODAQ_v1_BSU/Cohort_B2_results.csv')
```

```
In [42]: ODAQ_results
```

Out[42]:

	score	method	condition	process	item	subject
<b>0</b>	47.0	LP	LP3.5	LP35	LP_11_guitar	Subject 1: USLA08
<b>1</b>	5.0	LP	LP3.5	LP35	LP_11_guitar	Subject 2: DEID44
<b>2</b>	10.0	LP	LP3.5	LP35	LP_11_guitar	Subject 3: DEID1115
<b>3</b>	20.0	LP	LP3.5	LP35	LP_11_guitar	Subject 4: DEID337
<b>4</b>	30.0	LP	LP3.5	LP35	LP_11_guitar	Subject 5: USLA06
...	...	...	...	...	...	...
<b>6235</b>	100.0	DE	Ref	reference	DE_SitaSings_remix2_LD6	Subject 22: DEID2
<b>6236</b>	100.0	DE	Ref	reference	DE_SitaSings_remix2_LD6	Subject 23: USLA01
<b>6237</b>	100.0	DE	Ref	reference	DE_SitaSings_remix2_LD6	Subject 24: USLA05
<b>6238</b>	100.0	DE	Ref	reference	DE_SitaSings_remix2_LD6	Subject 25: DEID1
<b>6239</b>	100.0	DE	Ref	reference	DE_SitaSings_remix2_LD6	Subject 26: DEID3

6240 rows × 6 columns

```
In [43]: methods = ODAQ_results['method'].unique()
conditions = ODAQ_results['condition'].unique()
processes = ODAQ_results['process'].unique()
items = ODAQ_results['item'].unique()

print(methods)
print(conditions)
print(processes)
print(items)
```

```

['LP' 'TM' 'UN' 'SH' 'PE' 'DE']
['LP3.5' 'LP7' 'Q1' 'Q2' 'Q3' 'Q4' 'Q5' 'Ref']
['LP35' 'LP70' 'LP50' 'LP90' 'LP105' 'LP120' 'LP150' 'reference' 'TM3k'
'TM5k' 'TM7k' 'TM9k' 'TM10.5k' 'UN3k' 'UN5k' 'UN7k' 'UN9k' 'UN10.5k'
'SH70_MS' 'SH50_MS' 'SH30_MS' 'SH20_MS' 'SH10_MS' 'PE_4096_MS_NMR10'
'PE_2048_MS_NMR10' 'PE_1024_MS_NMR10' 'PE_2048_MS_NMR16'
'PE_1024_MS_NMR16' 'OpenUnmix_mid' 'TFC_TDF_U_Net_mid' 'Cocktail_mid'
'DeepFilterNet2_mid' 'PSM_quantize_mask']
['LP_11_guitar' 'LP_23_jazz' 'LP_AmateurOnPurpose'
'LP_CreatureFromTheBlackjackTable' 'TM_01b_trumpet' 'TM_02_violin'
'TM_AmateurOnPurpose' 'TM_CreatureFromTheBlackjackTable'
'UN_20c_accordion' 'UN_21_violin' 'UN_AmateurOnPurpose'
'UN_CreatureFromTheBlackjackTable' 'SH_04_choral' 'SH_13_glockenspiel'
'SH_AmateurOnPurpose' 'SH_CreatureFromTheBlackjackTable'
'PE_27_castanets' 'PE_39_clapping' 'PE_AmateurOnPurpose'
'PE_CreatureFromTheBlackjackTable' 'DE_CosmosLandromat_remix1_LD6'
'DE_CosmosLandromat_remix3_LD3' 'DE_ElephantsDream_LD0'
'DE_female_speech_music_1_LD0' 'DE_female_speech_music_2_LD9'
'DE_female_speech_music_3_LD3' 'DE_Meridian_remix1_LD3'
'DE_Meridian_remix2_LD6' 'DE_SitaSings_remix1_LD0'
'DE_SitaSings_remix2_LD6']

```

```

In [44]: # Get unique subjects from ODAQ_results
unique_subjects = ODAQ_results['subject'].unique()

print(unique_subjects)

# Dynamically create expert variables
for i, subject in enumerate(unique_subjects, start=1):
    globals()[f"expert{i}"] = ODAQ_results[ODAQ_results['subject'] ==

['Subject 1: USLA08' 'Subject 2: DEID44' 'Subject 3: DEID1115'
'Subject 4: DEID337' 'Subject 5: USLA06' 'Subject 6: DEID5'
'Subject 7: DEID9' 'Subject 8: DEID4' 'Subject 9: USLG04'
'Subject 10: USLA04' 'Subject 11: USLA07' 'Subject 12: DEID256'
'Subject 13: DEID6' 'Subject 14: USLG05' 'Subject 15: USLA09'
'Subject 16: USLG02' 'Subject 17: USLG03' 'Subject 18: DEID7'
'Subject 19: USLA12' 'Subject 20: DEID10' 'Subject 21: DEID8'
'Subject 22: DEID2' 'Subject 23: USLA01' 'Subject 24: USLA05'
'Subject 25: DEID1' 'Subject 26: DEID3']

```

```

In [45]: # Initialize score lists dynamically for 26 experts
for i in range(1, 27): # Assuming 26 experts
    globals()[f"expert{i}_scores"] = []

# Append scores systematically
for item in items:
    for i in range(1, 27):
        expert_df = globals()[f"expert{i}"] # Access expert data fram
        scores = expert_df[expert_df['item'] == item]['score'].values
        globals()[f"expert{i}_scores"].append(scores)

```

```

In [46]: # Function to compute rankings with penalty for ties

```

```
def competition_ranking(scores):
    """Returns competition-style rankings (ascending order), where tie

    sorted_indices = np.argsort(scores) # Sort in ascending order
    ranks = np.zeros_like(scores, dtype=int)

    rank = 1 # Start ranking from 1
    for i in range(len(scores)):
        if i > 0 and scores[sorted_indices[i]] == scores[sorted_indices[i-1]]:
            ranks[sorted_indices[i]] = ranks[sorted_indices[i-1]] #
        else:
            ranks[sorted_indices[i]] = rank # Assign new rank

            rank += 1 # Increment rank, ensuring skipped positions for tie

    return ranks
```

```
In [47]: # Compute rankings systematically for 26 experts
for i in range(1, 27): # Assuming 26 experts
    expert_scores = globals()[f"expert{i}_scores"] # Get the score list
    globals()[f"expert{i}_rankings"] = np.array([competition_ranking(r
```

```
In [48]: expert1_scores
```

```
Out[48]: [array([ 47.,  66.,  56.,  76.,  90., 100.,  91.,  94.]),
array([ 17.,  50.,  35.,  46., 100., 100., 100., 100.]),
array([ 13.,  43.,  35.,  55.,  53., 100.,  78., 100.]),
array([ 38.,  60.,  47.,  73.,  83., 100.,  92.,  92.]),
array([ 22.,  53.,  44.,  60.,  69.,  78., 100.,  82.]),
array([ 25.,  43.,  13.,  50.,  57.,  63.,  68., 100.]),
array([ 11.,  38.,  37.,  54.,  71.,  81.,  79., 100.]),
array([ 18.,  42.,  28.,  39.,  77.,  49.,  72., 100.]),
array([ 55.,  74.,  40.,  54.,  62.,  74., 100.,  85.]),
array([ 35.,  68.,  16.,  44.,  52.,  87., 100., 100.]),
array([ 25.,  42.,  59.,  79.,  75.,  89.,  60., 100.]),
array([ 16.,  32.,  64.,  85., 100., 100., 100., 100.]),
array([ 37.,  65.,  12.,  27.,  32.,  32.,  37., 100.]),
array([ 15.,  66.,  18.,  26.,  40.,  52.,  56., 100.]),
array([ 37.,  58.,  49.,  69.,  66.,  78.,  87., 100.]),
array([ 17.,  42.,  11.,  20.,  29.,  43.,  77., 100.]),
array([ 46.,  72.,  32.,  65.,  37.,  61.,  74., 100.]),
array([ 45.,  78.,  15.,  29.,  47.,  37.,  49., 100.]),
array([ 17.,  30.,  63.,  61.,  37.,  78., 100., 100.]),
array([ 44.,  63.,  67.,  74.,  80.,  83.,  83., 100.]),
array([ 20.,  36.,  18.,  45.,  55.,  74., 100.,  85.]),
array([ 26.,  51.,  18.,  35.,  59.,  60.,  82., 100.]),
array([ 13.,  63.,  43.,  62.,  59.,  60.,  75., 100.]),
array([ 22.,  52.,  28.,  38.,  28.,  32.,  85., 100.]),
array([ 17.,  40.,  29.,  76.,  51.,  75., 100., 100.]),
array([ 14.,  45.,  25.,  48.,  62.,  56.,  82., 100.]),
array([ 59.,  84.,  48.,  62.,  67.,  80.,  87., 100.]),
array([ 32.,  81.,  33.,  42.,  53.,  74.,  75., 100.]),
array([ 34.,  54.,  37.,  61.,  69.,  79.,  90., 100.]),
array([ 21.,  64.,  29.,  44.,  60.,  74.,  65., 100.])]
```

```
In [49]: expert1_rankings
```

```
Out[49]: array([[1, 3, 2, 4, 5, 8, 6, 7],
                [1, 4, 2, 3, 5, 5, 5, 5],
                [1, 3, 2, 5, 4, 7, 6, 7],
                [1, 3, 2, 4, 5, 8, 6, 6],
                [1, 3, 2, 4, 5, 6, 8, 7],
                [2, 3, 1, 4, 5, 6, 7, 8],
                [1, 3, 2, 4, 5, 7, 6, 8],
                [1, 4, 2, 3, 7, 5, 6, 8],
                [3, 5, 1, 2, 4, 5, 8, 7],
                [2, 5, 1, 3, 4, 6, 7, 7],
                [1, 2, 3, 6, 5, 7, 4, 8],
                [1, 2, 3, 4, 5, 5, 5, 5],
                [5, 7, 1, 2, 3, 3, 5, 8],
                [1, 7, 2, 3, 4, 5, 6, 8],
                [1, 3, 2, 5, 4, 6, 7, 8],
                [2, 5, 1, 3, 4, 6, 7, 8],
                [3, 6, 1, 5, 2, 4, 7, 8],
                [4, 7, 1, 2, 5, 3, 6, 8],
                [1, 2, 5, 4, 3, 6, 7, 7],
                [1, 2, 3, 4, 5, 6, 6, 8],
                [2, 3, 1, 4, 5, 6, 8, 7],
                [2, 4, 1, 3, 5, 6, 7, 8],
                [1, 6, 2, 5, 3, 4, 7, 8],
                [1, 6, 2, 5, 2, 4, 7, 8],
                [1, 3, 2, 6, 4, 5, 7, 7],
                [1, 3, 2, 4, 6, 5, 7, 8],
                [2, 6, 1, 3, 4, 5, 7, 8],
                [1, 7, 2, 3, 4, 5, 6, 8],
                [1, 3, 2, 4, 5, 6, 7, 8],
                [1, 5, 2, 3, 4, 7, 6, 8]])
```

```
In [51]: # Perfect ranking
perfect_ranking = np.array([1, 2, 3, 4, 5, 6, 7, 8])
```

```
In [52]: # Define a distance function (Euclidean distance)
def compute_distance(vec1, vec2):
    return np.linalg.norm(vec1 - vec2) # Euclidean distance
```

For  $\mathbf{v}_1 = [v_{1,1}, v_{1,2}, \dots, v_{1,n}]$  and  $\mathbf{v}_2 = [v_{2,1}, v_{2,2}, \dots, v_{2,n}]$ , with  $n = 8$ , we compute the euclidean distance between them as follows:

$$d(\mathbf{v}_1, \mathbf{v}_2) = \sqrt{\sum_{i=1}^n (v_{1,i} - v_{2,i})^2}$$

```
In [53]: # Initialize a 26x30 matrix to store distances
distance_matrix = np.zeros((26, 30))

# Compute distances systematically
for i in range(1, 27): # 26 experts
```

```
expert_rankings = globals()[f"expert{i}_rankings"] # Get expert r  
  
for j in range(30): # 30 ranking vectors per expert  
    distance_matrix[i-1, j] = compute_distance(expert_rankings[j],  
distance_matrix_df = pandas.DataFrame(distance_matrix, columns=items)
```

In [54]: distance\_matrix\_df

Out [54]:

	LP_11_guitar	LP_23_jazz	LP_AmateurOnPurpose	LP_CreatureFromTheBlack
0	2.828427	4.472136		2.645751
1	2.645751	1.414214		1.414214
2	3.162278	2.449490		2.000000
3	3.162278	1.732051		4.000000
4	3.316625	2.645751		1.000000
5	1.732051	1.732051		2.645751
6	1.414214	2.000000		2.000000
7	1.414214	1.414214		2.828427
8	4.898979	2.828427		1.414214
9	1.732051	3.872983		1.414214
10	1.414214	2.236068		2.000000
11	3.316625	3.162278		3.464102
12	2.000000	2.000000		1.414214
13	3.000000	5.000000		3.605551
14	2.828427	2.828427		2.449490
15	5.656854	2.645751		3.605551
16	2.236068	2.236068		1.732051
17	1.414214	3.162278		1.000000
18	1.414214	3.000000		4.358899
19	2.000000	2.000000		1.732051
20	2.000000	2.828427		2.000000
21	4.000000	3.316625		2.828427
22	1.732051	2.828427		1.414214
23	1.414214	3.464102		2.645751
24	2.645751	4.000000		2.645751
25	4.358899	3.316625		3.464102

26 rows × 30 columns

In [55]: `import matplotlib.pyplot as plt  
import seaborn as sns`

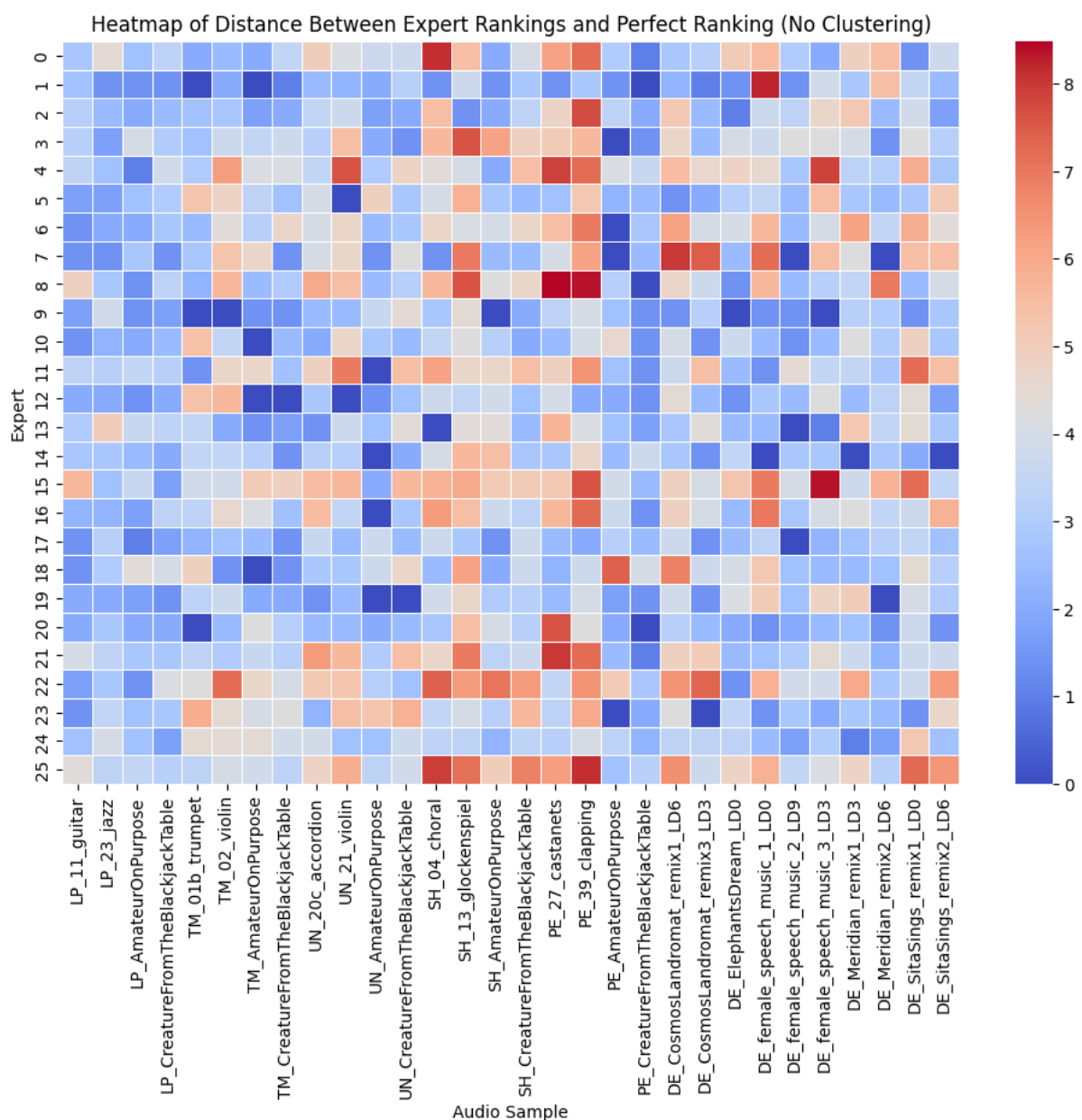


```
import numpy as np
import pandas as pd

# Create a heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(distance_matrix_df, cmap="coolwarm", annot=False, linewidth=1)

# Labels and title
plt.xlabel("Audio Sample")
plt.ylabel("Expert")
plt.title("Heatmap of Distance Between Expert Rankings and Perfect Ranking")

# Show the plot
plt.show()
```



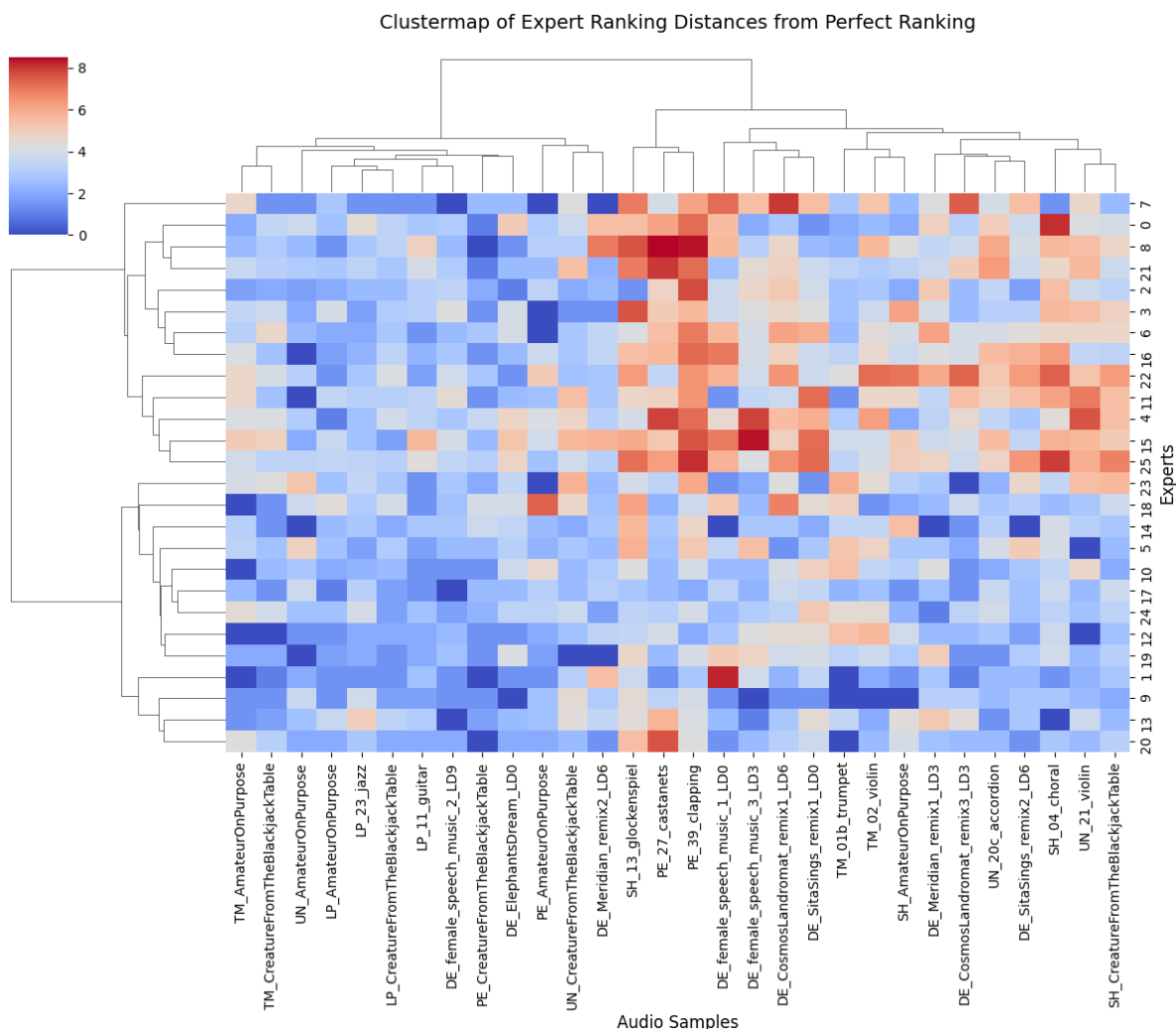
```
In [56]: from scipy.cluster.hierarchy import linkage, dendrogram
```

```
# Perform hierarchical clustering (using Ward's method)
linkage_matrix = linkage(distance_matrix, method='ward')

# Create a clustermap (heatmap with hierarchical clustering)
clustermap = sns.clustermap(
    distance_matrix_df,
    cmap="coolwarm",
    method="ward",
    figsize=(12, 10),
    xticklabels=True, # Display column labels (optional)
    yticklabels=True  # Display row labels (optional)
)

# Add axis labels
clustermap.ax_heatmap.set_xlabel("Audio Samples", fontsize=12)
clustermap.ax_heatmap.set_ylabel("Experts", fontsize=12)
clustermap.ax_heatmap.set_title("Clustermap of Expert Ranking Distance")

# Show the plot
plt.show()
```



In [57]: # PERFORMANCE-BASED CLUSTERING

```
from scipy.cluster.hierarchy import fcluster

# Extract clusters from the linkage matrix
num_clusters = 5 # Choose the number of clusters (you can adjust)
cluster_labels = fcluster(linkage_matrix, num_clusters, criterion='max')

# Create a DataFrame mapping experts to their cluster
cluster_df = pd.DataFrame({'Expert': [f"Expert {i}" for i in range(1,
                                'Cluster': cluster_labels)})

cluster_df
```

Out [57]:

	Expert	Cluster
0	Expert 1	1
1	Expert 2	5
2	Expert 3	1
3	Expert 4	1
4	Expert 5	2
5	Expert 6	4
6	Expert 7	1
7	Expert 8	3
8	Expert 9	1
9	Expert 10	5
10	Expert 11	4
11	Expert 12	2
12	Expert 13	4
13	Expert 14	5
14	Expert 15	4
15	Expert 16	2
16	Expert 17	1
17	Expert 18	4
18	Expert 19	4
19	Expert 20	4
20	Expert 21	5
21	Expert 22	1
22	Expert 23	2
23	Expert 24	4
24	Expert 25	4
25	Expert 26	2

In [58]: *# order cluster\_df by Cluster*

```
cluster_df_ordered = cluster_df.sort_values(by='Cluster')  
cluster_df_ordered
```

Out [58]:

	Expert	Cluster
0	Expert 1	1
2	Expert 3	1
3	Expert 4	1
21	Expert 22	1
16	Expert 17	1
6	Expert 7	1
8	Expert 9	1
22	Expert 23	2
15	Expert 16	2
11	Expert 12	2
25	Expert 26	2
4	Expert 5	2
7	Expert 8	3
24	Expert 25	4
14	Expert 15	4
5	Expert 6	4
17	Expert 18	4
18	Expert 19	4
19	Expert 20	4
23	Expert 24	4
10	Expert 11	4
12	Expert 13	4
9	Expert 10	5
13	Expert 14	5
20	Expert 21	5
1	Expert 2	5

```
In [59]: import seaborn as sns
import matplotlib.pyplot as plt

# Add cluster labels to the distance matrix
```

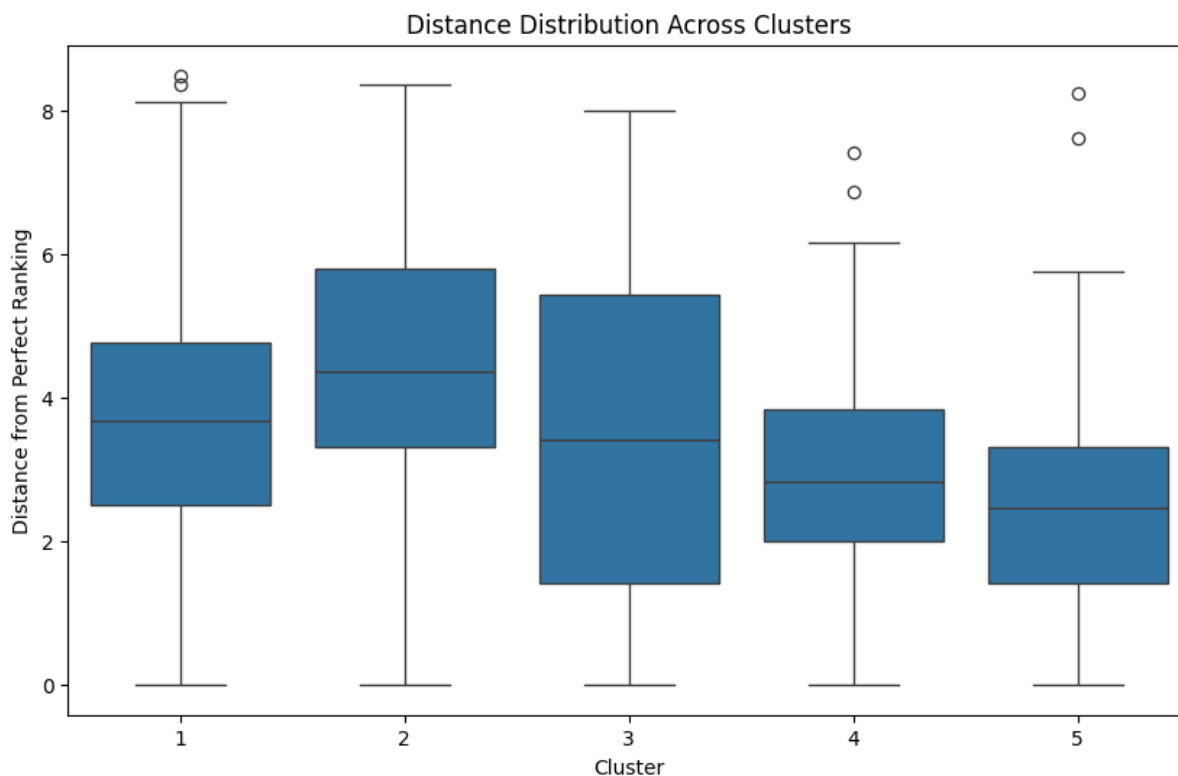
```

distance_matrix_df['Cluster'] = cluster_labels

# Melt data for visualization
melted_df = distance_matrix_df.melt(id_vars=['Cluster'], var_name='Ranking')

# Plot the distribution of distances per cluster
plt.figure(figsize=(10, 6))
sns.boxplot(x='Cluster', y='Distance', data=melted_df)
plt.xlabel("Cluster")
plt.ylabel("Distance from Perfect Ranking")
plt.title("Distance Distribution Across Clusters")
plt.show()

```



```

In [60]: # Example: Find which experts belong to Cluster 1
cluster_1_experts = cluster_df[cluster_df['Cluster'] == 1]
print(cluster_1_experts)

```

	Expert	Cluster
0	Expert 1	1
2	Expert 3	1
3	Expert 4	1
6	Expert 7	1
8	Expert 9	1
16	Expert 17	1
21	Expert 22	1