clustering-analysis

January 10, 2026

1 PHASE 3: CLUSTERING ANALYSIS

1.1 Find Optimal K using Elbow Method

[1]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[4]:
```
import numpy as np
PROJECT_ROOT= "/content/drive/MyDrive/image-clustering-retrieval"
features_normalized = np.load(f"{PROJECT_ROOT}/features/embeddings.npy")
labels = np.load(f"{PROJECT_ROOT}/features/labels.npy")

print(features_normalized.shape)
```

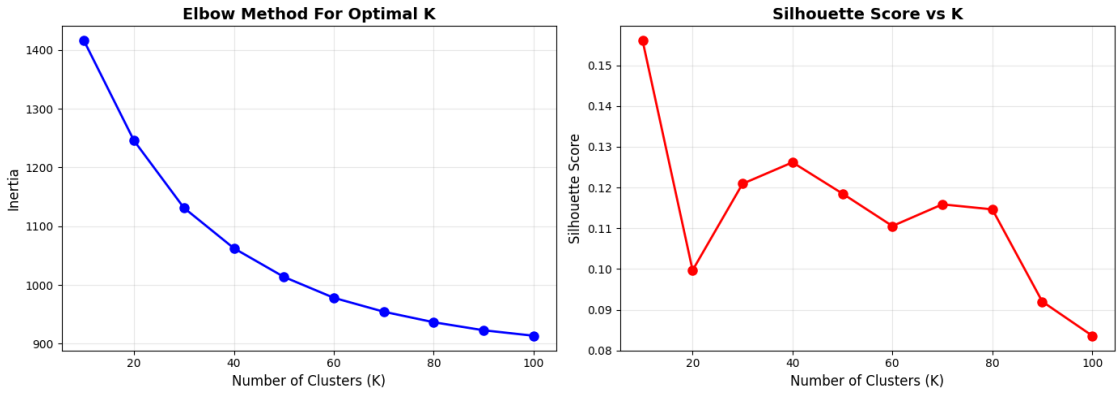
```
(4696, 2048)
```

[6]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
from tqdm import tqdm

# Set random seed for reproducibility
np.random.seed(42)
print("-"*60)
print("PHASE 3: CLUSTERING ANALYSIS")
print("-"*60)

def find_optimal_k(features, k_range=(10, 100), step=10, sample_size=5000):
    """Find optimal K using elbow method"""
    # Sample for faster computation
    if len(features) > sample_size:
        indices = np.random.choice(len(features), sample_size, replace=False)
        features_sample = features[indices]
    else:
        features_sample = features
```

```
    k_values = list(range(k_range[0], k_range[1] + 1, step))
    inertias = []
    silhouette_scores_list = []

    print(f"\n Finding optimal K (testing K={k_range[0]} to {k_range[1]})...")

    for k in tqdm(k_values, desc="Testing K values"):
        kmeans = KMeans(n_clusters=k, random_state=42, n_init=10)
        labels_pred = kmeans.fit_predict(features_sample)
        inertias.append(kmeans.inertia_)

        # Calculate silhouette score on smaller sample
        sample_for_sil = min(3000, len(features_sample))
        sil_indices = np.random.choice(len(features_sample), sample_for_sil,␣
↪replace=False)
        sil_score = silhouette_score(features_sample[sil_indices],␣
↪labels_pred[sil_indices])
        silhouette_scores_list.append(sil_score)

        print(f"  K={k:3d}: Inertia={kmeans.inertia_:.2f},␣
↪Silhouette={sil_score:.4f}")

    # Plot results
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(14, 5))
    ax1.plot(k_values, inertias, 'bo-', linewidth=2, markersize=8)
    ax1.set_xlabel('Number of Clusters (K)', fontsize=12)
    ax1.set_ylabel('Inertia', fontsize=12)
    ax1.set_title('Elbow Method For Optimal K', fontsize=14, fontweight='bold')
    ax1.grid(True, alpha=0.3)

    ax2.plot(k_values, silhouette_scores_list, 'ro-', linewidth=2, markersize=8)
    ax2.set_xlabel('Number of Clusters (K)', fontsize=12)
    ax2.set_ylabel('Silhouette Score', fontsize=12)
    ax2.set_title('Silhouette Score vs K', fontsize=14, fontweight='bold')
    ax2.grid(True, alpha=0.3)

    plt.tight_layout()
    plt.savefig(f'{PROJECT_ROOT}/results/clustering/elbow_curve.png', dpi=150,␣
↪bbox_inches='tight')
    plt.show()

    # Find optimal K
    optimal_k = k_values[np.argmax(silhouette_scores_list)]
    print(f"\n Recommended K: {optimal_k} (highest silhouette score)")

    return k_values, inertias, silhouette_scores_list, optimal_k
```

```
# Find optimal K using all features
k_vals, inertias, sil_scores, optimal_k = find_optimal_k(
    features_normalized,
    k_range=(10, 100),
    step=10,
    sample_size=5000)
```

```
------------------------------------------------------------
PHASE 3: CLUSTERING ANALYSIS
------------------------------------------------------------

 Finding optimal K (testing K=10 to 100)…
Testing K values:  10%|          | 1/10 [00:09<01:21,  9.04s/it]
  K= 10: Inertia=1415.76, Silhouette=0.1560
Testing K values:  20%|          | 2/10 [00:22<01:35, 11.92s/it]
  K= 20: Inertia=1245.85, Silhouette=0.0997
Testing K values:  30%|          | 3/10 [00:42<01:47, 15.34s/it]
  K= 30: Inertia=1131.32, Silhouette=0.1209
Testing K values:  40%|          | 4/10 [01:07<01:55, 19.32s/it]
  K= 40: Inertia=1062.57, Silhouette=0.1262
Testing K values:  50%|          | 5/10 [01:38<01:57, 23.59s/it]
  K= 50: Inertia=1013.82, Silhouette=0.1185
Testing K values:  60%|          | 6/10 [02:18<01:56, 29.16s/it]
  K= 60: Inertia=978.18, Silhouette=0.1105
Testing K values:  70%|          | 7/10 [03:01<01:40, 33.57s/it]
  K= 70: Inertia=954.51, Silhouette=0.1159
Testing K values:  80%|          | 8/10 [03:47<01:14, 37.35s/it]
  K= 80: Inertia=936.59, Silhouette=0.1146
Testing K values:  90%|          | 9/10 [04:41<00:42, 42.85s/it]
  K= 90: Inertia=922.88, Silhouette=0.0920
Testing K values: 100%|          | 10/10 [05:38<00:00, 33.84s/it]
  K=100: Inertia=913.61, Silhouette=0.0836
```




```
Recommended K: 10 (highest silhouette score)
```

2 Perform K-Means Clustering

[9]:
```python
import numpy as np
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score, davies_bouldin_score
import pickle
from datetime import datetime
import json

def perform_kmeans(features, n_clusters, save_path):
    """Perform K-Means clustering"""
    print(f"\n Training K-Means with K={n_clusters}...")
    kmeans =␣
 ↪KMeans(n_clusters=n_clusters,random_state=42,n_init=10,max_iter=300,verbose=1)
    cluster_labels = kmeans.fit_predict(features)

    # Evaluate
    print("\n Evaluating clustering quality...")
    sample_size = min(10000, len(features))
    indices = np.random.choice(len(features), sample_size, replace=False)

    sil_score = silhouette_score(features[indices], cluster_labels[indices])
    db_score = davies_bouldin_score(features, cluster_labels)

    print(f"\n{'-'*60}")
    print("CLUSTERING METRICS")
    print(f"{'-'*60}")
    print(f"Silhouette Score:     {sil_score:.4f}  (higher is better)")
    print(f"Davies-Bouldin Index: {db_score:.4f}  (lower is better)")
```

```
    print(f"{'-'*60}")

    # Cluster statistics
    unique, counts = np.unique(cluster_labels, return_counts=True)
    print("\n Cluster Distribution:")
    for cluster_id, count in zip(unique[:10], counts[:10]):
        print(f"  Cluster {cluster_id:3d}: {count:5d} images ({count/
 ↪len(cluster_labels)*100:.1f}%)")
    if len(unique) > 10:
        print(f"  ... and {len(unique)-10} more clusters")

    # Save model
    with open(f'{save_path}/kmeans_k{n_clusters}.pkl', 'wb') as f:
        pickle.dump(kmeans, f)

    # Save cluster labels
    np.save(f'{save_path}/cluster_labels.npy', cluster_labels)

    # Save metrics
    metrics = {
        'n_clusters': n_clusters,
        'silhouette_score': float(sil_score),
        'davies_bouldin_score': float(db_score),
        'cluster_sizes': {int(k): int(v) for k, v in zip(unique, counts)},
        'created_at': datetime.now().strftime('%Y-%m-%d %H:%M:%S')
    }

    with open(f'{save_path}/clustering_metrics.json', 'w') as f:
        json.dump(metrics, f, indent=2)

    print(f"\n K-Means model saved to {save_path}")

    return kmeans, cluster_labels, metrics

# Run clustering on all features
n_clusters = optimal_k
kmeans_model, cluster_labels, clustering_metrics = perform_kmeans(
    features_normalized,
    n_clusters=n_clusters,
    save_path=f'{PROJECT_ROOT}/models/clustering'
)
```

```
 Training K-Means with K=10…
Initialization complete
Iteration 0, inertia 2601.984375.
Iteration 1, inertia 1508.302978515625.
```

```
Iteration 2, inertia 1458.3720703125.
Iteration 3, inertia 1446.654052734375.
Iteration 4, inertia 1442.485595703125.
Iteration 5, inertia 1440.44189453125.
Iteration 6, inertia 1438.144775390625.
Iteration 7, inertia 1434.223876953125.
Iteration 8, inertia 1431.161865234375.
Iteration 9, inertia 1430.2640380859375.
Iteration 10, inertia 1429.9620361328125.
Iteration 11, inertia 1429.7301025390625.
Iteration 12, inertia 1429.576904296875.
Iteration 13, inertia 1429.2808837890625.
Iteration 14, inertia 1428.7164306640625.
Iteration 15, inertia 1428.16845703125.
Iteration 16, inertia 1427.9051513671875.
Iteration 17, inertia 1427.8409423828125.
Iteration 18, inertia 1427.822021484375.
Iteration 19, inertia 1427.8212890625.
Converged at iteration 19: strict convergence.
Initialization complete
Iteration 0, inertia 2514.159423828125.
Iteration 1, inertia 1471.175048828125.
Iteration 2, inertia 1453.6182861328125.
Iteration 3, inertia 1444.779541015625.
Iteration 4, inertia 1437.613525390625.
Iteration 5, inertia 1431.40185546875.
Iteration 6, inertia 1426.8890380859375.
Iteration 7, inertia 1425.1907958984375.
Iteration 8, inertia 1424.6138916015625.
Iteration 9, inertia 1424.4996337890625.
Iteration 10, inertia 1424.4857177734375.
Iteration 11, inertia 1424.4747314453125.
Iteration 12, inertia 1424.4501953125.
Iteration 13, inertia 1424.4168701171875.
Iteration 14, inertia 1424.411376953125.
Iteration 15, inertia 1424.40771484375.
Iteration 16, inertia 1424.400634765625.
Iteration 17, inertia 1424.3900146484375.
Iteration 18, inertia 1424.385986328125.
Converged at iteration 18: strict convergence.
Initialization complete
Iteration 0, inertia 2581.439453125.
Iteration 1, inertia 1478.2677001953125.
Iteration 2, inertia 1453.471435546875.
Iteration 3, inertia 1445.3914794921875.
Iteration 4, inertia 1441.7608642578125.
Iteration 5, inertia 1439.459716796875.
Iteration 6, inertia 1437.7947998046875.
```

```
Iteration 7, inertia 1436.30126953125.
Iteration 8, inertia 1435.5294189453125.
Iteration 9, inertia 1435.15625.
Iteration 10, inertia 1434.744384765625.
Iteration 11, inertia 1434.23974609375.
Iteration 12, inertia 1434.0787353515625.
Iteration 13, inertia 1434.0081787109375.
Iteration 14, inertia 1433.9842529296875.
Iteration 15, inertia 1433.974853515625.
Iteration 16, inertia 1433.97119140625.
Iteration 17, inertia 1433.9683837890625.
Iteration 18, inertia 1433.9671630859375.
Iteration 19, inertia 1433.9659423828125.
Iteration 20, inertia 1433.96484375.
Converged at iteration 20: strict convergence.
Initialization complete
Iteration 0, inertia 2650.808349609375.
Iteration 1, inertia 1500.4649658203125.
Iteration 2, inertia 1467.735107421875.
Iteration 3, inertia 1457.30810546875.
Iteration 4, inertia 1450.9610595703125.
Iteration 5, inertia 1445.843994140625.
Iteration 6, inertia 1443.68896484375.
Iteration 7, inertia 1442.059326171875.
Iteration 8, inertia 1441.154296875.
Iteration 9, inertia 1440.389404296875.
Iteration 10, inertia 1439.8507080078125.
Iteration 11, inertia 1439.5782470703125.
Iteration 12, inertia 1439.3458251953125.
Iteration 13, inertia 1438.8021240234375.
Iteration 14, inertia 1438.3492431640625.
Iteration 15, inertia 1437.8011474609375.
Iteration 16, inertia 1436.6248779296875.
Iteration 17, inertia 1432.8123779296875.
Iteration 18, inertia 1432.0577392578125.
Iteration 19, inertia 1431.970947265625.
Iteration 20, inertia 1431.9041748046875.
Iteration 21, inertia 1431.864990234375.
Iteration 22, inertia 1431.793701171875.
Iteration 23, inertia 1431.6175537109375.
Iteration 24, inertia 1431.347900390625.
Iteration 25, inertia 1430.9505615234375.
Iteration 26, inertia 1430.166259765625.
Iteration 27, inertia 1429.070068359375.
Iteration 28, inertia 1427.9664306640625.
Iteration 29, inertia 1427.4512939453125.
Iteration 30, inertia 1427.2574462890625.
Iteration 31, inertia 1427.1793212890625.
```

```
Iteration 32, inertia 1427.157470703125.
Iteration 33, inertia 1427.1507568359375.
Iteration 34, inertia 1427.1422119140625.
Iteration 35, inertia 1427.1412353515625.
Converged at iteration 35: strict convergence.
Initialization complete
Iteration 0, inertia 2579.285888671875.
Iteration 1, inertia 1494.8487548828125.
Iteration 2, inertia 1464.019775390625.
Iteration 3, inertia 1453.90087890625.
Iteration 4, inertia 1447.9822998046875.
Iteration 5, inertia 1444.5777587890625.
Iteration 6, inertia 1440.6290283203125.
Iteration 7, inertia 1437.1995849609375.
Iteration 8, inertia 1436.9449462890625.
Iteration 9, inertia 1436.8541259765625.
Iteration 10, inertia 1436.823486328125.
Iteration 11, inertia 1436.7684326171875.
Iteration 12, inertia 1436.6715087890625.
Iteration 13, inertia 1436.4739990234375.
Iteration 14, inertia 1436.1474609375.
Iteration 15, inertia 1435.5057373046875.
Iteration 16, inertia 1434.623291015625.
Iteration 17, inertia 1433.45166015625.
Iteration 18, inertia 1432.6064453125.
Iteration 19, inertia 1432.359375.
Iteration 20, inertia 1432.2596435546875.
Iteration 21, inertia 1432.2027587890625.
Iteration 22, inertia 1432.1746826171875.
Iteration 23, inertia 1432.168701171875.
Iteration 24, inertia 1432.16748046875.
Iteration 25, inertia 1432.1612548828125.
Converged at iteration 25: strict convergence.
Initialization complete
Iteration 0, inertia 2560.073974609375.
Iteration 1, inertia 1491.8878173828125.
Iteration 2, inertia 1478.8916015625.
Iteration 3, inertia 1474.7847900390625.
Iteration 4, inertia 1468.5697021484375.
Iteration 5, inertia 1462.215576171875.
Iteration 6, inertia 1460.7454833984375.
Iteration 7, inertia 1459.793212890625.
Iteration 8, inertia 1458.984130859375.
Iteration 9, inertia 1457.8570556640625.
Iteration 10, inertia 1455.9803466796875.
Iteration 11, inertia 1454.714599609375.
Iteration 12, inertia 1454.2564697265625.
Iteration 13, inertia 1454.0057373046875.
```

```
Iteration 14, inertia 1453.859130859375.
Iteration 15, inertia 1453.7694091796875.
Iteration 16, inertia 1453.6903076171875.
Iteration 17, inertia 1453.633544921875.
Iteration 18, inertia 1453.5927734375.
Iteration 19, inertia 1453.54541015625.
Iteration 20, inertia 1453.512939453125.
Iteration 21, inertia 1453.5001220703125.
Iteration 22, inertia 1453.49658203125.
Iteration 23, inertia 1453.494384765625.
Iteration 24, inertia 1453.4847412109375.
Iteration 25, inertia 1453.4788818359375.
Iteration 26, inertia 1453.4754638671875.
Converged at iteration 26: strict convergence.
Initialization complete
Iteration 0, inertia 2493.096435546875.
Iteration 1, inertia 1479.5706787109375.
Iteration 2, inertia 1455.7708740234375.
Iteration 3, inertia 1448.552734375.
Iteration 4, inertia 1444.1993408203125.
Iteration 5, inertia 1439.89892578125.
Iteration 6, inertia 1435.0693359375.
Iteration 7, inertia 1430.9129638671875.
Iteration 8, inertia 1427.9764404296875.
Iteration 9, inertia 1426.57275390625.
Iteration 10, inertia 1426.029296875.
Iteration 11, inertia 1425.846923828125.
Iteration 12, inertia 1425.7537841796875.
Iteration 13, inertia 1425.69970703125.
Iteration 14, inertia 1425.67333984375.
Iteration 15, inertia 1425.62060546875.
Iteration 16, inertia 1425.584716796875.
Iteration 17, inertia 1425.551025390625.
Iteration 18, inertia 1425.500732421875.
Iteration 19, inertia 1425.4110107421875.
Iteration 20, inertia 1425.294189453125.
Iteration 21, inertia 1425.2027587890625.
Iteration 22, inertia 1425.1512451171875.
Iteration 23, inertia 1425.0849609375.
Iteration 24, inertia 1425.0341796875.
Iteration 25, inertia 1424.9462890625.
Iteration 26, inertia 1424.7705078125.
Iteration 27, inertia 1424.4029541015625.
Iteration 28, inertia 1423.4154052734375.
Iteration 29, inertia 1422.7559814453125.
Iteration 30, inertia 1422.712646484375.
Iteration 31, inertia 1422.6934814453125.
Iteration 32, inertia 1422.6888427734375.
```

```
Converged at iteration 32: strict convergence.
Initialization complete
Iteration 0, inertia 2607.656982421875.
Iteration 1, inertia 1448.917724609375.
Iteration 2, inertia 1429.6248779296875.
Iteration 3, inertia 1423.13330078125.
Iteration 4, inertia 1419.1138916015625.
Iteration 5, inertia 1418.2630615234375.
Iteration 6, inertia 1417.9937744140625.
Iteration 7, inertia 1417.917236328125.
Iteration 8, inertia 1417.7974853515625.
Iteration 9, inertia 1417.5791015625.
Iteration 10, inertia 1417.3201904296875.
Iteration 11, inertia 1416.514404296875.
Iteration 12, inertia 1416.056396484375.
Iteration 13, inertia 1415.8837890625.
Iteration 14, inertia 1415.7828369140625.
Iteration 15, inertia 1415.7598876953125.
Iteration 16, inertia 1415.7586669921875.
Converged at iteration 16: strict convergence.
Initialization complete
Iteration 0, inertia 2564.997314453125.
Iteration 1, inertia 1474.4376220703125.
Iteration 2, inertia 1455.86376953125.
Iteration 3, inertia 1451.4910888671875.
Iteration 4, inertia 1449.07666015625.
Iteration 5, inertia 1447.4832763671875.
Iteration 6, inertia 1445.598388671875.
Iteration 7, inertia 1443.613037109375.
Iteration 8, inertia 1443.38623046875.
Iteration 9, inertia 1443.32373046875.
Iteration 10, inertia 1443.265869140625.
Iteration 11, inertia 1443.2427978515625.
Iteration 12, inertia 1443.2130126953125.
Iteration 13, inertia 1443.131591796875.
Iteration 14, inertia 1442.909912109375.
Iteration 15, inertia 1442.4122314453125.
Iteration 16, inertia 1441.45751953125.
Iteration 17, inertia 1440.38525390625.
Iteration 18, inertia 1439.99267578125.
Iteration 19, inertia 1439.707763671875.
Iteration 20, inertia 1439.4822998046875.
Iteration 21, inertia 1439.3619384765625.
Iteration 22, inertia 1439.2252197265625.
Iteration 23, inertia 1438.9354248046875.
Iteration 24, inertia 1438.6865234375.
Iteration 25, inertia 1438.202880859375.
Iteration 26, inertia 1437.0946044921875.
```

```
Iteration 27, inertia 1436.1478271484375.
Iteration 28, inertia 1435.6534423828125.
Iteration 29, inertia 1435.398681640625.
Iteration 30, inertia 1435.007568359375.
Iteration 31, inertia 1434.1806640625.
Iteration 32, inertia 1431.8421630859375.
Iteration 33, inertia 1430.253173828125.
Iteration 34, inertia 1430.07470703125.
Iteration 35, inertia 1430.029052734375.
Iteration 36, inertia 1430.007080078125.
Iteration 37, inertia 1429.9366455078125.
Iteration 38, inertia 1429.8521728515625.
Iteration 39, inertia 1429.7005615234375.
Iteration 40, inertia 1429.5906982421875.
Iteration 41, inertia 1429.46142578125.
Iteration 42, inertia 1429.3702392578125.
Iteration 43, inertia 1429.330078125.
Iteration 44, inertia 1429.301025390625.
Iteration 45, inertia 1429.274169921875.
Iteration 46, inertia 1429.2218017578125.
Iteration 47, inertia 1429.1685791015625.
Iteration 48, inertia 1429.126220703125.
Iteration 49, inertia 1429.0826416015625.
Iteration 50, inertia 1429.01123046875.
Iteration 51, inertia 1428.9881591796875.
Iteration 52, inertia 1428.97802734375.
Iteration 53, inertia 1428.955322265625.
Iteration 54, inertia 1428.9215087890625.
Iteration 55, inertia 1428.87109375.
Iteration 56, inertia 1428.81298828125.
Iteration 57, inertia 1428.7725830078125.
Iteration 58, inertia 1428.738037109375.
Iteration 59, inertia 1428.7205810546875.
Iteration 60, inertia 1428.7109375.
Iteration 61, inertia 1428.7078857421875.
Iteration 62, inertia 1428.7056884765625.
Converged at iteration 62: strict convergence.
Initialization complete
Iteration 0, inertia 2562.861328125.
Iteration 1, inertia 1491.04345703125.
Iteration 2, inertia 1467.11181640625.
Iteration 3, inertia 1456.6881103515625.
Iteration 4, inertia 1448.0089111328125.
Iteration 5, inertia 1445.9937744140625.
Iteration 6, inertia 1444.612060546875.
Iteration 7, inertia 1443.261962890625.
Iteration 8, inertia 1441.7308349609375.
Iteration 9, inertia 1440.7359619140625.
```

```
Iteration 10, inertia 1440.3162841796875.
Iteration 11, inertia 1440.18017578125.
Iteration 12, inertia 1440.1165771484375.
Iteration 13, inertia 1440.0660400390625.
Iteration 14, inertia 1440.0543212890625.
Iteration 15, inertia 1440.044921875.
Iteration 16, inertia 1440.0423583984375.
Iteration 17, inertia 1440.038330078125.
Iteration 18, inertia 1440.0252685546875.
Iteration 19, inertia 1439.990966796875.
Iteration 20, inertia 1439.9173583984375.
Iteration 21, inertia 1439.8406982421875.
Iteration 22, inertia 1439.8013916015625.
Iteration 23, inertia 1439.759521484375.
Iteration 24, inertia 1439.6865234375.
Iteration 25, inertia 1439.668701171875.
Iteration 26, inertia 1439.6624755859375.
Iteration 27, inertia 1439.6624755859375.
Converged at iteration 27: strict convergence.

  Evaluating clustering quality…

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CLUSTERING METRICS
------------------------------------------------------------
Silhouette Score:     0.1538  (higher is better)
Davies-Bouldin Index: 2.9048  (lower is better)
------------------------------------------------------------

  Cluster Distribution:
   Cluster   0:   862 images (18.4%)
   Cluster   1:   381 images (8.1%)
   Cluster   2:   504 images (10.7%)
   Cluster   3:   554 images (11.8%)
   Cluster   4:   345 images (7.3%)
   Cluster   5:   545 images (11.6%)
   Cluster   6:    97 images (2.1%)
   Cluster   7:   544 images (11.6%)
   Cluster   8:   107 images (2.3%)
   Cluster   9:   757 images (16.1%)

  K-Means model saved to /content/drive/MyDrive/image-clustering-
retrieval/models/clustering
```
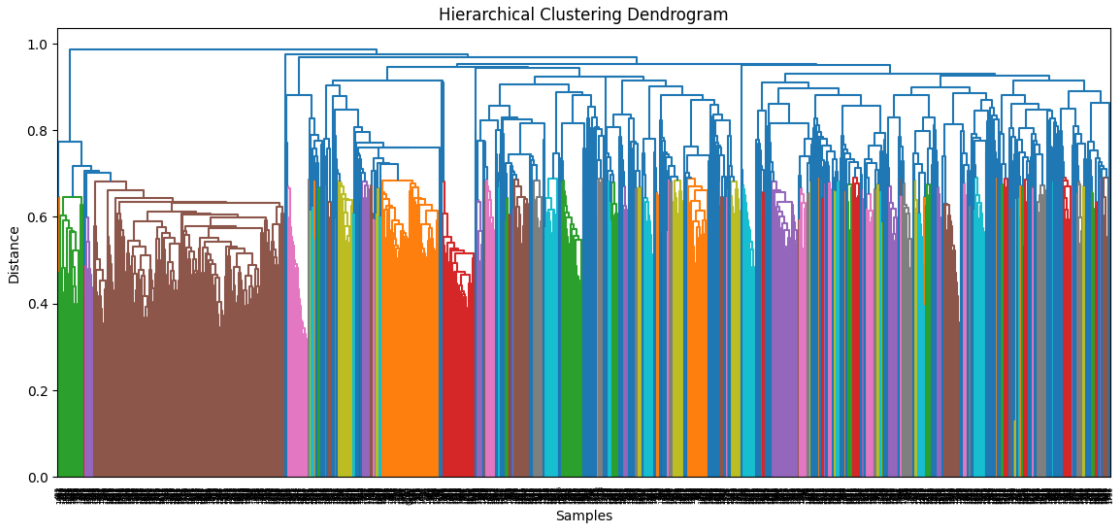

3 HIERARCHICAL CLUSTERING (WITH K SELECTION)

[11]:
```
import numpy as np
import matplotlib.pyplot as plt
from scipy.cluster.hierarchy import linkage, dendrogram

# --------------------------
# STEP 1: Sample Features (Optional)
# --------------------------
def sample_features(features, sample_size=2000, random_state=42):
    if len(features) > sample_size:
        np.random.seed(random_state)
        indices = np.random.choice(len(features), sample_size, replace=False)
        return features[indices], indices
    return features, np.arange(len(features))

# --------------------------
# STEP 2: Build Linkage Matrix
# --------------------------
def build_linkage_matrix(features, method='average'):
    print(f"  Building linkage matrix (method={method})")
    Z = linkage(features, method=method)
    return Z

# --------------------------
# STEP 3: Plot Dendrogram
# --------------------------
def plot_dendrogram(Z, truncate_level=30, max_d=None):
    plt.figure(figsize=(14, 6))
    dendrogram(Z, truncate_mode='level', p=truncate_level)
    if max_d:
        plt.axhline(y=max_d, c='r', linestyle='--')
    plt.title("Hierarchical Clustering Dendrogram")
    plt.xlabel("Samples")
    plt.ylabel("Distance")
    plt.show()

# --------------------------
# STEP 4: Run Dendrogram Analysis
# --------------------------
# Sample features for efficiency
features_sampled, sample_indices = sample_features(features_normalized,␣
 ↪sample_size=2000)

# Build linkage
Z = build_linkage_matrix(features_sampled, method='average')
```

```
# Plot dendrogram
plot_dendrogram(Z, truncate_level=30)
```

```
Building linkage matrix (method=average)
```



4 Perform Hierarchical Clustering

[12]:
```
import os
import json
import pickle
import numpy as np

from datetime import datetime

from sklearn.cluster import AgglomerativeClustering
from sklearn.metrics import silhouette_score, davies_bouldin_score

# ---------------------------
# STEP 1: Train Hierarchical Clustering with Exact K
# ---------------------------
def train_hierarchical_exact_k(features, k=50, linkage_type='average'):
    """
    Train AgglomerativeClustering to produce exactly K clusters
    """
    model = AgglomerativeClustering(
        n_clusters=k,       # Force exact K clusters
        linkage=linkage_type
    )
```

```
    labels = model.fit_predict(features)

    sil = silhouette_score(features, labels)
    db = davies_bouldin_score(features, labels)

    print("\nFINAL HIERARCHICAL RESULTS")
    print("-" * 50)
    print(f"Linkage:    {linkage_type}")
    print(f"K:          {k}")
    print(f"Silhouette: {sil:.4f}")
    print(f"DB Index:   {db:.4f}")
    print("-" * 50)

    return model, labels, sil, db

# --------------------------
# STEP 2: Full HIR Pipeline
# --------------------------
def perform_hir_pipeline(features, k=50, linkage_type='average',␣
 ↪sample_size=5000, save_path=None):
    # 1  Sample features if needed
    if len(features) > sample_size:
        indices = np.random.choice(len(features), sample_size, replace=False)
        features_used = features[indices]
        print(f"Using {len(features_used)}/{len(features)} samples")
    else:
        features_used = features

    # 2  Train hierarchical clustering
    model, cluster_labels, sil, db = train_hierarchical_exact_k(features_used,␣
 ↪k=k, linkage_type=linkage_type)

    # 3  Save model, labels, and metrics
    if save_path:
        os.makedirs(save_path, exist_ok=True)
        with open(f'{save_path}/hir_model_k{k}.pkl', 'wb') as f:
            pickle.dump(model, f)
        np.save(f'{save_path}/hir_labels_k{k}.npy', cluster_labels)
        metrics = {
            'k': k,
            'linkage': linkage_type,
            'silhouette_score': float(sil),
            'davies_bouldin_score': float(db),
            'cluster_sizes': {int(c): int(np.sum(cluster_labels==c)) for c in␣
 ↪np.unique(cluster_labels)},
            'sample_size': len(features_used),
            'created_at': datetime.now().strftime('%Y-%m-%d %H:%M:%S')
```

```
        }
        with open(f'{save_path}/hir_metrics_k{k}.json', 'w') as f:
            json.dump(metrics, f, indent=2)
        print(f"\n  HIR model, labels, and metrics saved to {save_path}")

    return model, cluster_labels, sil, db

# --------------------------
# STEP 3: Run HIR
# --------------------------
hir_model, hir_labels, sil_score, db_score = perform_hir_pipeline(
    features_normalized,
    k=50,
    linkage_type='average',
    sample_size=5000,
    save_path=f'{PROJECT_ROOT}/models/clustering'
)

# Check clusters
print("Unique cluster IDs:", np.unique(hir_labels))
print("Number of clusters:", len(np.unique(hir_labels)))
```

```
FINAL HIERARCHICAL RESULTS
--------------------------------------------------
Linkage:    average
K:          50
Silhouette: 0.1819
DB Index:   2.1500
--------------------------------------------------

  HIR model, labels, and metrics saved to /content/drive/MyDrive/image-
clustering-retrieval/models/clustering
Unique cluster IDs: [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19
20 21 22 23
 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47
 48 49]
Number of clusters: 50
```

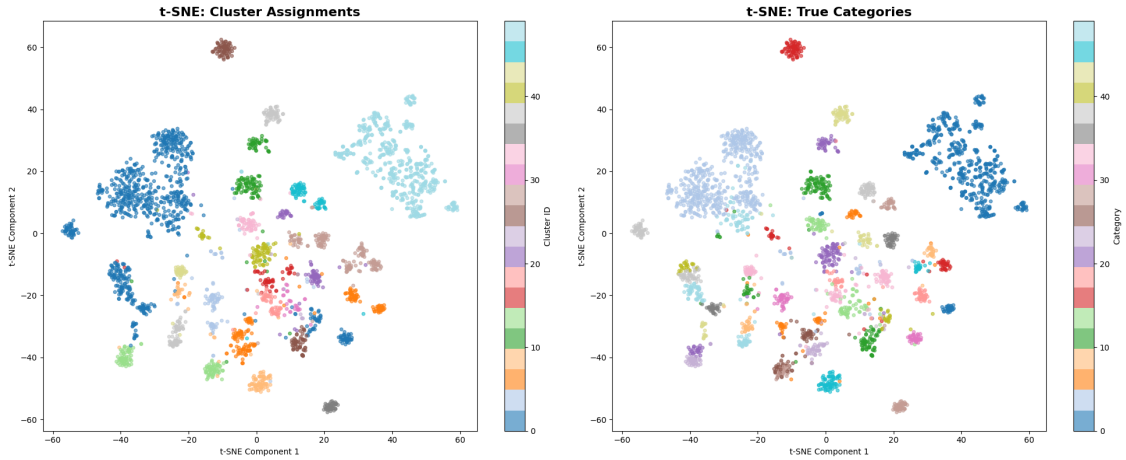
5 Visualize Clusters with t-SNE

[14]:
```
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt
import numpy as np

def visualize_tsne(features, labels, cluster_labels, categories=None,␣
 ↪sample_size=3000, save_path=None):
```

```
    """
    Create t-SNE visualization for hierarchical clusters and true categories␣
↪side by side.

    Args:
        features (np.array): CNN embeddings (n_samples, n_features)
        labels (np.array): True labels/categories
        cluster_labels (np.array): Cluster labels from Hierarchical/KMeans
        categories (list or dict): Optional mapping of label indices to␣
↪category names
        sample_size (int): Max samples to speed up t-SNE
        save_path (str): Path to save the figure
    """
    print("\n Creating t-SNE visualization...")

    # ---- Sampling ----
    n_samples = min(sample_size, len(features))
    indices = np.random.choice(len(features), n_samples, replace=False)
    features_sample = features[indices]
    labels_sample = labels[indices]
    cluster_sample = cluster_labels[indices]

    # ---- t-SNE projection ----
    print("  Computing t-SNE (this may take a few minutes)...")
    tsne = TSNE(n_components=2, random_state=42, perplexity=30, n_iter=1000,␣
↪init='pca', learning_rate='auto')
    features_2d = tsne.fit_transform(features_sample)

    # ---- Plotting ----
    fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(20, 8))

    # Cluster assignments
    scatter1 = ax1.scatter(
        features_2d[:, 0], features_2d[:, 1],
        c=cluster_sample, cmap='tab20', alpha=0.6, s=15
    )
    ax1.set_title('t-SNE: Cluster Assignments', fontsize=16, fontweight='bold')
    ax1.set_xlabel('t-SNE Component 1')
    ax1.set_ylabel('t-SNE Component 2')
    plt.colorbar(scatter1, ax=ax1, label='Cluster ID')

    # True categories
    scatter2 = ax2.scatter(
        features_2d[:, 0], features_2d[:, 1],
        c=labels_sample, cmap='tab20', alpha=0.6, s=15
    )
    ax2.set_title('t-SNE: True Categories', fontsize=16, fontweight='bold')
```

```
    ax2.set_xlabel('t-SNE Component 1')
    ax2.set_ylabel('t-SNE Component 2')
    plt.colorbar(scatter2, ax=ax2, label='Category')

    plt.tight_layout()

    # ---- Save figure ----
    if save_path:
        plt.savefig(save_path, dpi=150, bbox_inches='tight')

    plt.show()
    print("  t-SNE visualization complete!")

# ================================
# USAGE EXAMPLE
# ================================
visualize_tsne(
    features=features_normalized,
    labels=labels,                  # True labels of dataset
    cluster_labels=hir_labels,    # Hierarchical cluster labels
    categories=None,                # Optional: list of category names
    sample_size=3000,
    save_path=f'{PROJECT_ROOT}/results/clustering/tsne_plot.png'
)
```

```
  Creating t-SNE visualization…
   Computing t-SNE (this may take a few minutes)…
/usr/local/lib/python3.12/dist-packages/sklearn/manifold/_t_sne.py:1164:
FutureWarning: 'n_iter' was renamed to 'max_iter' in version 1.5 and will be
removed in 1.7.
  warnings.warn(
```



```
t-SNE visualization complete!
```

6 Analyze Cluster Composition

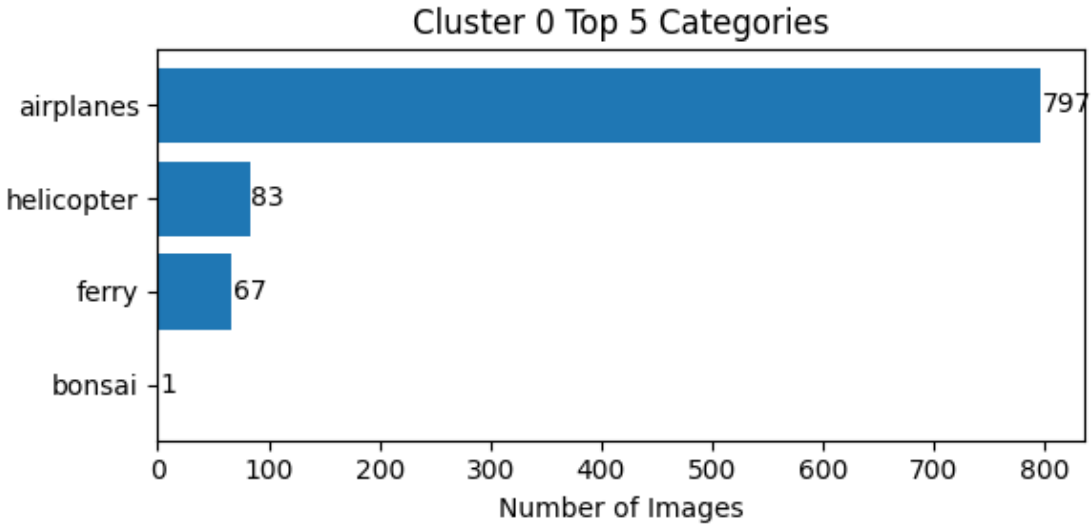
[19]:
```python
import os
import numpy as np
import matplotlib.pyplot as plt

def analyze_clusters_hir_plot(cluster_labels, true_labels, categories,␣
↪top_n=50, top_k_per_cluster=5):
    """
    Analyze cluster composition for HIR and plot horizontal bar plots for top␣
↪categories.
    """
    print("\n Analyzing HIR cluster composition...")
    n_clusters = len(np.unique(cluster_labels))
    cluster_info = []

    for cluster_id in range(min(top_n, n_clusters)):
        mask = cluster_labels == cluster_id
        cluster_true_labels = true_labels[mask]
        cluster_size = len(cluster_true_labels)

        if cluster_size == 0:
            continue

        unique, counts = np.unique(cluster_true_labels, return_counts=True)
        sorted_idx = np.argsort(counts)[::-1][:top_k_per_cluster]

        top_categories = [
            (categories[unique[i]], counts[i], counts[i] / cluster_size * 100)
            for i in sorted_idx
        ]

        probs = counts / counts.sum()
        entropy = -np.sum(probs * np.log2(probs + 1e-9))

        cluster_info.append({
            "cluster_id": cluster_id,
            "size": cluster_size,
            "top_categories": top_categories,
            "entropy": entropy
        })
```

```
        print(f"\nCluster {cluster_id} ({cluster_size} images, entropy={entropy:
 ↪.2f}):")
        for cat, count, pct in top_categories:
            print(f"  • {cat}: {count} ({pct:.1f}%)")

        plt.figure(figsize=(6, 3))
        cats = [cat for cat, _, _ in top_categories][::-1]
        counts_plot = [count for _, count, _ in top_categories][::-1]

        plt.barh(cats, counts_plot)
        plt.xlabel("Number of Images")
        plt.title(f"Cluster {cluster_id} Top {top_k_per_cluster} Categories")

        for i, v in enumerate(counts_plot):
            plt.text(v + 0.5, i, str(v), va="center")

        plt.tight_layout()
        plt.show()

    return cluster_info


# --------------------------
# LOAD REQUIRED DATA (NO DATASET OBJECTS)
# --------------------------

features_normalized = np.load(f"{PROJECT_ROOT}/features/embeddings.npy")
labels = np.load(f"{PROJECT_ROOT}/features/labels.npy")

dataset_path = os.path.join(PROJECT_ROOT, "data/processed/object")
categories = sorted([
    d for d in os.listdir(dataset_path)
    if os.path.isdir(os.path.join(dataset_path, d))
])

# --------------------------
# RUN ANALYSIS
# --------------------------

cluster_analysis_hir = analyze_clusters_hir_plot(
    cluster_labels=hir_labels,
    true_labels=labels,
    categories=categories,
    top_n=50,
    top_k_per_cluster=5
)
```

Analyzing HIR cluster composition…

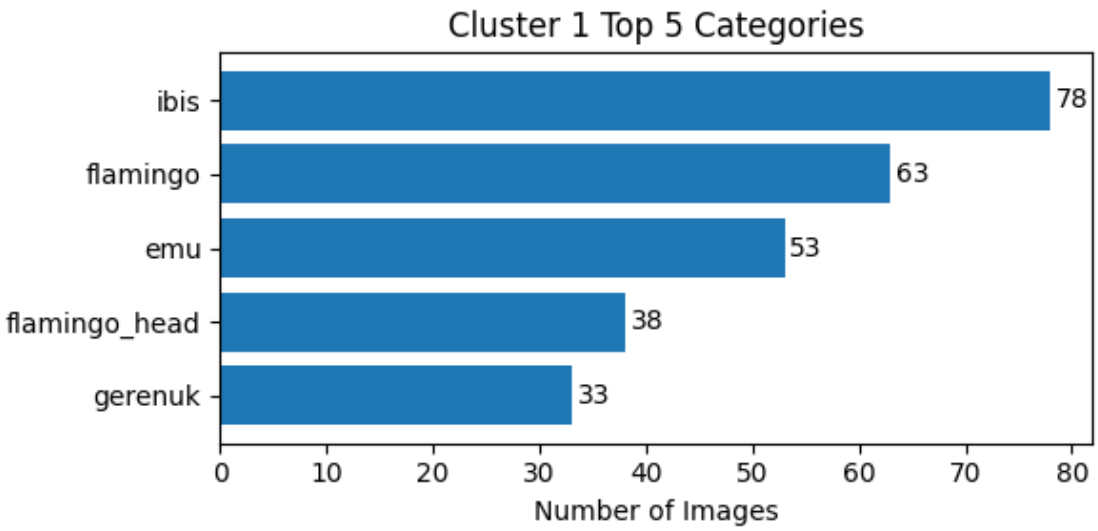
Cluster 0 (948 images, entropy=0.80):

- airplanes: 797 (84.1%)
- helicopter: 83 (8.8%)
- ferry: 67 (7.1%)
- bonsai: 1 (0.1%)



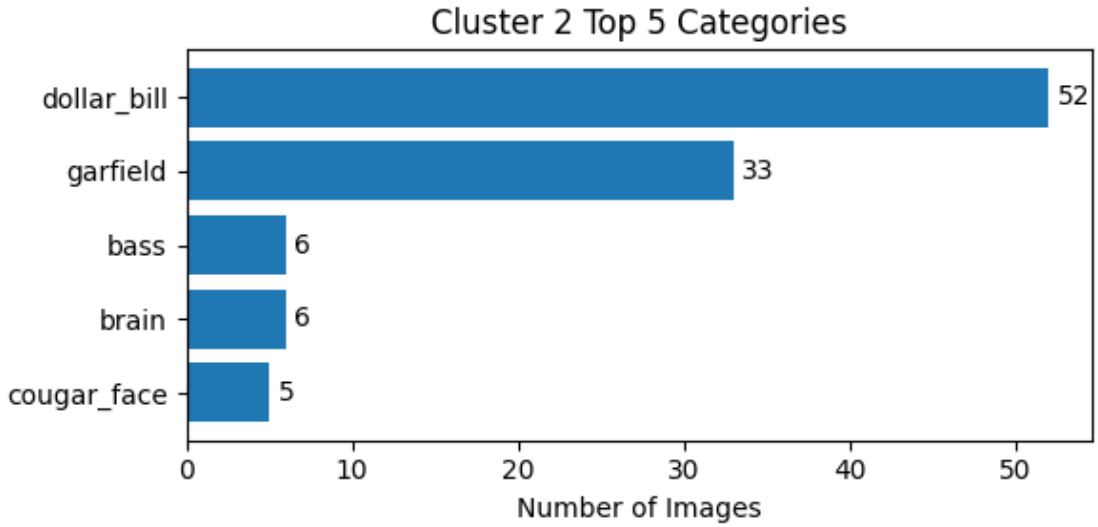
Cluster 1 (287 images, entropy=2.67):

- ibis: 78 (27.2%)
- flamingo: 63 (22.0%)
- emu: 53 (18.5%)
- flamingo_head: 38 (13.2%)
- gerenuk: 33 (11.5%)



Cluster 2 (119 images, entropy=2.54):

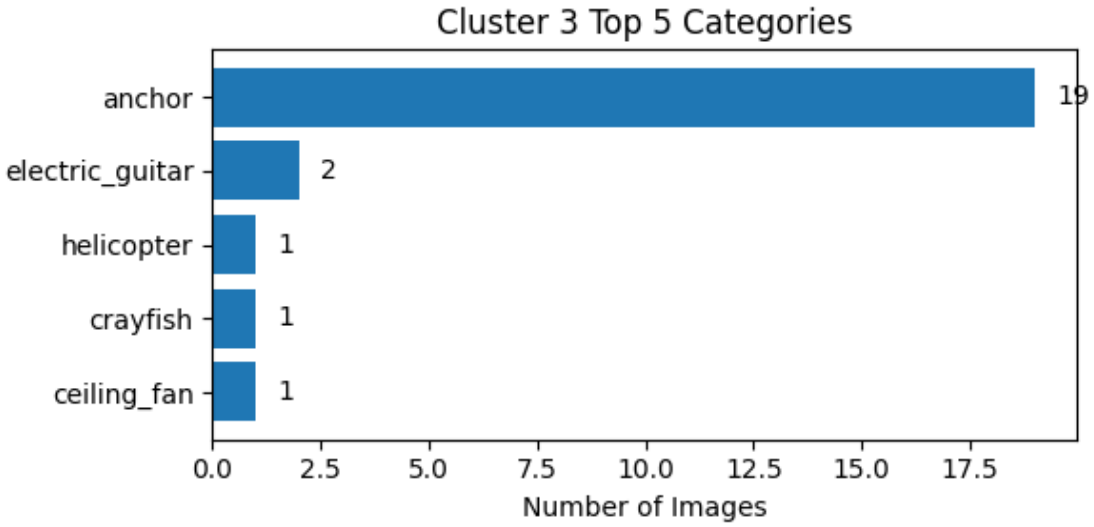
- dollar_bill: 52 (43.7%)
- garfield: 33 (27.7%)
- bass: 6 (5.0%)
- brain: 6 (5.0%)
- cougar_face: 5 (4.2%)



Cluster 3 (26 images, entropy=1.52):

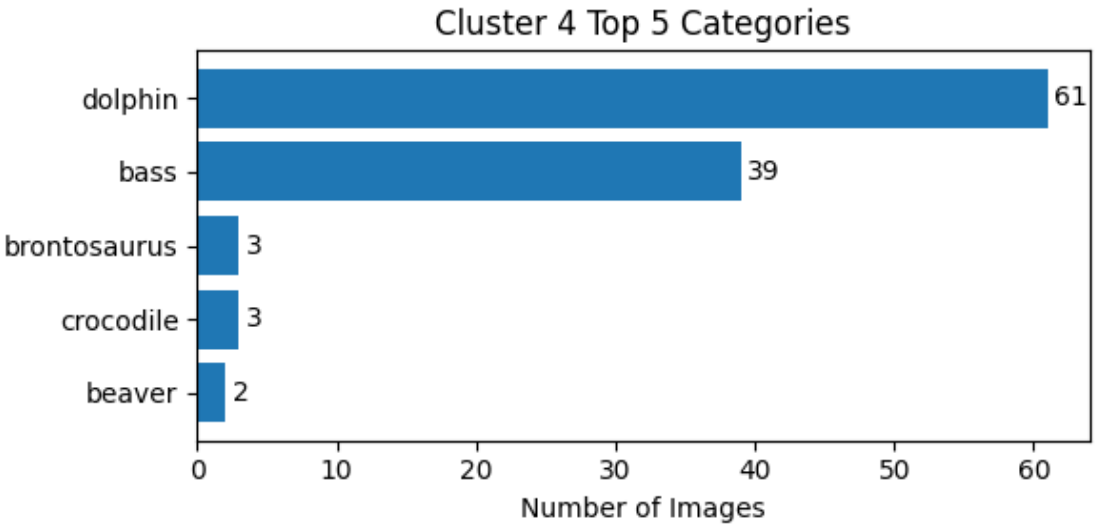
- anchor: 19 (73.1%)

- electric_guitar: 2 (7.7%)
- helicopter: 1 (3.8%)
- crayfish: 1 (3.8%)
- ceiling_fan: 1 (3.8%)



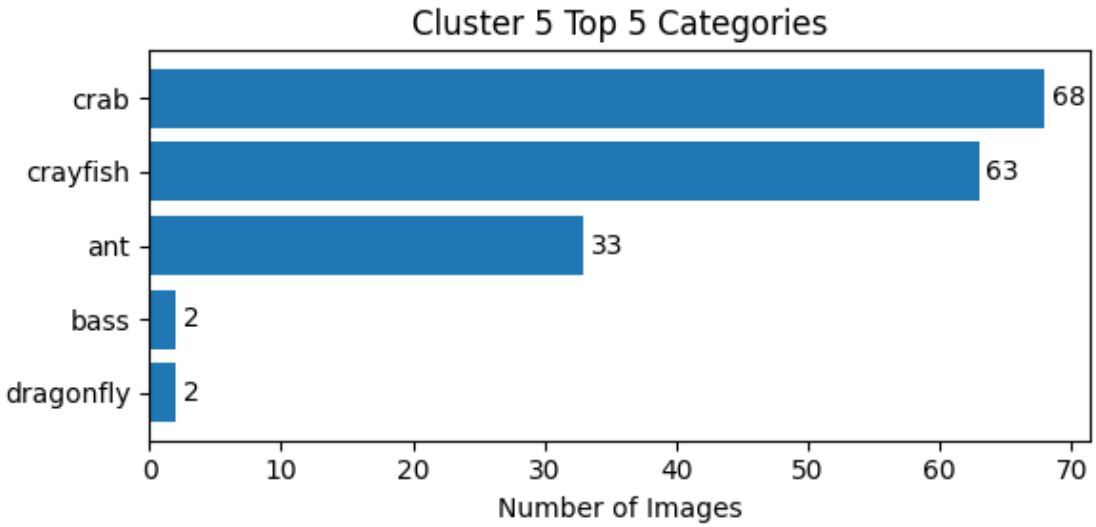
Cluster 4 (114 images, entropy=1.73):

- dolphin: 61 (53.5%)
- bass: 39 (34.2%)
- brontosaurus: 3 (2.6%)
- crocodile: 3 (2.6%)
- beaver: 2 (1.8%)



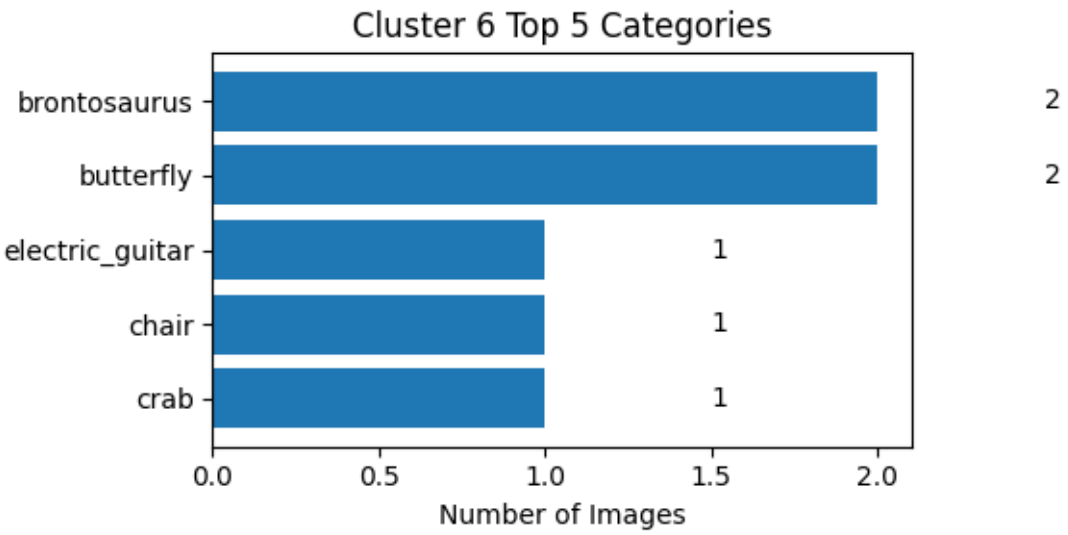
Cluster 5 (170 images, entropy=1.76):

- crab: 68 (40.0%)
- crayfish: 63 (37.1%)
- ant: 33 (19.4%)
- bass: 2 (1.2%)
- dragonfly: 2 (1.2%)



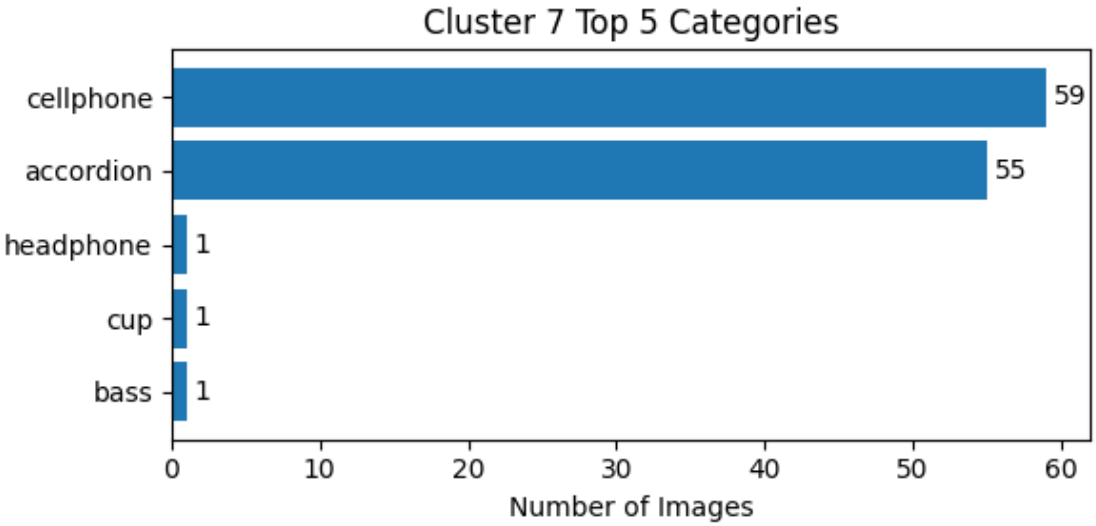
Cluster 6 (7 images, entropy=2.24):

- brontosaurus: 2 (28.6%)
- butterfly: 2 (28.6%)
- electric_guitar: 1 (14.3%)
- chair: 1 (14.3%)
- crab: 1 (14.3%)



Cluster 7 (117 images, entropy=1.19):

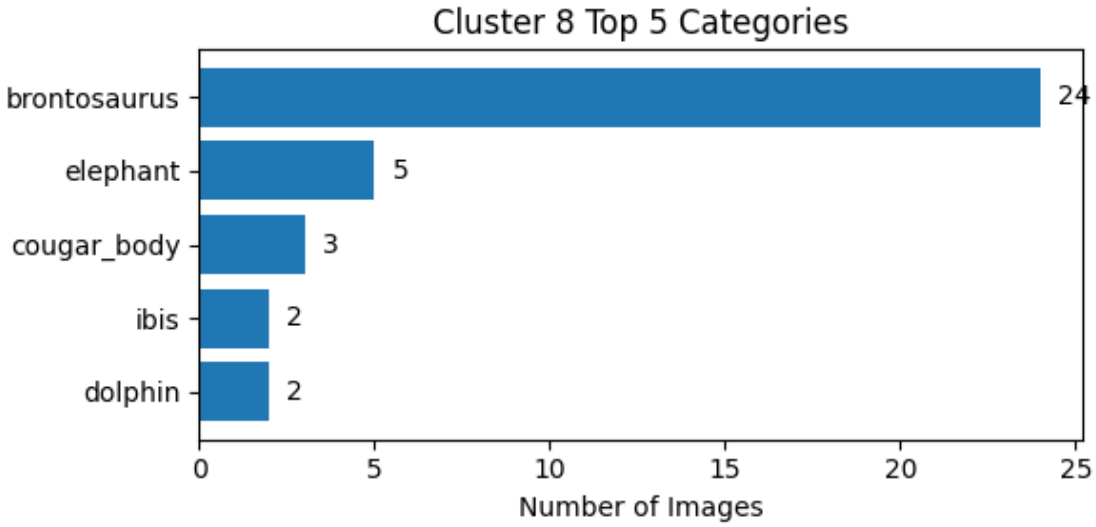
- cellphone: 59 (50.4%)
- accordion: 55 (47.0%)
- headphone: 1 (0.9%)
- cup: 1 (0.9%)
- bass: 1 (0.9%)



Cluster 8 (44 images, entropy=2.50):

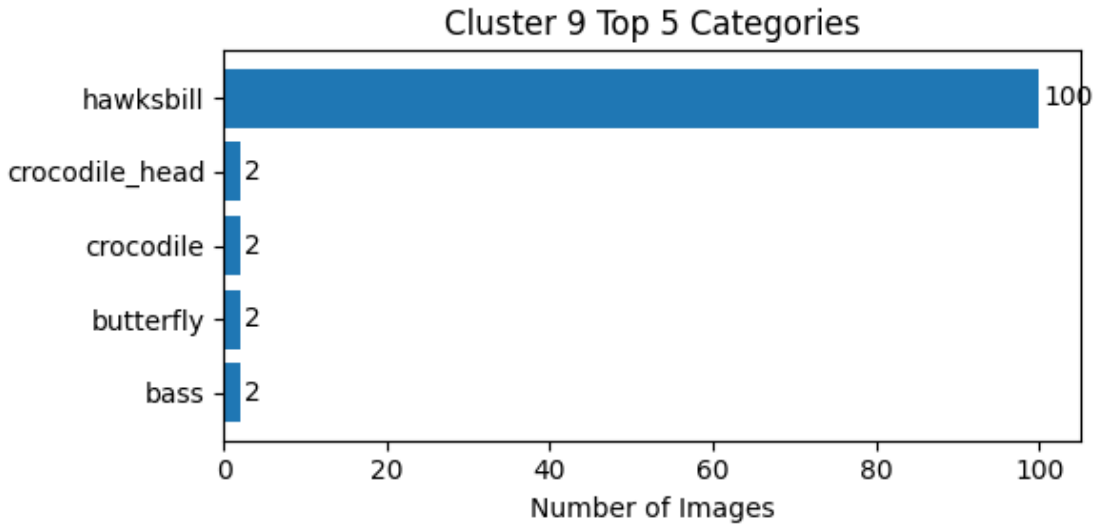
- brontosaurus: 24 (54.5%)

- elephant: 5 (11.4%)
- cougar_body: 3 (6.8%)
- ibis: 2 (4.5%)
- dolphin: 2 (4.5%)



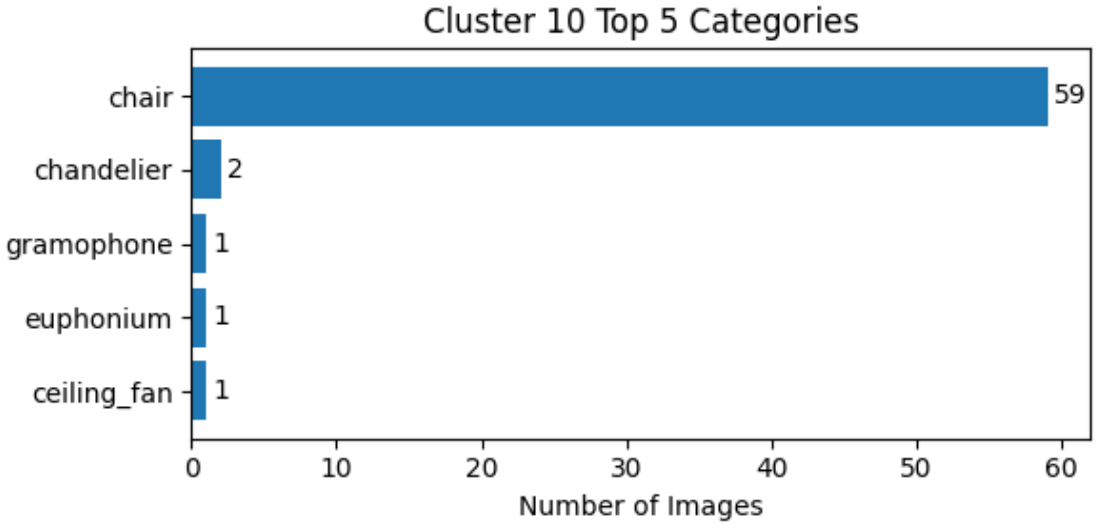
Cluster 9 (109 images, entropy=0.60):

- hawksbill: 100 (91.7%)
- crocodile_head: 2 (1.8%)
- crocodile: 2 (1.8%)
- butterfly: 2 (1.8%)
- bass: 2 (1.8%)



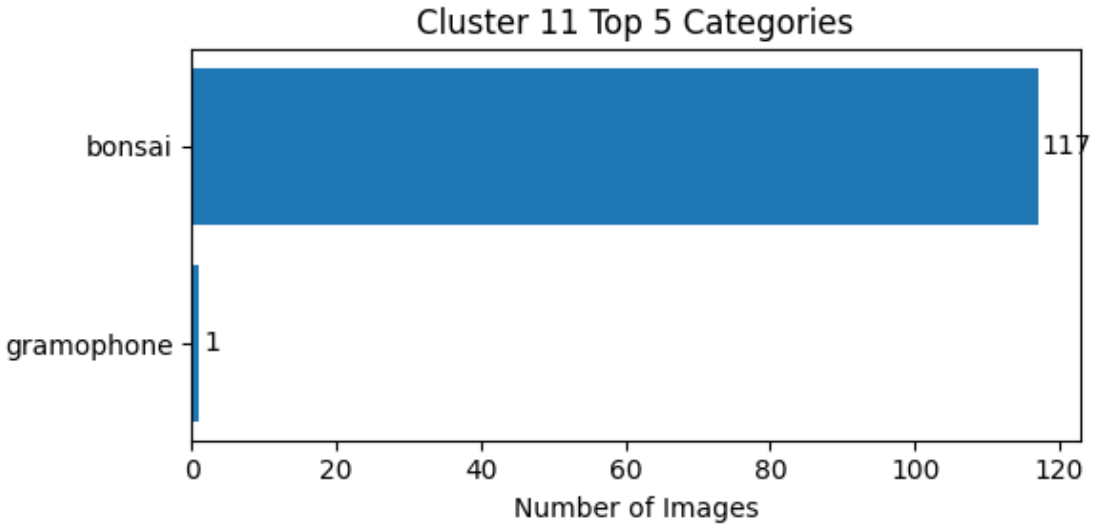
Cluster 10 (64 images, entropy=0.55):

- chair: 59 (92.2%)
- chandelier: 2 (3.1%)
- gramophone: 1 (1.6%)
- euphonium: 1 (1.6%)
- ceiling_fan: 1 (1.6%)



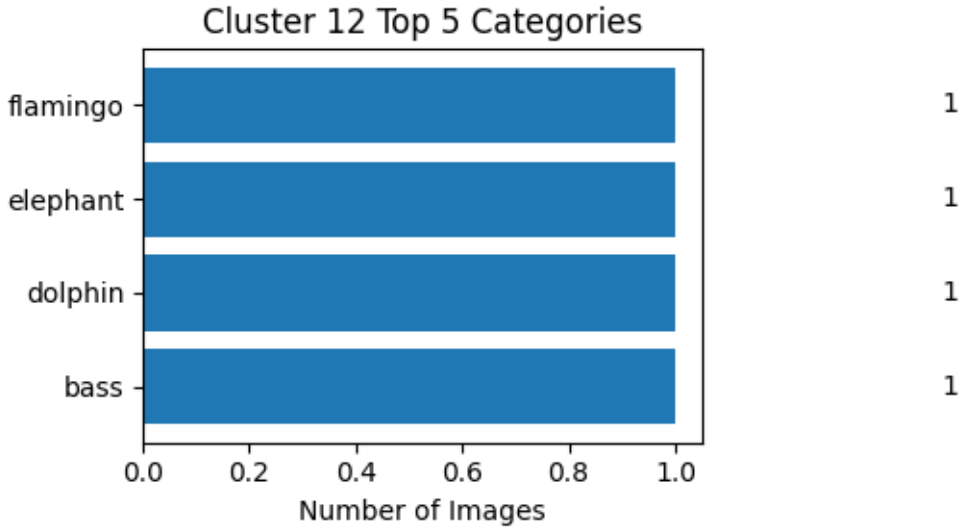
Cluster 11 (118 images, entropy=0.07):

- bonsai: 117 (99.2%)
- gramophone: 1 (0.8%)



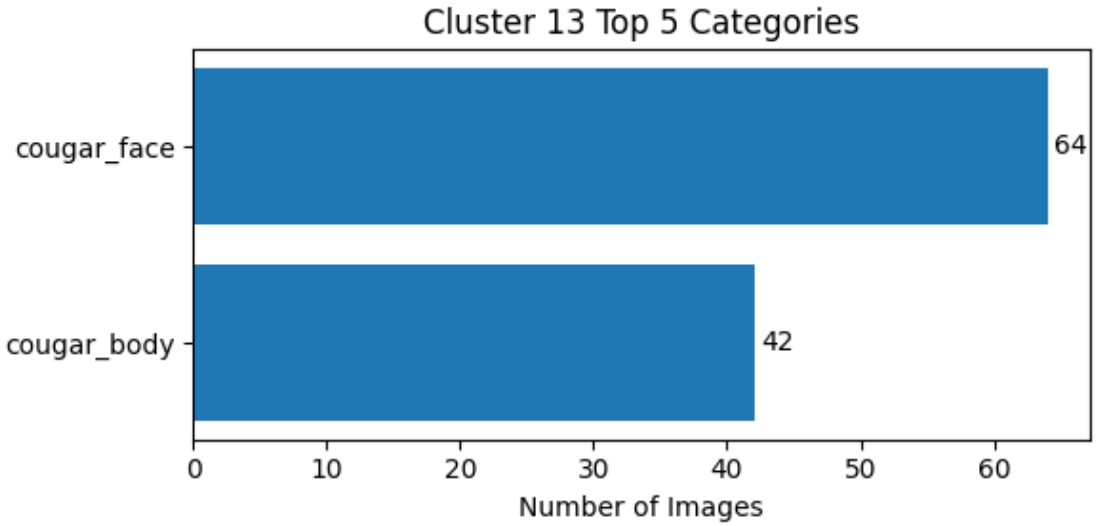
Cluster 12 (4 images, entropy=2.00):

- flamingo: 1 (25.0%)
- elephant: 1 (25.0%)
- dolphin: 1 (25.0%)
- bass: 1 (25.0%)



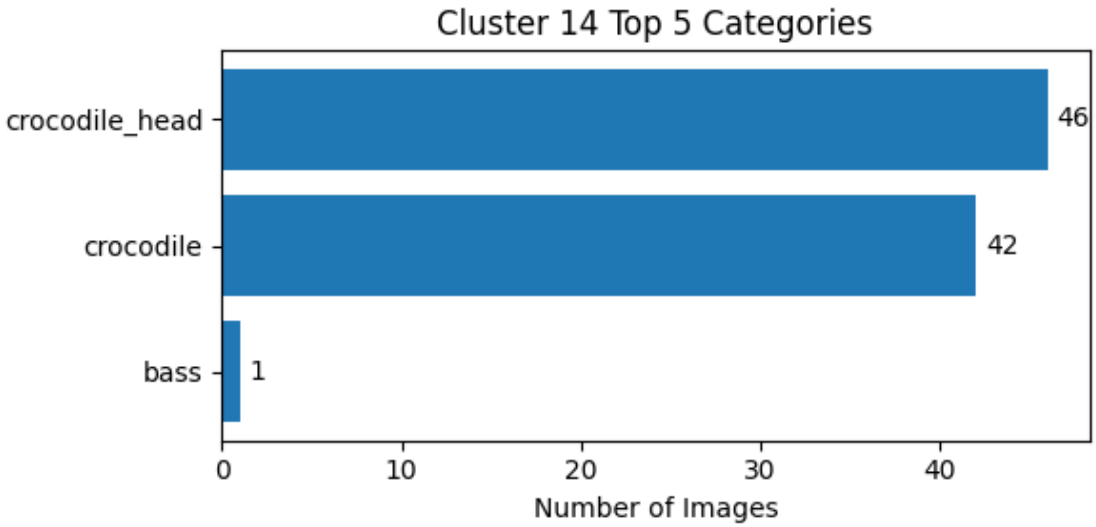
Cluster 13 (106 images, entropy=0.97):

- cougar_face: 64 (60.4%)
- cougar_body: 42 (39.6%)



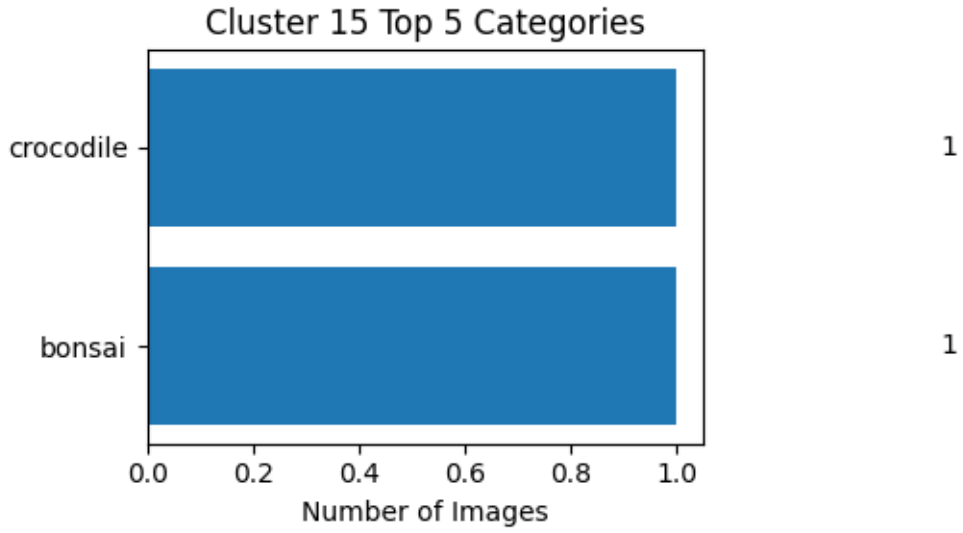
Cluster 14 (89 images, entropy=1.08):

- crocodile_head: 46 (51.7%)
- crocodile: 42 (47.2%)
- bass: 1 (1.1%)



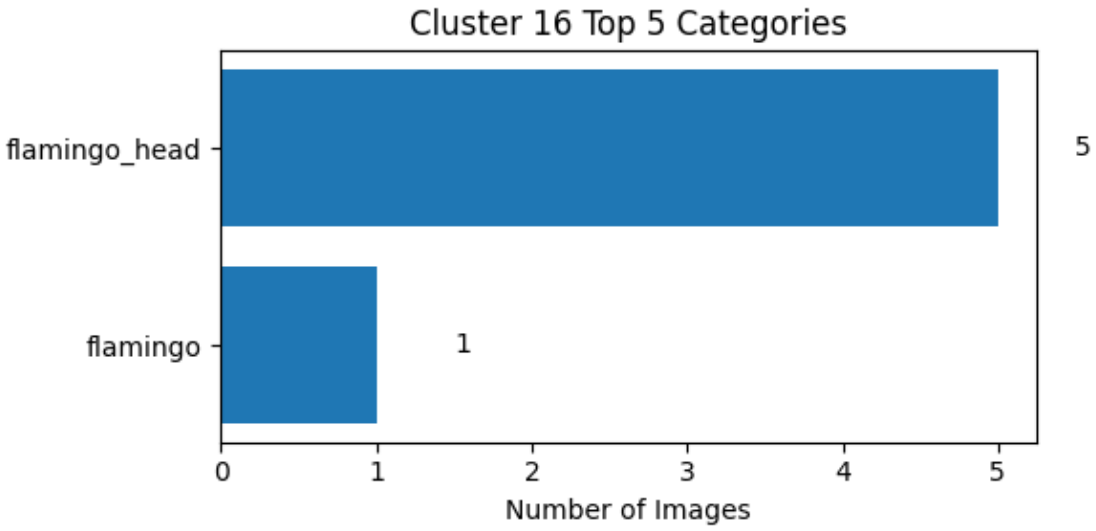
Cluster 15 (2 images, entropy=1.00):

- crocodile: 1 (50.0%)
- bonsai: 1 (50.0%)



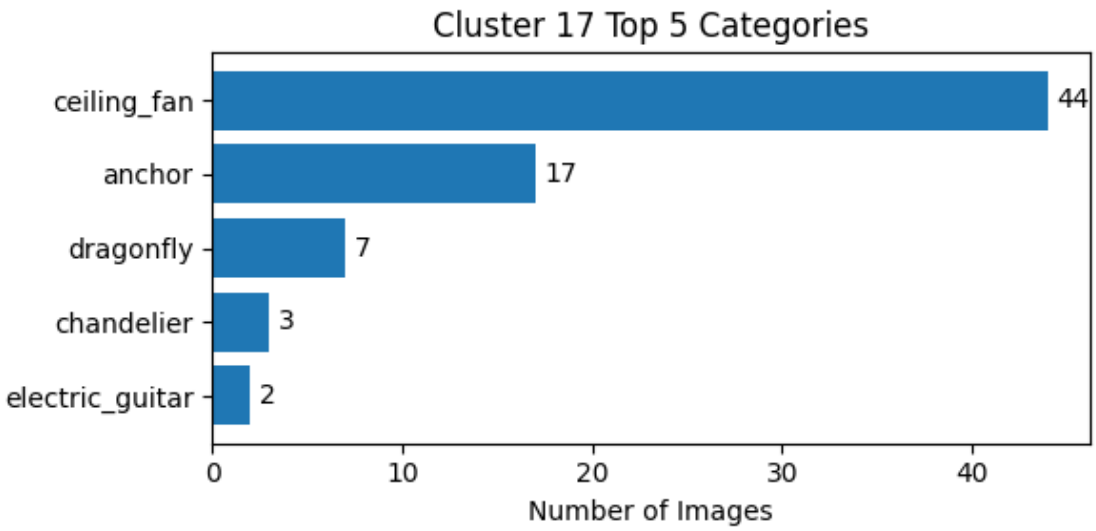
Cluster 16 (6 images, entropy=0.65):

- flamingo_head: 5 (83.3%)
- flamingo: 1 (16.7%)



Cluster 17 (76 images, entropy=1.80):

- ceiling_fan: 44 (57.9%)
- anchor: 17 (22.4%)
- dragonfly: 7 (9.2%)
- chandelier: 3 (3.9%)
- electric_guitar: 2 (2.6%)

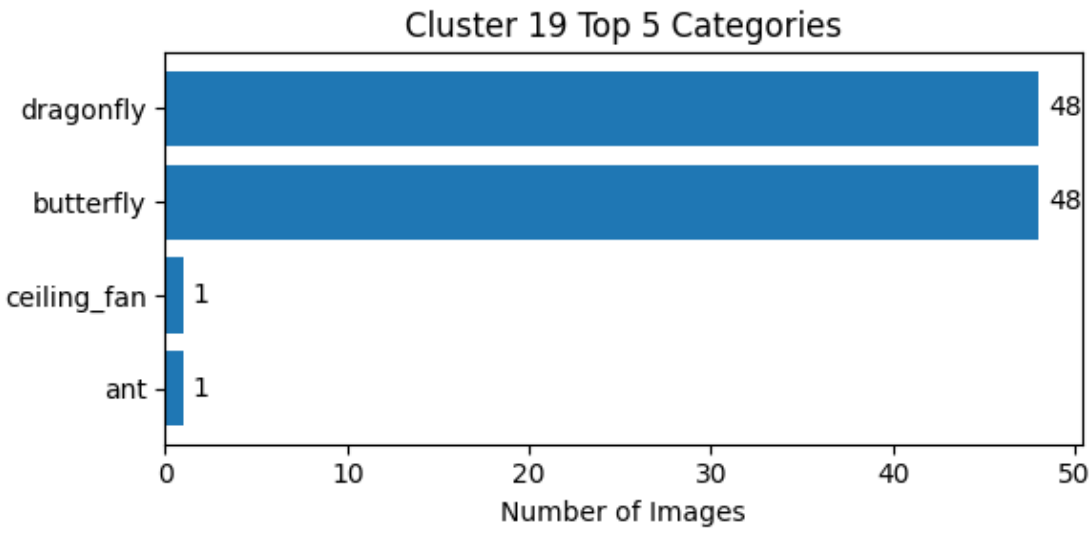


Cluster 18 (2 images, entropy=-0.00):

- crayfish: 2 (100.0%)

Cluster 19 (98 images, entropy=1.14):

- dragonfly: 48 (49.0%)
- butterfly: 48 (49.0%)
- ceiling_fan: 1 (1.0%)
- ant: 1 (1.0%)

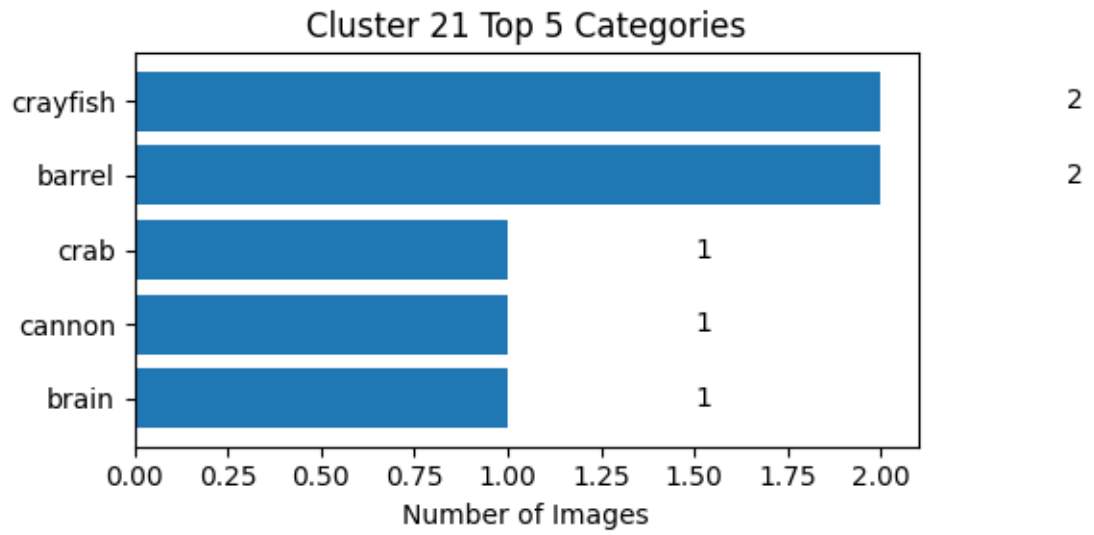


Cluster 20 (42 images, entropy=-0.00):

- barrel: 42 (100.0%)

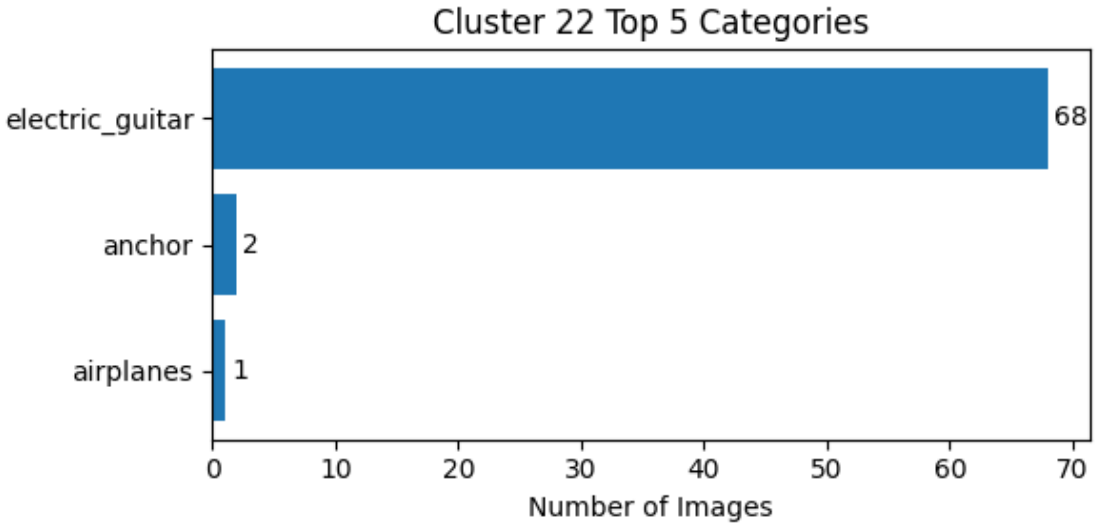
Cluster 21 (8 images, entropy=2.50):

- crayfish: 2 (25.0%)
- barrel: 2 (25.0%)
- crab: 1 (12.5%)
- cannon: 1 (12.5%)
- brain: 1 (12.5%)



Cluster 22 (71 images, entropy=0.29):

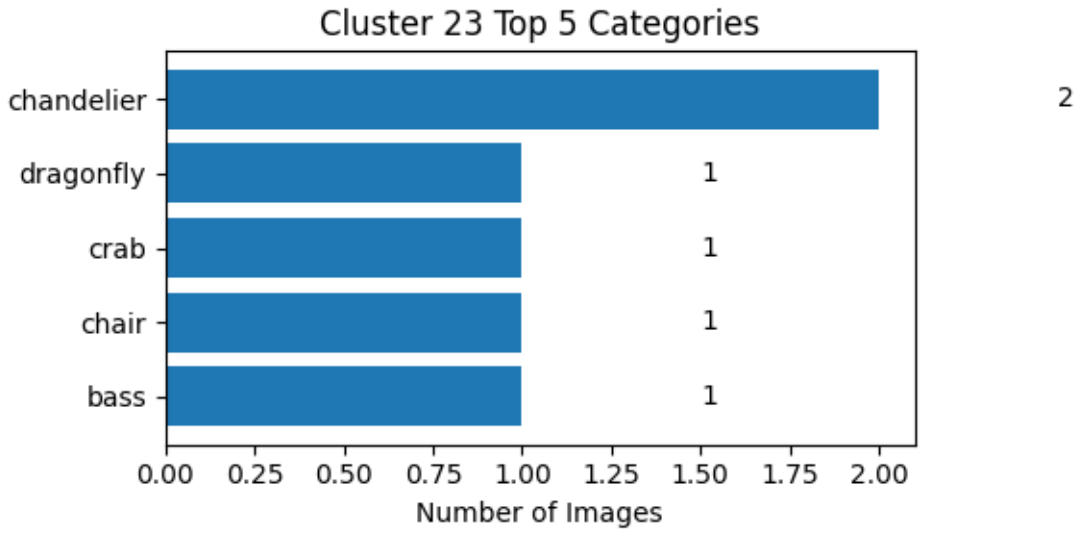
- electric_guitar: 68 (95.8%)
- anchor: 2 (2.8%)
- airplanes: 1 (1.4%)



Cluster 23 (7 images, entropy=2.52):

- chandelier: 2 (28.6%)
- dragonfly: 1 (14.3%)
- crab: 1 (14.3%)

- chair: 1 (14.3%)
- bass: 1 (14.3%)

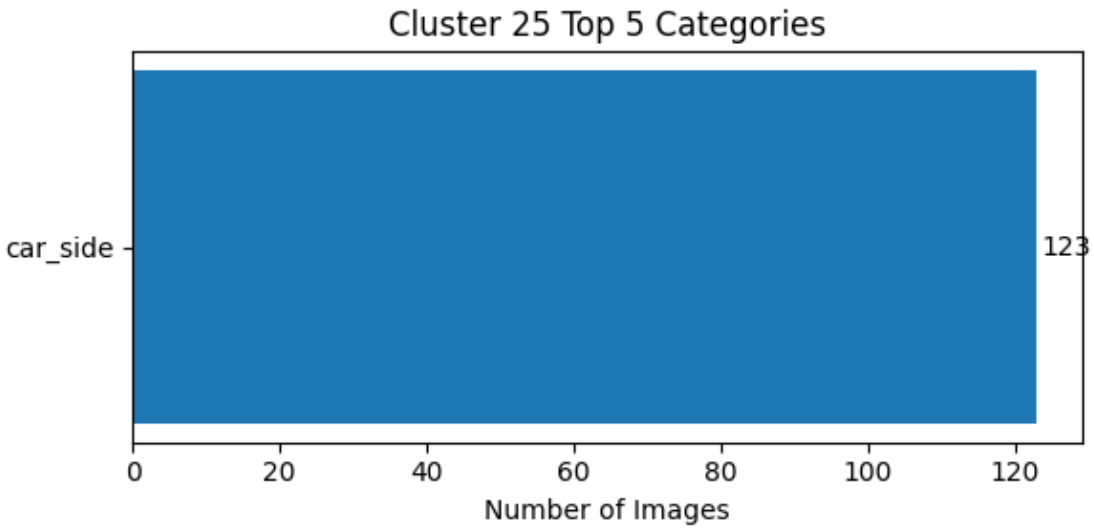


Cluster 24 (2 images, entropy=1.00):

- flamingo_head: 1 (50.0%)
- buddha: 1 (50.0%)

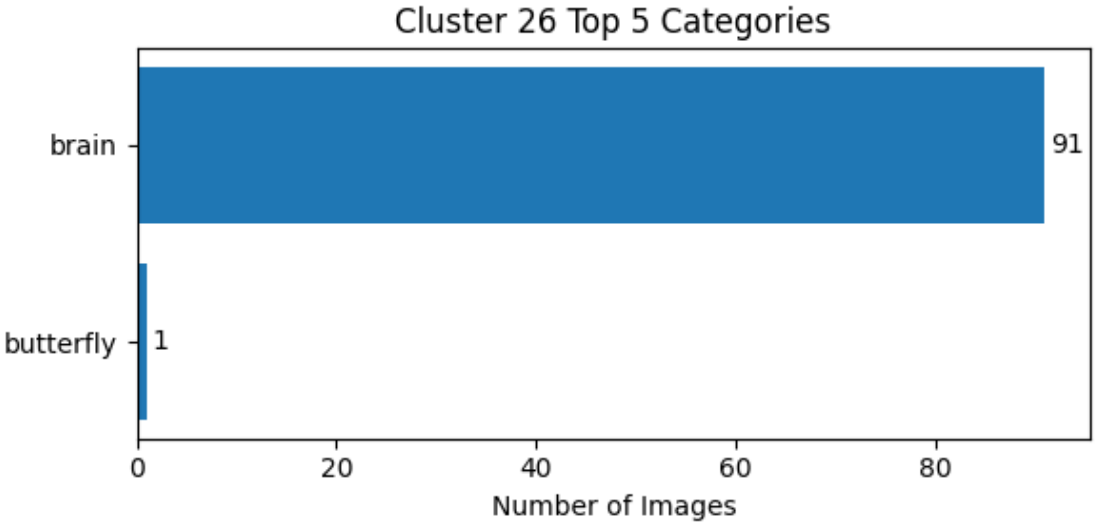
Cluster 25 (123 images, entropy=-0.00):

- car_side: 123 (100.0%)



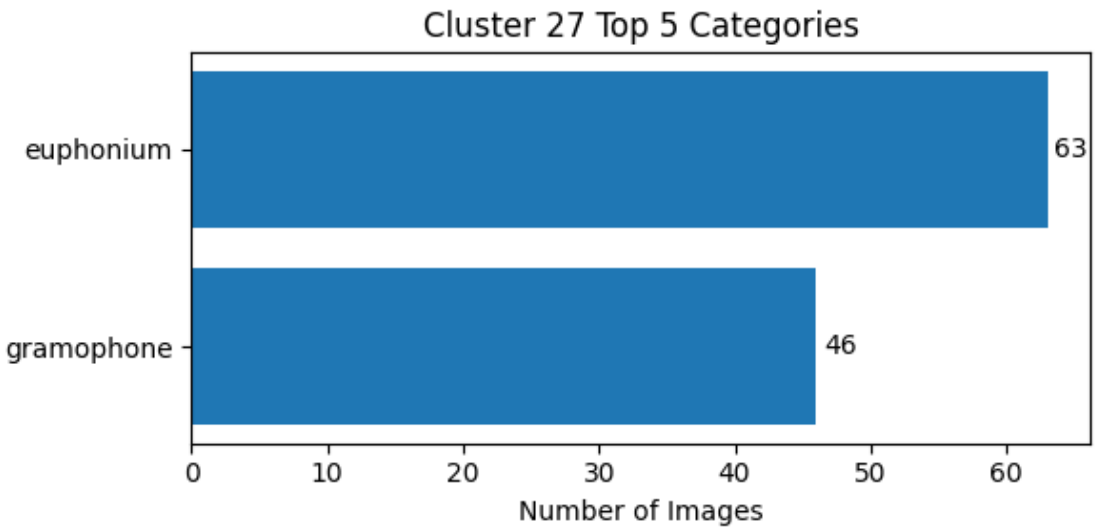
Cluster 26 (92 images, entropy=0.09):

- brain: 91 (98.9%)
- butterfly: 1 (1.1%)



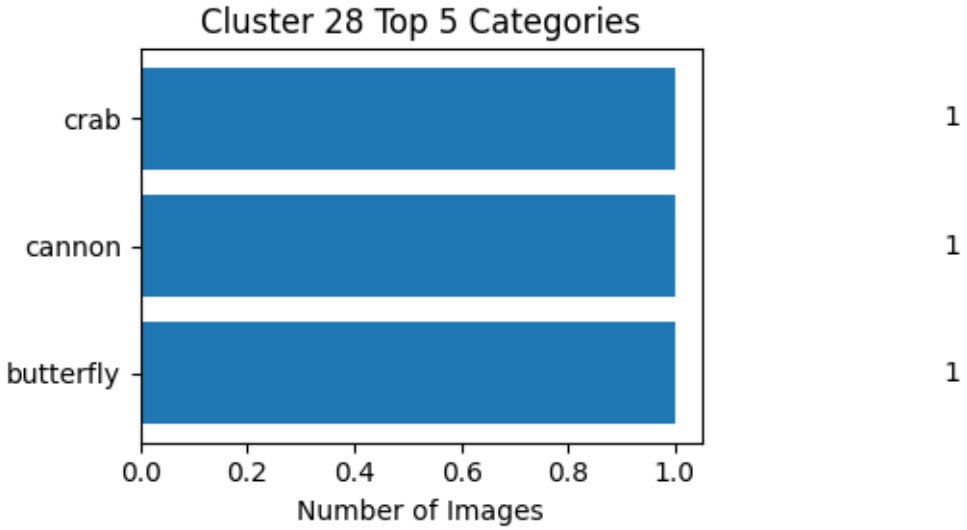
Cluster 27 (109 images, entropy=0.98):

- euphonium: 63 (57.8%)
- gramophone: 46 (42.2%)



Cluster 28 (3 images, entropy=1.58):

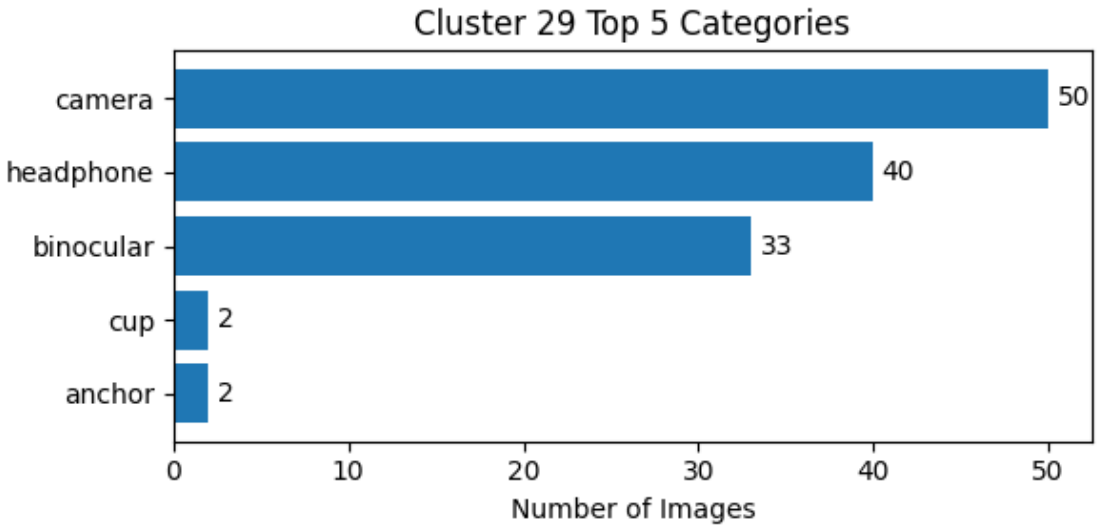
- crab: 1 (33.3%)
- cannon: 1 (33.3%)
- butterfly: 1 (33.3%)



Cluster 29 (131 images, entropy=1.94):

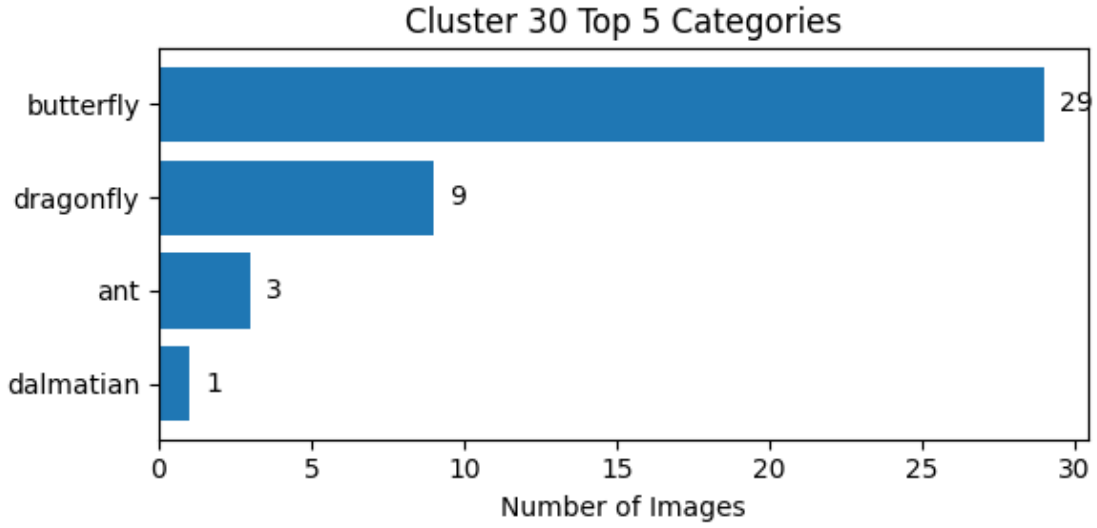
- camera: 50 (38.2%)
- headphone: 40 (30.5%)
- binocular: 33 (25.2%)

- cup: 2 (1.5%)
- anchor: 2 (1.5%)



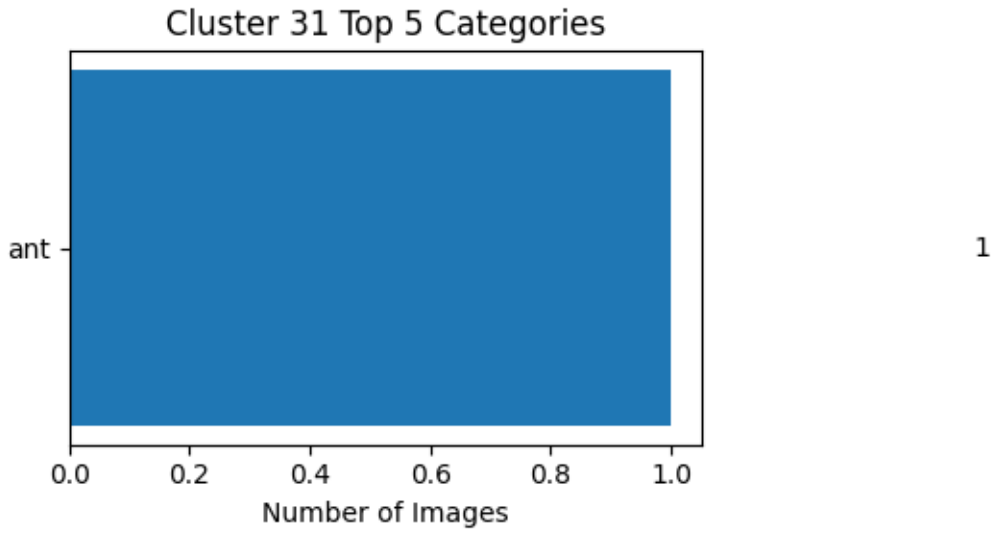
Cluster 30 (42 images, entropy=1.25):

- butterfly: 29 (69.0%)
- dragonfly: 9 (21.4%)
- ant: 3 (7.1%)
- dalmatian: 1 (2.4%)



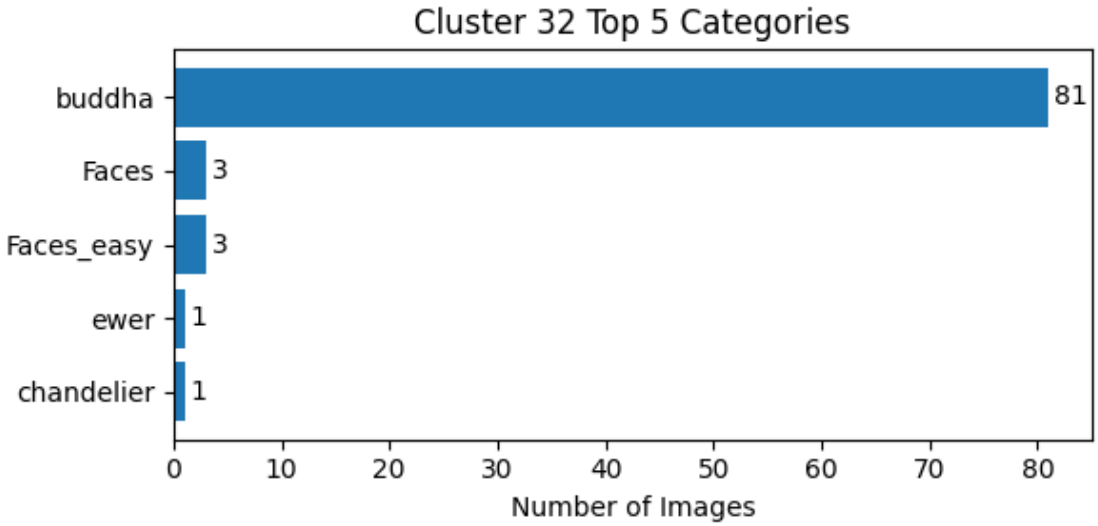
Cluster 31 (1 images, entropy=-0.00):

- ant: 1 (100.0%)



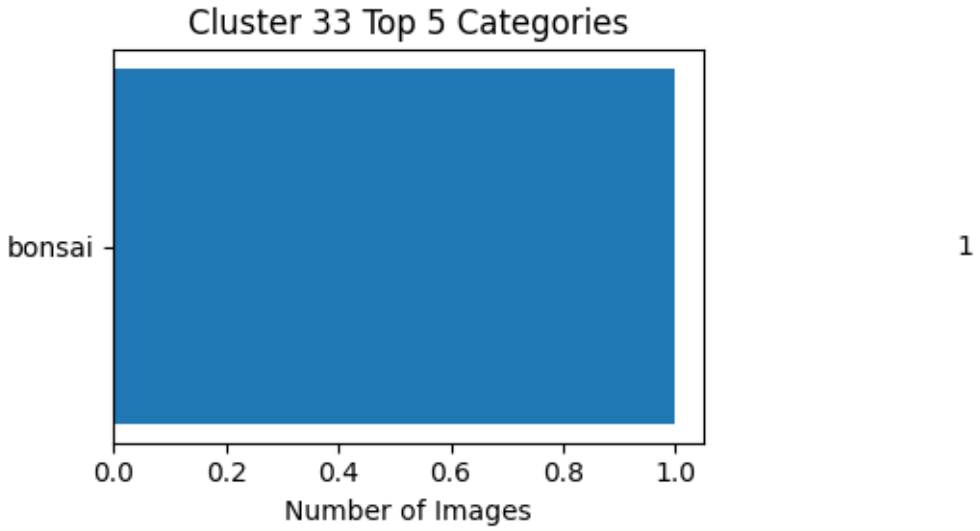
Cluster 32 (89 images, entropy=0.60):

- buddha: 81 (91.0%)
- Faces: 3 (3.4%)
- Faces_easy: 3 (3.4%)
- ewer: 1 (1.1%)
- chandelier: 1 (1.1%)



Cluster 33 (1 images, entropy=-0.00):

- bonsai: 1 (100.0%)

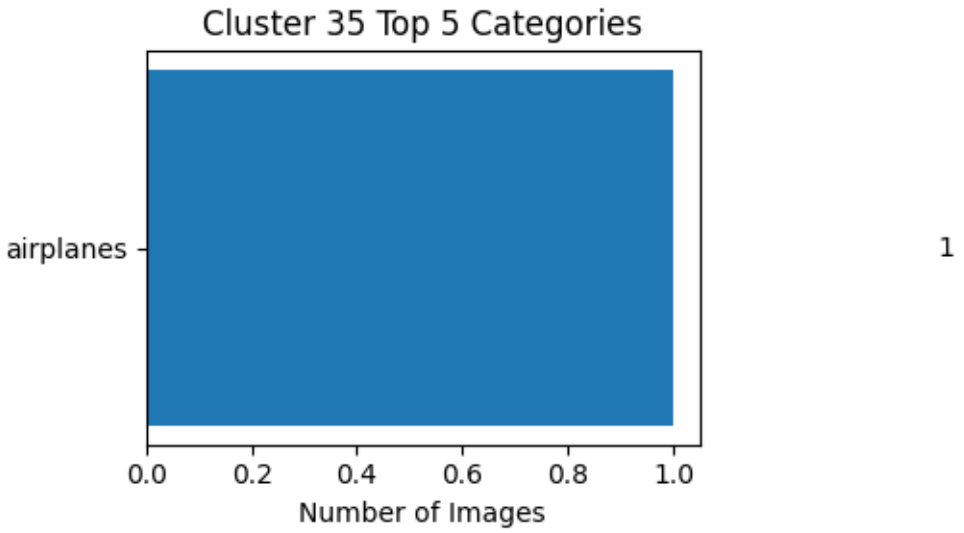


Cluster 34 (3 images, entropy=1.58):

- helicopter: 1 (33.3%)
- grand_piano: 1 (33.3%)
- chandelier: 1 (33.3%)

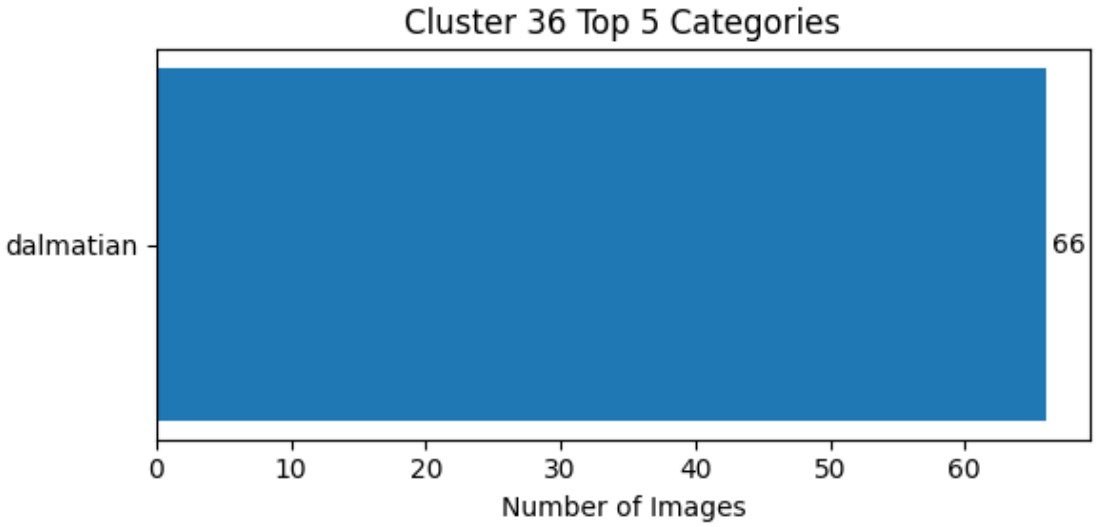
Cluster 35 (1 images, entropy=-0.00):

- airplanes: 1 (100.0%)



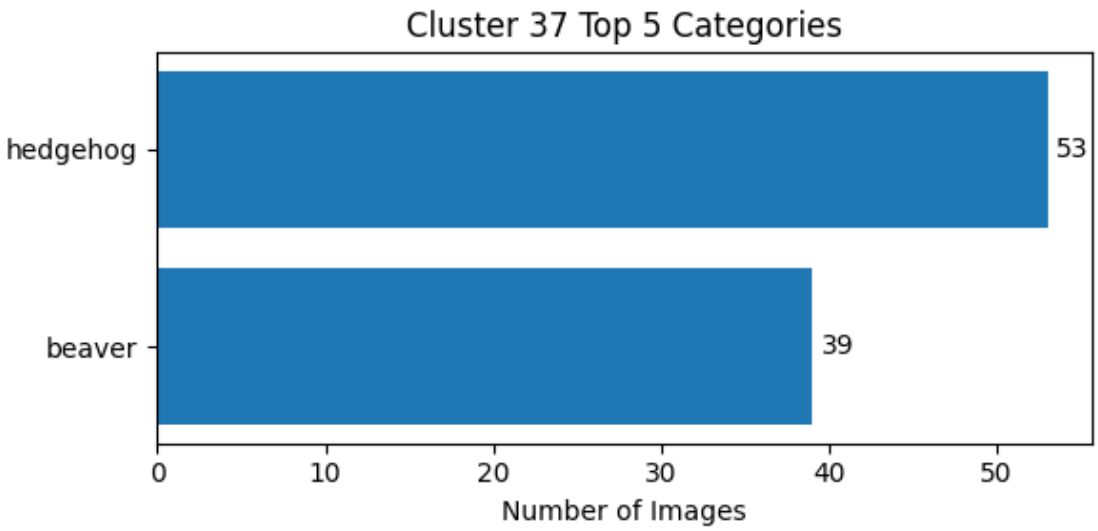
Cluster 36 (66 images, entropy=-0.00):

- dalmatian: 66 (100.0%)



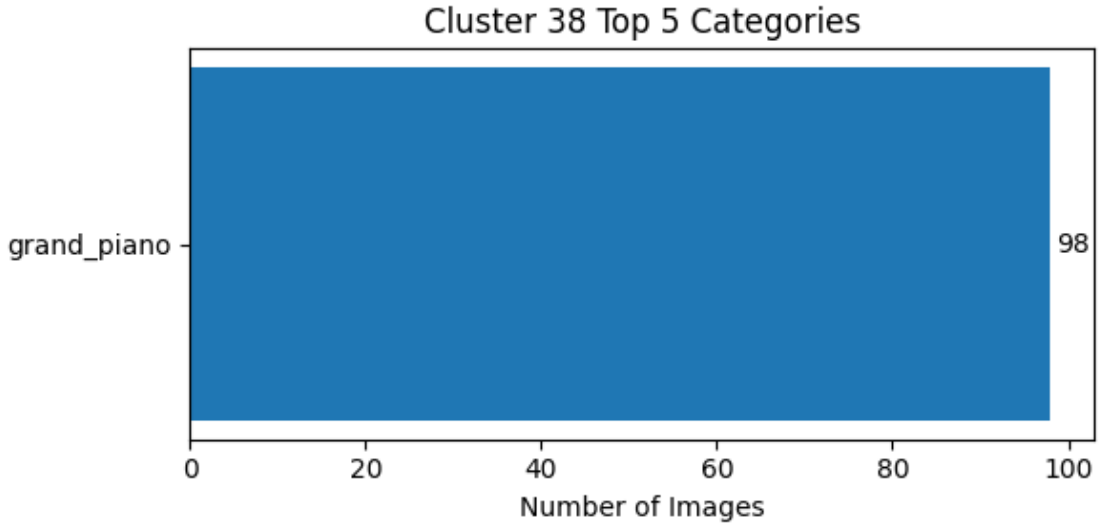
Cluster 37 (92 images, entropy=0.98):

- hedgehog: 53 (57.6%)
- beaver: 39 (42.4%)



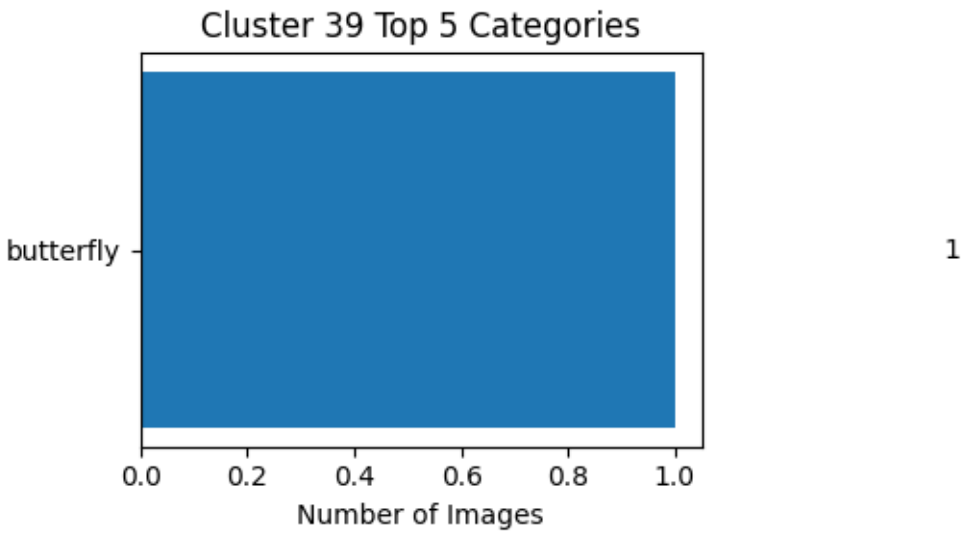
Cluster 38 (98 images, entropy=-0.00):

- grand_piano: 98 (100.0%)



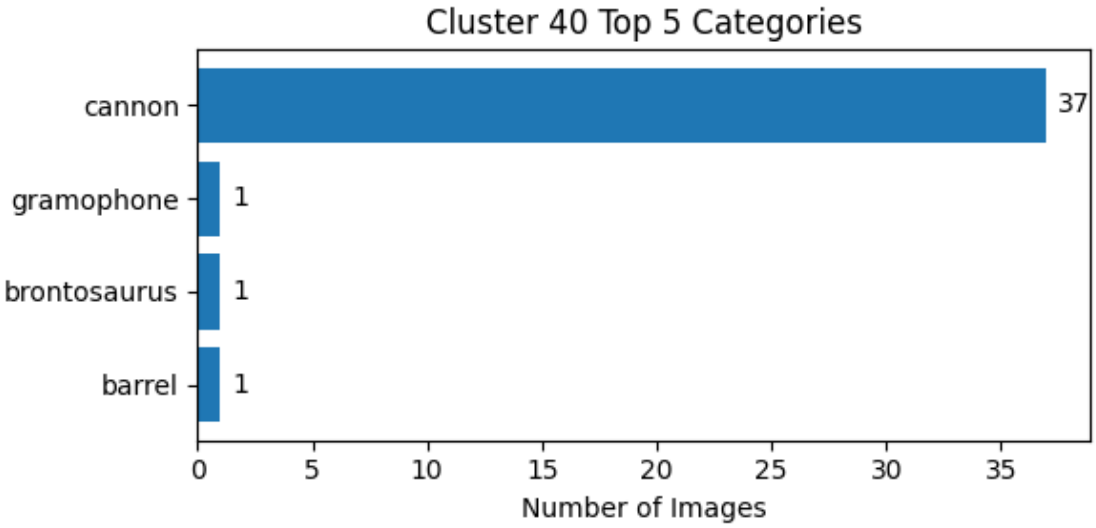
Cluster 39 (1 images, entropy=-0.00):

- butterfly: 1 (100.0%)



Cluster 40 (40 images, entropy=0.50):

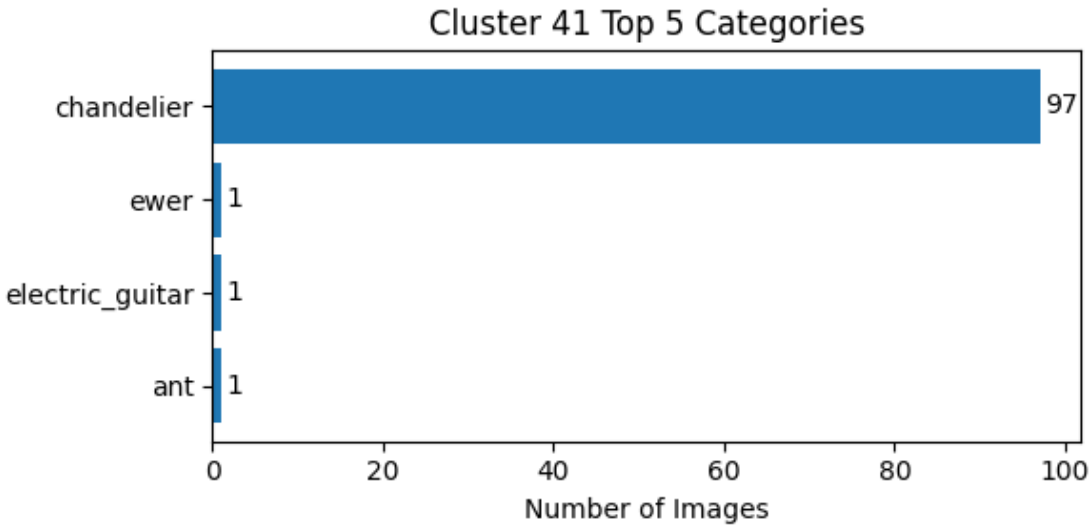
- cannon: 37 (92.5%)
- gramophone: 1 (2.5%)
- brontosaurus: 1 (2.5%)
- barrel: 1 (2.5%)



Cluster 41 (100 images, entropy=0.24):

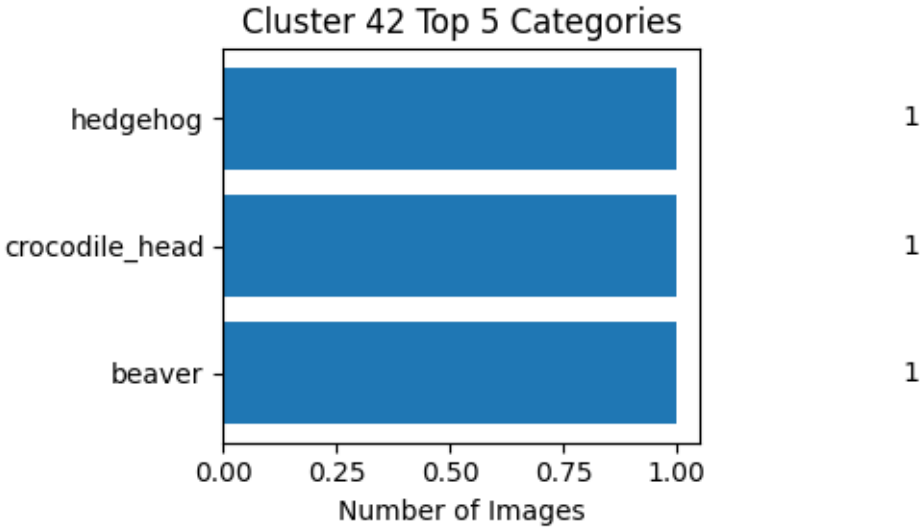
- chandelier: 97 (97.0%)
- ewer: 1 (1.0%)

- electric_guitar: 1 (1.0%)
- ant: 1 (1.0%)



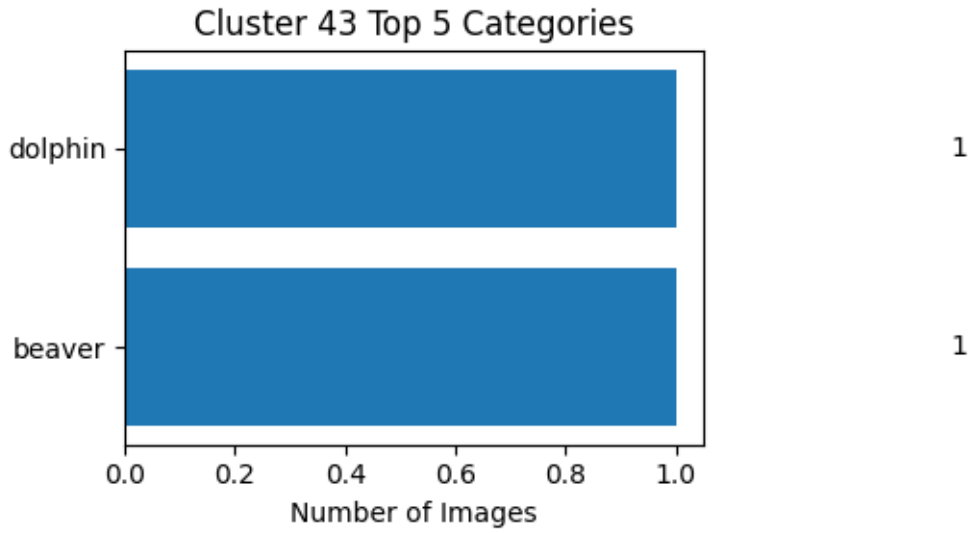
Cluster 42 (3 images, entropy=1.58):

- hedgehog: 1 (33.3%)
- crocodile_head: 1 (33.3%)
- beaver: 1 (33.3%)



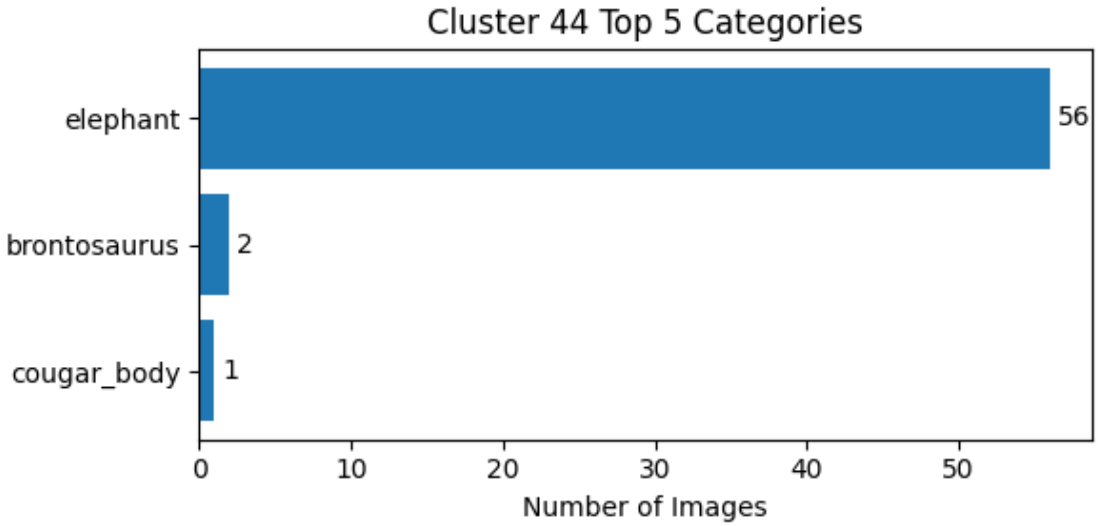
Cluster 43 (2 images, entropy=1.00):

- dolphin: 1 (50.0%)
- beaver: 1 (50.0%)



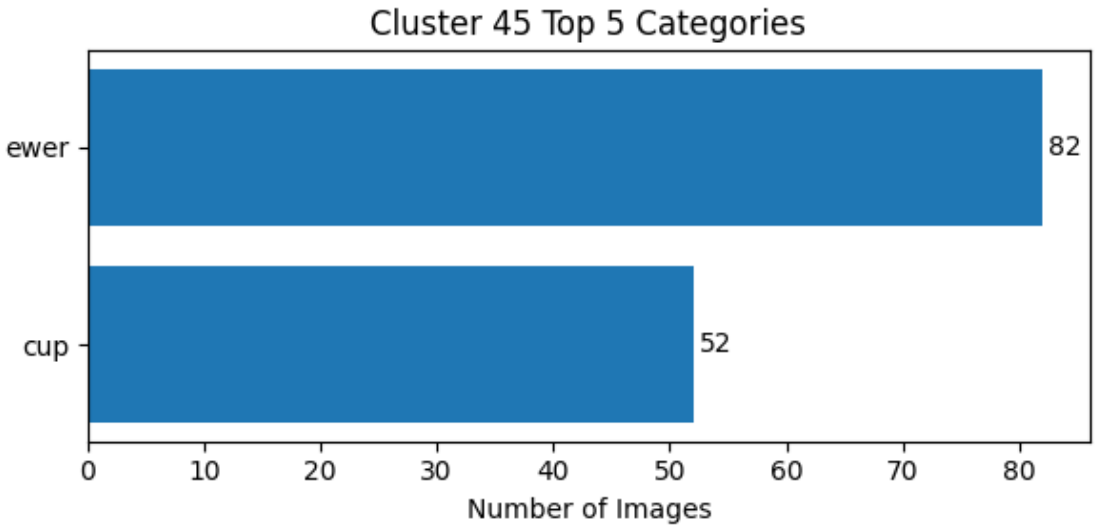
Cluster 44 (59 images, entropy=0.34):

- elephant: 56 (94.9%)
- brontosaurus: 2 (3.4%)
- cougar_body: 1 (1.7%)



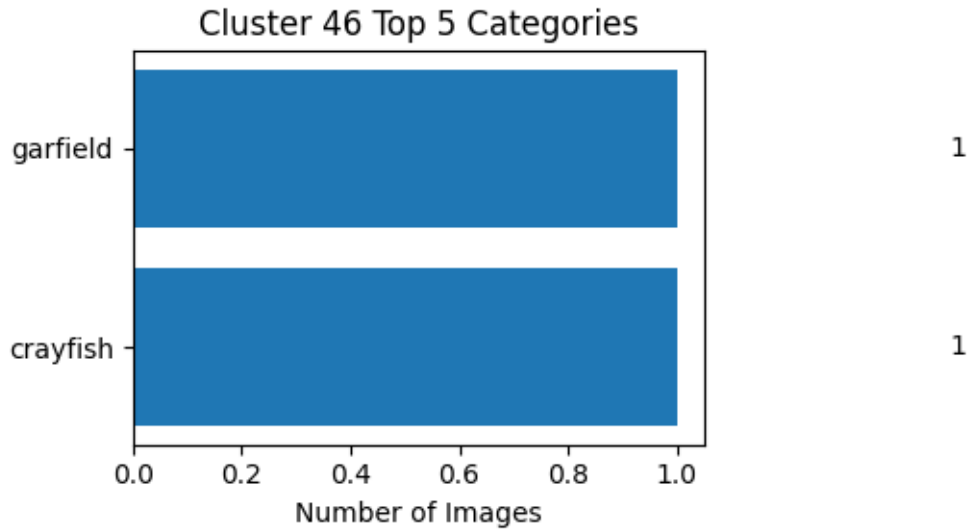
Cluster 45 (134 images, entropy=0.96):

- ewer: 82 (61.2%)
- cup: 52 (38.8%)



Cluster 46 (2 images, entropy=1.00):

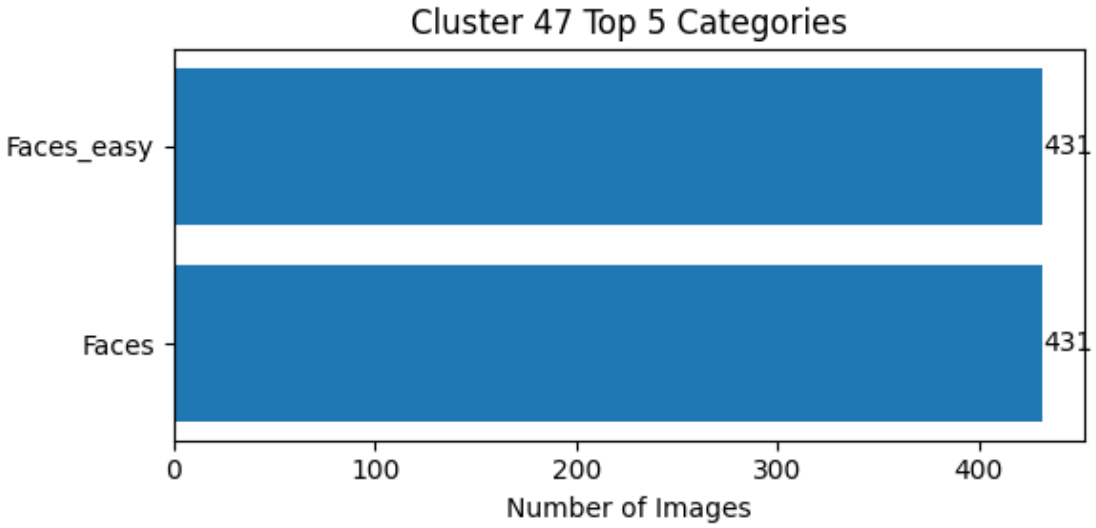
- garfield: 1 (50.0%)
- crayfish: 1 (50.0%)



Cluster 47 (862 images, entropy=1.00):

- Faces_easy: 431 (50.0%)

- Faces: 431 (50.0%)

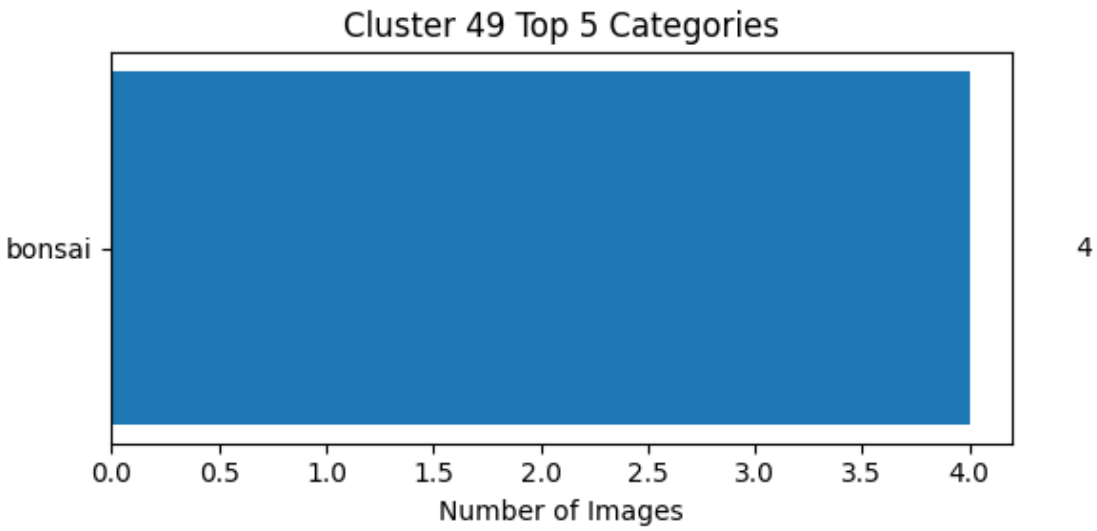


Cluster 48 (2 images, entropy=1.00):

- chandelier: 1 (50.0%)
- butterfly: 1 (50.0%)

Cluster 49 (4 images, entropy=-0.00):

- bonsai: 4 (100.0%)


Cluster 49 Top 5 Categories
bonsai
4
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Number of Images

[ ]: