

# Testing repeatability of distance between clusters in a UMAP space, given a changing input dataset

In this script, we compute multiple UMAP representations of a changing dataset of digits (0, 2-9). For each combination of these digits, we generate a separate UMAP representation.

We don't change any parameters for UMAP generation, except the input dataset (= combination of digits included).

Then, we compute the pairwise distances b/w the clusters of a given pair of digits, across the multiple UMAP representations. The UMAP representations where the given digit pair was not included were not considered.

For distance b/w clusters, the centroid of the cluster is computed as the geometric mean.

MNIST dataset:- [https://en.wikipedia.org/wiki/MNIST\\_database](https://en.wikipedia.org/wiki/MNIST_database)

[LeCun et al., 1998a] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner. "Gradient-based learning applied to document recognition." Proceedings of the IEEE, 86(11):2278-2324, November 1998. [on-line version]

In [ ]:

## Auxilliary set up

In [1]:

```
# Import packages

import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.datasets import load_digits
import umap
import hdbscan
from scipy.spatial import distance
from scipy.stats import gmean, mode
from mpl_toolkits.axes_grid1 import make_axes_locatable
import sklearn.cluster as cluster
from itertools import permutations, combinations
from tqdm import tqdm
import warnings
```

```
/opt/anaconda3/envs/umap-proof/lib/python3.12/site-packages/tqdm/auto.py:2
1: TqdmWarning: IProgress not found. Please update jupyter and ipywidgets.
See https://ipywidgets.readthedocs.io/en/stable/user_install.html
from .autonotebook import tqdm as notebook_tqdm
```

In [3]:

In [2]: *#### Auxilliary functions*

```
In [3]: def calc_gm(cluster):
        """ Caclulate the geometric mean of a cluster. """
        center_x = gmean(cluster[:,0])
        center_y = gmean(cluster[:,1])

        return np.array([center_x, center_y])
```

```
In [4]: def collect_cluster(cluster_no):
        """ Collect all points in a cluster. """
        indices = np.where(labels == cluster_no)
        cluster_points = embedding[indices]

        return cluster_points
```

```
In [5]: def calc_distance(cluster1, cluster2, cluster_gmeans):
        """ Calculate the euclidean distance between two clusters. """

        center1 = cluster_gmeans[cluster1]
        center2 = cluster_gmeans[cluster2]

        euc_dist = distance.euclidean(center1, center2)

        return euc_dist
```

```
In [6]: def switch_labels(orig_labels, mnist):
        """
        Switch the labels of the clusters to the most common label in the
        Explanation:
        Normally, the clusters are labelled randomly. This function match
        It also makes all the labels in a cluster the same (= the most co

        """
        new_labels = np.zeros((orig_labels.shape))

        # The manually assigned labels (ground-truth)
        targets = mnist['target']

        sublabel = 1

        for k in np.arange(n_clusters):
            # Collect all the labels in a given cluster
            ind = np.where(orig_labels==k)
```

```

# Find the ground truth label for the cluster
t = mnist['target'][ind]
# Find the mode of the ground truth labels in the cluster (to be
cluster_mode = mode(t).mode

# 2 clusters represent the same digit 1. In this case, we label 0
## I have removed the digit 1 from the dataset, so this is not ne
### The + 1000 is just a placeholder while swapping the labels. C
if cluster_mode==1:
    new_label = sublabel + 1000
    sublabel = 10
else:
    new_label = cluster_mode + 1000
# Switch to the new label
new_labels[ind] = new_label

return new_labels - 1000

```

In [ ]:

## Setting the dataset up

In [7]: *### Load MNIST dataset of handwritten digits*

```

mnist = load_digits()
mnist.keys()

```

Out[7]: dict\_keys(['data', 'target', 'frame', 'feature\_names', 'target\_names', 'images', 'DESCR'])

In [8]: *# Filter out the digit 1 from the mnist dataset and create a new dataset*

```

mnist2 = {}
mnist2['data'] = mnist['data'][(mnist['target'] != 1)]
mnist2['target'] = mnist['target'][(mnist['target'] != 1)]
mnist2['frame'] = mnist['frame']
mnist2['feature_names'] = mnist['feature_names']
mnist2['target_names'] = mnist['target_names'][(mnist['target_names'] !=
mnist2['images'] = mnist['images'][(mnist['target'] != 1)]
mnist2['DESCR'] = mnist['DESCR']

```

In [9]: *# Visualize a subset of the data*

```

fig, ax_array = plt.subplots(20, 20)
axes = ax_array.flatten()
for i, ax in enumerate(axes):
    ax.imshow(mnist2['images'][i], cmap='gray_r')
plt.setp(axes, xticks=[], yticks=[], frame_on=False)
plt.tight_layout(h_pad=0.5, w_pad=0.01)

```

```

0 2 3 4 5 6 7 8 9 0 1 3 4 5 6 7 8 9 0 2
3 4 5 6 7 8 9 0 1 3 5 5 6 5 0 3 8 9 8 4 7
7 3 5 0 0 2 2 7 8 2 0 2 6 3 3 7 3 3 4 6
6 6 4 7 5 0 3 5 2 8 2 0 0 7 6 3 2 7 4 6
3 3 9 7 6 8 4 3 4 0 5 3 6 3 6 7 5 4 4 7
2 8 2 2 5 7 9 5 4 8 8 4 9 0 7 9 1 0 2 3
4 5 6 7 8 9 0 2 3 4 5 6 7 8 9 0 2 3 4 5
6 7 8 9 0 3 5 5 6 5 0 9 8 9 8 4 7 7 3 5
0 0 2 2 7 8 1 0 2 6 3 3 7 3 3 4 6 6 6 4
9 5 0 9 5 2 8 1 0 0 7 6 3 2 7 3 3 9 7 6
8 4 7 4 0 5 7 6 9 6 7 5 4 4 7 1 8 2 1 5
5 4 8 8 4 9 0 8 9 8 0 2 3 4 5 6 7 8 9 0
2 3 4 5 6 7 8 9 0 2 3 4 5 6 7 8 9 0 9 5
5 6 5 0 9 8 9 8 4 7 7 3 5 0 0 2 2 7 8 2
0 2 6 3 3 7 3 3 4 6 6 6 4 7 5 0 9 5 2 8
2 0 0 7 6 3 2 7 4 6 3 3 9 7 6 8 4 3 4 0
5 3 6 7 6 7 5 4 4 7 2 8 2 2 5 7 9 5 4 8
8 4 9 0 8 9 3 0 1 3 4 5 6 7 8 9 0 1 3 4
5 6 7 8 9 0 1 3 4 5 6 7 8 9 0 9 5 5 6 5
0 9 8 9 8 4 7 7 3 5 0 0 1 2 7 8 1 0 1 6

```

In [ ]:

In [ ]:

We generate multiple UMAP representations of the digits dataset

```
In [10]: # Initialising a global seed for the random number generator
np.random.seed(0)
```

```
In [11]: # Set up the path for saving the results
results_path = 'Figures/wo1_digits/exclusion/'

# Describing the included digits
all_digits = [0, 2, 3, 4, 5, 6, 7, 8, 9]
all_digits.sort()
n_all_digits = len(all_digits)
max_digit = np.max(all_digits)
```

```
In [12]: # Generate all possible pairs of digits with the given set
all_pair_combinations = list(combinations(all_digits, 2))
all_pair_combinations = np.array(all_pair_combinations)
n_pairs = len(all_pair_combinations)
print('All pair combinations:', all_pair_combinations)
```

```

All pair combinations: [[0 2]
 [0 3]
 [0 4]
 [0 5]
 [0 6]
 [0 7]
 [0 8]
 [0 9]
 [2 3]
 [2 4]
 [2 5]
 [2 6]
 [2 7]
 [2 8]
 [2 9]
 [3 4]
 [3 5]
 [3 6]
 [3 7]
 [3 8]
 [3 9]
 [4 5]
 [4 6]
 [4 7]
 [4 8]
 [4 9]
 [5 6]
 [5 7]
 [5 8]
 [5 9]
 [6 7]
 [6 8]
 [6 9]
 [7 8]
 [7 9]
 [8 9]]

```

```

In [13]: # Calculate all combinations of all_digits with minimum length 2
all_combinations = []
for r in range(2, len(all_digits) + 1):
    all_combinations.extend(combinations(all_digits, r))

n_combos = len(all_combinations)
# n_combos = len(combo_embedding['combination'])

# all_combinations = np.array(all_combinations)
print('All combinations:', all_combinations)

```

```

All combinations: [(0, 2), (0, 3), (0, 4), (0, 5), (0, 6), (0, 7), (0, 8),
 (0, 9), (2, 3), (2, 4), (2, 5), (2, 6), (2, 7), (2, 8), (2, 9), (3, 4), (
 3, 5), (3, 6), (3, 7), (3, 8), (3, 9), (4, 5), (4, 6), (4, 7), (4, 8), (4,
 9), (5, 6), (5, 7), (5, 8), (5, 9), (6, 7), (6, 8), (6, 9), (7, 8), (7,
 9), (8, 9), (0, 2, 3), (0, 2, 4), (0, 2, 5), (0, 2, 6), (0, 2, 7), (0, 2,
 8), (0, 2, 9), (0, 3, 4), (0, 3, 5), (0, 3, 6), (0, 3, 7), (0, 3, 8), (0,

```

Page 6 of 47

```

4, 8, 9), (2, 3, 5, 6, 7), (2, 3, 5, 6, 8), (2, 3, 5, 6, 9), (2, 3, 5, 7,
8), (2, 3, 5, 7, 9), (2, 3, 5, 8, 9), (2, 3, 6, 7, 8), (2, 3, 6, 7, 9), (
2, 3, 6, 8, 9), (2, 3, 7, 8, 9), (2, 4, 5, 6, 7), (2, 4, 5, 6, 8), (2, 4,
5, 6, 9), (2, 4, 5, 7, 8), (2, 4, 5, 7, 9), (2, 4, 5, 8, 9), (2, 4, 6, 7,
8), (2, 4, 6, 7, 9), (2, 4, 6, 8, 9), (2, 4, 7, 8, 9), (2, 5, 6, 7, 8), (
2, 5, 6, 7, 9), (2, 5, 6, 8, 9), (2, 5, 7, 8, 9), (2, 6, 7, 8, 9), (3, 4,
5, 6, 7), (3, 4, 5, 6, 8), (3, 4, 5, 6, 9), (3, 4, 5, 7, 8), (3, 4, 5, 7,
9), (3, 4, 5, 8, 9), (3, 4, 6, 7, 8), (3, 4, 6, 7, 9), (3, 4, 6, 8, 9), (
3, 4, 7, 8, 9), (3, 5, 6, 7, 8), (3, 5, 6, 7, 9), (3, 5, 6, 8, 9), (3, 5,
7, 8, 9), (3, 6, 7, 8, 9), (4, 5, 6, 7, 8), (4, 5, 6, 7, 9), (4, 5, 6, 8,
9), (4, 5, 7, 8, 9), (4, 6, 7, 8, 9), (5, 6, 7, 8, 9), (0, 2, 3, 4, 5, 6),
(0, 2, 3, 4, 5, 7), (0, 2, 3, 4, 5, 8), (0, 2, 3, 4, 5, 9), (0, 2, 3, 4,
6, 7), (0, 2, 3, 4, 6, 8), (0, 2, 3, 4, 6, 9), (0, 2, 3, 4, 7, 8), (0, 2,
3, 4, 7, 9), (0, 2, 3, 4, 8, 9), (0, 2, 3, 5, 6, 7), (0, 2, 3, 5, 6, 8), (
0, 2, 3, 5, 6, 9), (0, 2, 3, 5, 7, 8), (0, 2, 3, 5, 7, 9), (0, 2, 3, 5, 8,
9), (0, 2, 3, 6, 7, 8), (0, 2, 3, 6, 7, 9), (0, 2, 3, 6, 8, 9), (0, 2, 3,
7, 8, 9), (0, 2, 4, 5, 6, 7), (0, 2, 4, 5, 6, 8), (0, 2, 4, 5, 6, 9), (0,
2, 4, 5, 7, 8), (0, 2, 4, 5, 7, 9), (0, 2, 4, 5, 8, 9), (0, 2, 4, 6, 7,
8), (0, 2, 4, 6, 7, 9), (0, 2, 4, 6, 8, 9), (0, 2, 4, 7, 8, 9), (0, 2, 5,
6, 7, 8), (0, 2, 5, 6, 7, 9), (0, 2, 5, 6, 8, 9), (0, 2, 5, 7, 8, 9), (0,
2, 6, 7, 8, 9), (0, 3, 4, 5, 6, 7), (0, 3, 4, 5, 6, 8), (0, 3, 4, 5, 6,
9), (0, 3, 4, 5, 7, 8), (0, 3, 4, 5, 7, 9), (0, 3, 4, 5, 8, 9), (0, 3, 4,
6, 7, 8), (0, 3, 4, 6, 7, 9), (0, 3, 4, 6, 8, 9), (0, 3, 4, 7, 8, 9), (0,
3, 5, 6, 7, 8), (0, 3, 5, 6, 7, 9), (0, 3, 5, 6, 8, 9), (0, 3, 5, 7, 8,
9), (0, 3, 6, 7, 8, 9), (0, 4, 5, 6, 7, 8), (0, 4, 5, 6, 7, 9), (0, 4, 5,
6, 8, 9), (0, 4, 5, 7, 8, 9), (0, 4, 6, 7, 8, 9), (0, 5, 6, 7, 8, 9), (2,
3, 4, 5, 6, 7), (2, 3, 4, 5, 6, 8), (2, 3, 4, 5, 6, 9), (2, 3, 4, 5, 7,
8), (2, 3, 4, 5, 7, 9), (2, 3, 4, 5, 8, 9), (2, 3, 4, 6, 7, 8), (2, 3, 4,
6, 7, 9), (2, 3, 4, 6, 8, 9), (2, 3, 4, 7, 8, 9), (2, 3, 5, 6, 7, 8), (2,
3, 5, 6, 7, 9), (2, 3, 5, 6, 8, 9), (2, 3, 5, 7, 8, 9), (2, 3, 6, 7, 8,
9), (2, 4, 5, 6, 7, 8), (2, 4, 5, 6, 7, 9), (2, 4, 5, 6, 8, 9), (2, 4, 5,
7, 8, 9), (2, 4, 6, 7, 8, 9), (2, 5, 6, 7, 8, 9), (3, 4, 5, 6, 7, 8), (3,
4, 5, 6, 7, 9), (3, 4, 5, 6, 8, 9), (3, 4, 5, 7, 8, 9), (3, 4, 6, 7, 8,
9), (3, 5, 6, 7, 8, 9), (4, 5, 6, 7, 8, 9), (0, 2, 3, 4, 5, 6, 7), (0, 2,
3, 4, 5, 6, 8), (0, 2, 3, 4, 5, 6, 9), (0, 2, 3, 4, 5, 7, 8), (0, 2, 3, 4,
5, 7, 9), (0, 2, 3, 4, 5, 8, 9), (0, 2, 3, 4, 6, 7, 8), (0, 2, 3, 4, 6, 7,
9), (0, 2, 3, 4, 6, 8, 9), (0, 2, 3, 4, 7, 8, 9), (0, 2, 3, 5, 6, 7, 8), (
0, 2, 3, 5, 6, 7, 9), (0, 2, 3, 5, 6, 8, 9), (0, 2, 3, 5, 7, 8, 9), (0, 2,
3, 6, 7, 8, 9), (0, 2, 4, 5, 6, 7, 8), (0, 2, 4, 5, 6, 7, 9), (0, 2, 4, 5,
6, 8, 9), (0, 2, 4, 5, 7, 8, 9), (0, 2, 4, 6, 7, 8, 9), (0, 2, 5, 6, 7, 8,
9), (0, 3, 4, 5, 6, 7, 8), (0, 3, 4, 5, 6, 7, 9), (0, 3, 4, 5, 6, 8, 9), (
0, 3, 4, 5, 7, 8, 9), (0, 3, 4, 6, 7, 8, 9), (0, 3, 5, 6, 7, 8, 9), (0, 4,
5, 6, 7, 8, 9), (2, 3, 4, 5, 6, 7, 8), (2, 3, 4, 5, 6, 7, 9), (2, 3, 4, 5,
6, 8, 9), (2, 3, 4, 5, 7, 8, 9), (2, 3, 4, 6, 7, 8, 9), (2, 3, 5, 6, 7, 8,
9), (2, 4, 5, 6, 7, 8, 9), (3, 4, 5, 6, 7, 8, 9), (0, 2, 3, 4, 5, 6, 7,
8), (0, 2, 3, 4, 5, 6, 7, 9), (0, 2, 3, 4, 5, 6, 8, 9), (0, 2, 3, 4, 5, 7,
8, 9), (0, 2, 3, 4, 6, 7, 8, 9), (0, 2, 3, 5, 6, 7, 8, 9), (0, 2, 4, 5, 6,
7, 8, 9), (0, 3, 4, 5, 6, 7, 8, 9), (2, 3, 4, 5, 6, 7, 8, 9), (0, 2, 3, 4,
5, 6, 7, 8, 9)]

```

```

In [14]: # Make a container to store the details of the UMAP representation of each
        combo_embedding = {
            'combination': [],
            'cluster_gmeans': [],

```

```
'distance_matrix': []
}
```

```
In [15]: # Using a fixed seed for all UMAP projections
rseed = np.random.randint(0,1e9)

# Run the dimension reduction and clustering for each combination of digits
for n_combo, combo in tqdm(enumerate(all_combinations)):
    print('n_combo #: ', n_combo)
    print('combo : ', np.array(combo))

    # Sort the digits in the combination
    curr_digits = np.array(combo)
    curr_digits.sort()

    # Filter mnist2 dataset to only have curr_digits
    indices = np.where(np.isin(mnist2['target'], curr_digits))

    mnist2_curr = {}
    mnist2_curr['data'] = mnist2['data'][indices]
    mnist2_curr['target'] = mnist2['target'][indices]
    mnist2_curr['images'] = mnist2['images'][indices]

    # Create a UMAP embedding of the data
    reducer = umap.UMAP(random_state=rseed)
    reducer.fit(mnist2_curr['data'])
    embedding = reducer.transform(mnist2_curr['data'])

    # Normalise the embedding (VERIFY: Is normalisation needed?)
    embedding = (embedding - embedding.min())
    embedding = embedding / embedding.max()

    # the number of clusters = the number of digits in the combination
    n_clusters = len(curr_digits)

    # Cluster the UMAP embedding
    labels = cluster.KMeans(n_clusters=n_clusters).fit_predict(embedding)
    # # labels = hdbscan.HDBSCAN(min_samples=10, min_cluster_size=50).fit(embedding)

    # Cleaning
    ## Matching the generated labels to the digit it represents
    new_labels = switch_labels(labels, mnist2_curr)

    # Find the centroid = geometric mean of each cluster
    cluster_gmeans = np.zeros((n_clusters, 2))
    cluster_gmeans_dict = {}
    for nc in np.arange(n_clusters):
        cluster_points = collect_cluster(nc)

        cluster_gmeans[nc] = calc_gm(cluster_points)
        cluster_gmeans_dict[curr_digits[nc]] = cluster_gmeans[nc]
```



```

# Make a plot of the UMAP embedding and clusters
fig = plt.figure()
plt.scatter(embedding[:, 0], embedding[:, 1], c=new_labels, cmap='tab

plt.gca().set_aspect('equal', 'datalim')
# plt.colorbar(boundaries=np.arange(new_labels.min()+2, new_labels.ma
plt.colorbar(boundaries=np.arange(new_labels.min(), new_labels.max()+

plt.scatter(cluster_gmeans[:,0], cluster_gmeans[:,1], c='black', s=10

plt.title('UMAP projection of the Digits dataset', fontsize=14)

plt.savefig(results_path + 'UMAPs/n' + str(n_combo) + '_combo' + str(

plt.close()

# Create a distance matrix for the pairwise distances in the given UM
distance_matrix = np.zeros((max_digit+2, max_digit+2))

# Find distance between all pairs of clusters
for digit1 in all_digits:
    for digit2 in all_digits:
        if digit1 < digit2:
            if digit1 in curr_digits and digit2 in curr_digits:

                dist = calc_distance(digit1, digit2, cluster_gmeans_d

                distance_matrix[digit1, digit2] = dist
                # distance_matrix[digit1, digit2] = 0

# Save the details of the UMAP embedding
combo_embedding['combination'].append(curr_digits)
combo_embedding['cluster_gmeans'].append(cluster_gmeans_dict)
combo_embedding['distance_matrix'].append(distance_matrix)

# BEGIN: Suppress warnings
warnings.filterwarnings('ignore')
# END:

```

```
0it [00:00, ?it/s]
```

```
n_combo #: 0
```

```
combo : [0 2]
```

```
/opt/anaconda3/envs/umap-proof/lib/python3.12/site-packages/umap/umap.py:
1945: UserWarning: n_jobs value 1 overridden to 1 by setting random_state.
Use no seed for parallelism.
```

```
    warn(f"n_jobs value {self.n_jobs} overridden to 1 by setting random_stat
e. Use no seed for parallelism.")
```

```
1it [00:06, 6.18s/it]
```

```
n_combo #: 1
```

```
combo : [0 3]
```

```
2it [00:07, 3.36s/it]
```

n\_combo #: 2  
combo : [0 4]  
3it [00:08, 2.42s/it]  
n\_combo #: 3  
combo : [0 5]  
4it [00:10, 2.02s/it]  
n\_combo #: 4  
combo : [0 6]  
5it [00:11, 1.77s/it]  
n\_combo #: 5  
combo : [0 7]  
6it [00:12, 1.61s/it]  
n\_combo #: 6  
combo : [0 8]  
7it [00:14, 1.49s/it]  
n\_combo #: 7  
combo : [0 9]  
8it [00:15, 1.41s/it]  
n\_combo #: 8  
combo : [2 3]  
9it [00:17, 1.48s/it]  
n\_combo #: 9  
combo : [2 4]  
10it [00:18, 1.40s/it]  
n\_combo #: 10  
combo : [2 5]  
11it [00:19, 1.35s/it]  
n\_combo #: 11  
combo : [2 6]  
12it [00:20, 1.34s/it]  
n\_combo #: 12  
combo : [2 7]  
13it [00:22, 1.31s/it]  
n\_combo #: 13  
combo : [2 8]  
14it [00:23, 1.30s/it]  
n\_combo #: 14  
combo : [2 9]  
15it [00:24, 1.27s/it]  
n\_combo #: 15  
combo : [3 4]  
16it [00:25, 1.29s/it]  
n\_combo #: 16  
combo : [3 5]  
17it [00:27, 1.42s/it]  
n\_combo #: 17  
combo : [3 6]  
18it [00:28, 1.37s/it]

n\_combo #: 18  
combo : [3 7]  
19it [00:30, 1.34s/it]  
n\_combo #: 19  
combo : [3 8]  
20it [00:31, 1.32s/it]  
n\_combo #: 20  
combo : [3 9]  
21it [00:32, 1.31s/it]  
n\_combo #: 21  
combo : [4 5]  
22it [00:33, 1.29s/it]  
n\_combo #: 22  
combo : [4 6]  
23it [00:35, 1.26s/it]  
n\_combo #: 23  
combo : [4 7]  
24it [00:36, 1.27s/it]  
n\_combo #: 24  
combo : [4 8]  
25it [00:37, 1.29s/it]  
n\_combo #: 25  
combo : [4 9]  
26it [00:39, 1.44s/it]  
n\_combo #: 26  
combo : [5 6]  
27it [00:40, 1.39s/it]  
n\_combo #: 27  
combo : [5 7]  
28it [00:42, 1.36s/it]  
n\_combo #: 28  
combo : [5 8]  
29it [00:43, 1.36s/it]  
n\_combo #: 29  
combo : [5 9]  
30it [00:44, 1.38s/it]  
n\_combo #: 30  
combo : [6 7]  
31it [00:46, 1.40s/it]  
n\_combo #: 31  
combo : [6 8]  
32it [00:47, 1.36s/it]  
n\_combo #: 32  
combo : [6 9]  
33it [00:48, 1.33s/it]  
n\_combo #: 33  
combo : [7 8]  
34it [00:50, 1.37s/it]

n\_combo #: 34  
combo : [7 9]  
35it [00:51, 1.44s/it]  
n\_combo #: 35  
combo : [8 9]  
36it [00:53, 1.58s/it]  
n\_combo #: 36  
combo : [0 2 3]  
37it [00:55, 1.62s/it]  
n\_combo #: 37  
combo : [0 2 4]  
38it [00:57, 1.76s/it]  
n\_combo #: 38  
combo : [0 2 5]  
39it [00:59, 1.74s/it]  
n\_combo #: 39  
combo : [0 2 6]  
40it [01:00, 1.72s/it]  
n\_combo #: 40  
combo : [0 2 7]  
41it [01:02, 1.69s/it]  
n\_combo #: 41  
combo : [0 2 8]  
42it [01:04, 1.67s/it]  
n\_combo #: 42  
combo : [0 2 9]  
43it [01:05, 1.67s/it]  
n\_combo #: 43  
combo : [0 3 4]  
44it [01:07, 1.69s/it]  
n\_combo #: 44  
combo : [0 3 5]  
45it [01:09, 1.68s/it]  
n\_combo #: 45  
combo : [0 3 6]  
46it [01:11, 1.89s/it]  
n\_combo #: 46  
combo : [0 3 7]  
47it [01:13, 2.01s/it]  
n\_combo #: 47  
combo : [0 3 8]  
48it [01:16, 2.07s/it]  
n\_combo #: 48  
combo : [0 3 9]  
49it [01:18, 2.03s/it]  
n\_combo #: 49  
combo : [0 4 5]  
50it [01:19, 1.97s/it]

n\_combo #: 50  
combo : [0 4 6]  
51it [01:21, 1.98s/it]  
n\_combo #: 51  
combo : [0 4 7]  
52it [01:23, 1.92s/it]  
n\_combo #: 52  
combo : [0 4 8]  
53it [01:25, 1.86s/it]  
n\_combo #: 53  
combo : [0 4 9]  
54it [01:27, 1.85s/it]  
n\_combo #: 54  
combo : [0 5 6]  
55it [01:29, 2.12s/it]  
n\_combo #: 55  
combo : [0 5 7]  
56it [01:31, 2.00s/it]  
n\_combo #: 56  
combo : [0 5 8]  
57it [01:33, 1.89s/it]  
n\_combo #: 57  
combo : [0 5 9]  
58it [01:34, 1.82s/it]  
n\_combo #: 58  
combo : [0 6 7]  
59it [01:36, 1.79s/it]  
n\_combo #: 59  
combo : [0 6 8]  
60it [01:38, 1.78s/it]  
n\_combo #: 60  
combo : [0 6 9]  
61it [01:40, 1.82s/it]  
n\_combo #: 61  
combo : [0 7 8]  
62it [01:42, 1.86s/it]  
n\_combo #: 62  
combo : [0 7 9]  
63it [01:44, 1.95s/it]  
n\_combo #: 63  
combo : [0 8 9]  
64it [01:46, 1.92s/it]  
n\_combo #: 64  
combo : [2 3 4]  
65it [01:47, 1.84s/it]  
n\_combo #: 65  
combo : [2 3 5]  
66it [01:50, 1.98s/it]

```
n_combo #: 66
combo : [2 3 6]
67it [01:52, 1.94s/it]
n_combo #: 67
combo : [2 3 7]
68it [01:54, 2.00s/it]
n_combo #: 68
combo : [2 3 8]
69it [01:56, 2.05s/it]
n_combo #: 69
combo : [2 3 9]
70it [01:58, 2.09s/it]
n_combo #: 70
combo : [2 4 5]
71it [02:01, 2.25s/it]
n_combo #: 71
combo : [2 4 6]
72it [02:03, 2.29s/it]
n_combo #: 72
combo : [2 4 7]
73it [02:06, 2.35s/it]
n_combo #: 73
combo : [2 4 8]
74it [02:08, 2.34s/it]
n_combo #: 74
combo : [2 4 9]
75it [02:10, 2.22s/it]
n_combo #: 75
combo : [2 5 6]
76it [02:12, 2.09s/it]
n_combo #: 76
combo : [2 5 7]
77it [02:14, 2.15s/it]
n_combo #: 77
combo : [2 5 8]
78it [02:16, 2.03s/it]
n_combo #: 78
combo : [2 5 9]
79it [02:17, 1.93s/it]
n_combo #: 79
combo : [2 6 7]
80it [02:19, 1.83s/it]
n_combo #: 80
combo : [2 6 8]
81it [02:21, 1.78s/it]
n_combo #: 81
combo : [2 6 9]
82it [02:22, 1.77s/it]
```

n\_combo #: 82  
combo : [2 7 8]  
83it [02:24, 1.73s/it]  
n\_combo #: 83  
combo : [2 7 9]  
84it [02:26, 1.72s/it]  
n\_combo #: 84  
combo : [2 8 9]  
85it [02:27, 1.72s/it]  
n\_combo #: 85  
combo : [3 4 5]  
86it [02:29, 1.70s/it]  
n\_combo #: 86  
combo : [3 4 6]  
87it [02:31, 1.69s/it]  
n\_combo #: 87  
combo : [3 4 7]  
88it [02:33, 1.91s/it]  
n\_combo #: 88  
combo : [3 4 8]  
89it [02:35, 1.84s/it]  
n\_combo #: 89  
combo : [3 4 9]  
90it [02:37, 1.79s/it]  
n\_combo #: 90  
combo : [3 5 6]  
91it [02:38, 1.77s/it]  
n\_combo #: 91  
combo : [3 5 7]  
92it [02:40, 1.74s/it]  
n\_combo #: 92  
combo : [3 5 8]  
93it [02:42, 1.72s/it]  
n\_combo #: 93  
combo : [3 5 9]  
94it [02:43, 1.72s/it]  
n\_combo #: 94  
combo : [3 6 7]  
95it [02:45, 1.69s/it]  
n\_combo #: 95  
combo : [3 6 8]  
96it [02:47, 1.68s/it]  
n\_combo #: 96  
combo : [3 6 9]  
97it [02:48, 1.71s/it]  
n\_combo #: 97  
combo : [3 7 8]  
98it [02:50, 1.73s/it]

n\_combo #: 98  
combo : [3 7 9]  
99it [02:52, 1.77s/it]  
n\_combo #: 99  
combo : [3 8 9]  
100it [02:55, 1.99s/it]  
n\_combo #: 100  
combo : [4 5 6]  
101it [02:56, 1.96s/it]  
n\_combo #: 101  
combo : [4 5 7]  
102it [02:58, 1.89s/it]  
n\_combo #: 102  
combo : [4 5 8]  
103it [03:00, 1.81s/it]  
n\_combo #: 103  
combo : [4 5 9]  
104it [03:01, 1.76s/it]  
n\_combo #: 104  
combo : [4 6 7]  
105it [03:03, 1.74s/it]  
n\_combo #: 105  
combo : [4 6 8]  
106it [03:05, 1.71s/it]  
n\_combo #: 106  
combo : [4 6 9]  
107it [03:07, 1.71s/it]  
n\_combo #: 107  
combo : [4 7 8]  
108it [03:08, 1.70s/it]  
n\_combo #: 108  
combo : [4 7 9]  
109it [03:10, 1.67s/it]  
n\_combo #: 109  
combo : [4 8 9]  
110it [03:11, 1.65s/it]  
n\_combo #: 110  
combo : [5 6 7]  
111it [03:13, 1.66s/it]  
n\_combo #: 111  
combo : [5 6 8]  
112it [03:15, 1.65s/it]  
n\_combo #: 112  
combo : [5 6 9]  
113it [03:17, 1.92s/it]  
n\_combo #: 113  
combo : [5 7 8]  
114it [03:19, 1.85s/it]



n\_combo #: 114  
combo : [5 7 9]  
115it [03:21, 1.84s/it]  
n\_combo #: 115  
combo : [5 8 9]  
116it [03:22, 1.81s/it]  
n\_combo #: 116  
combo : [6 7 8]  
117it [03:24, 1.79s/it]  
n\_combo #: 117  
combo : [6 7 9]  
118it [03:26, 1.77s/it]  
n\_combo #: 118  
combo : [6 8 9]  
119it [03:28, 1.85s/it]  
n\_combo #: 119  
combo : [7 8 9]  
120it [03:30, 1.82s/it]  
n\_combo #: 120  
combo : [0 2 3 4]  
121it [03:32, 1.93s/it]  
n\_combo #: 121  
combo : [0 2 3 5]  
122it [03:34, 2.01s/it]  
n\_combo #: 122  
combo : [0 2 3 6]  
123it [03:36, 2.01s/it]  
n\_combo #: 123  
combo : [0 2 3 7]  
124it [03:38, 2.02s/it]  
n\_combo #: 124  
combo : [0 2 3 8]  
125it [03:40, 2.02s/it]  
n\_combo #: 125  
combo : [0 2 3 9]  
126it [03:43, 2.26s/it]  
n\_combo #: 126  
combo : [0 2 4 5]  
127it [03:45, 2.20s/it]  
n\_combo #: 127  
combo : [0 2 4 6]  
128it [03:47, 2.15s/it]  
n\_combo #: 128  
combo : [0 2 4 7]  
129it [03:49, 2.15s/it]  
n\_combo #: 129  
combo : [0 2 4 8]  
130it [03:51, 2.12s/it]

n\_combo #: 130  
combo : [0 2 4 9]  
131it [03:53, 2.10s/it]  
n\_combo #: 131  
combo : [0 2 5 6]  
132it [03:55, 2.09s/it]  
n\_combo #: 132  
combo : [0 2 5 7]  
133it [03:57, 2.08s/it]  
n\_combo #: 133  
combo : [0 2 5 8]  
134it [04:00, 2.07s/it]  
n\_combo #: 134  
combo : [0 2 5 9]  
135it [04:02, 2.06s/it]  
n\_combo #: 135  
combo : [0 2 6 7]  
136it [04:04, 2.09s/it]  
n\_combo #: 136  
combo : [0 2 6 8]  
137it [04:06, 2.07s/it]  
n\_combo #: 137  
combo : [0 2 6 9]  
138it [04:09, 2.45s/it]  
n\_combo #: 138  
combo : [0 2 7 8]  
139it [04:12, 2.53s/it]  
n\_combo #: 139  
combo : [0 2 7 9]  
140it [04:15, 2.86s/it]  
n\_combo #: 140  
combo : [0 2 8 9]  
141it [04:18, 2.89s/it]  
n\_combo #: 141  
combo : [0 3 4 5]  
142it [04:21, 2.79s/it]  
n\_combo #: 142  
combo : [0 3 4 6]  
143it [04:23, 2.63s/it]  
n\_combo #: 143  
combo : [0 3 4 7]  
144it [04:25, 2.45s/it]  
n\_combo #: 144  
combo : [0 3 4 8]  
145it [04:27, 2.35s/it]  
n\_combo #: 145  
combo : [0 3 4 9]  
146it [04:29, 2.26s/it]

n\_combo #: 146  
combo : [0 3 5 6]  
147it [04:32, 2.22s/it]  
n\_combo #: 147  
combo : [0 3 5 7]  
148it [04:34, 2.18s/it]  
n\_combo #: 148  
combo : [0 3 5 8]  
149it [04:36, 2.16s/it]  
n\_combo #: 149  
combo : [0 3 5 9]  
150it [04:38, 2.14s/it]  
n\_combo #: 150  
combo : [0 3 6 7]  
151it [04:40, 2.12s/it]  
n\_combo #: 151  
combo : [0 3 6 8]  
152it [04:42, 2.15s/it]  
n\_combo #: 152  
combo : [0 3 6 9]  
153it [04:44, 2.13s/it]  
n\_combo #: 153  
combo : [0 3 7 8]  
154it [04:47, 2.35s/it]  
n\_combo #: 154  
combo : [0 3 7 9]  
155it [04:49, 2.28s/it]  
n\_combo #: 155  
combo : [0 3 8 9]  
156it [04:51, 2.23s/it]  
n\_combo #: 156  
combo : [0 4 5 6]  
157it [04:53, 2.18s/it]  
n\_combo #: 157  
combo : [0 4 5 7]  
158it [04:55, 2.15s/it]  
n\_combo #: 158  
combo : [0 4 5 8]  
159it [04:57, 2.12s/it]  
n\_combo #: 159  
combo : [0 4 5 9]  
160it [05:00, 2.12s/it]  
n\_combo #: 160  
combo : [0 4 6 7]  
161it [05:02, 2.10s/it]  
n\_combo #: 161  
combo : [0 4 6 8]  
162it [05:04, 2.11s/it]

n\_combo #: 162  
combo : [0 4 6 9]  
163it [05:06, 2.13s/it]  
n\_combo #: 163  
combo : [0 4 7 8]  
164it [05:08, 2.13s/it]  
n\_combo #: 164  
combo : [0 4 7 9]  
165it [05:10, 2.14s/it]  
n\_combo #: 165  
combo : [0 4 8 9]  
166it [05:12, 2.11s/it]  
n\_combo #: 166  
combo : [0 5 6 7]  
167it [05:14, 2.10s/it]  
n\_combo #: 167  
combo : [0 5 6 8]  
168it [05:17, 2.37s/it]  
n\_combo #: 168  
combo : [0 5 6 9]  
169it [05:19, 2.28s/it]  
n\_combo #: 169  
combo : [0 5 7 8]  
170it [05:21, 2.22s/it]  
n\_combo #: 170  
combo : [0 5 7 9]  
171it [05:24, 2.21s/it]  
n\_combo #: 171  
combo : [0 5 8 9]  
172it [05:26, 2.17s/it]  
n\_combo #: 172  
combo : [0 6 7 8]  
173it [05:28, 2.16s/it]  
n\_combo #: 173  
combo : [0 6 7 9]  
174it [05:30, 2.20s/it]  
n\_combo #: 174  
combo : [0 6 8 9]  
175it [05:33, 2.26s/it]  
n\_combo #: 175  
combo : [0 7 8 9]  
176it [05:35, 2.27s/it]  
n\_combo #: 176  
combo : [2 3 4 5]  
177it [05:37, 2.27s/it]  
n\_combo #: 177  
combo : [2 3 4 6]  
178it [05:39, 2.27s/it]

n\_combo #: 178  
combo : [2 3 4 7]  
179it [05:42, 2.29s/it]  
n\_combo #: 179  
combo : [2 3 4 8]  
180it [05:44, 2.25s/it]  
n\_combo #: 180  
combo : [2 3 4 9]  
181it [05:46, 2.24s/it]  
n\_combo #: 181  
combo : [2 3 5 6]  
182it [05:48, 2.21s/it]  
n\_combo #: 182  
combo : [2 3 5 7]  
183it [05:51, 2.49s/it]  
n\_combo #: 183  
combo : [2 3 5 8]  
184it [05:54, 2.41s/it]  
n\_combo #: 184  
combo : [2 3 5 9]  
185it [05:56, 2.38s/it]  
n\_combo #: 185  
combo : [2 3 6 7]  
186it [05:58, 2.36s/it]  
n\_combo #: 186  
combo : [2 3 6 8]  
187it [06:01, 2.36s/it]  
n\_combo #: 187  
combo : [2 3 6 9]  
188it [06:03, 2.38s/it]  
n\_combo #: 188  
combo : [2 3 7 8]  
189it [06:05, 2.38s/it]  
n\_combo #: 189  
combo : [2 3 7 9]  
190it [06:08, 2.38s/it]  
n\_combo #: 190  
combo : [2 3 8 9]  
191it [06:10, 2.32s/it]  
n\_combo #: 191  
combo : [2 4 5 6]  
192it [06:12, 2.25s/it]  
n\_combo #: 192  
combo : [2 4 5 7]  
193it [06:14, 2.22s/it]  
n\_combo #: 193  
combo : [2 4 5 8]  
194it [06:16, 2.17s/it]

n\_combo #: 194  
combo : [2 4 5 9]  
195it [06:18, 2.14s/it]  
n\_combo #: 195  
combo : [2 4 6 7]  
196it [06:20, 2.11s/it]  
n\_combo #: 196  
combo : [2 4 6 8]  
197it [06:22, 2.10s/it]  
n\_combo #: 197  
combo : [2 4 6 9]  
198it [06:25, 2.13s/it]  
n\_combo #: 198  
combo : [2 4 7 8]  
199it [06:27, 2.28s/it]  
n\_combo #: 199  
combo : [2 4 7 9]  
200it [06:31, 2.65s/it]  
n\_combo #: 200  
combo : [2 4 8 9]  
201it [06:33, 2.57s/it]  
n\_combo #: 201  
combo : [2 5 6 7]  
202it [06:36, 2.57s/it]  
n\_combo #: 202  
combo : [2 5 6 8]  
203it [06:38, 2.61s/it]  
n\_combo #: 203  
combo : [2 5 6 9]  
204it [06:41, 2.61s/it]  
n\_combo #: 204  
combo : [2 5 7 8]  
205it [06:44, 2.55s/it]  
n\_combo #: 205  
combo : [2 5 7 9]  
206it [06:46, 2.48s/it]  
n\_combo #: 206  
combo : [2 5 8 9]  
207it [06:48, 2.34s/it]  
n\_combo #: 207  
combo : [2 6 7 8]  
208it [06:50, 2.25s/it]  
n\_combo #: 208  
combo : [2 6 7 9]  
209it [06:52, 2.19s/it]  
n\_combo #: 209  
combo : [2 6 8 9]  
210it [06:54, 2.15s/it]

n\_combo #: 210  
combo : [2 7 8 9]  
211it [06:56, 2.12s/it]  
n\_combo #: 211  
combo : [3 4 5 6]  
212it [06:58, 2.13s/it]  
n\_combo #: 212  
combo : [3 4 5 7]  
213it [07:00, 2.10s/it]  
n\_combo #: 213  
combo : [3 4 5 8]  
214it [07:02, 2.09s/it]  
n\_combo #: 214  
combo : [3 4 5 9]  
215it [07:04, 2.08s/it]  
n\_combo #: 215  
combo : [3 4 6 7]  
216it [07:06, 2.08s/it]  
n\_combo #: 216  
combo : [3 4 6 8]  
217it [07:09, 2.37s/it]  
n\_combo #: 217  
combo : [3 4 6 9]  
218it [07:12, 2.28s/it]  
n\_combo #: 218  
combo : [3 4 7 8]  
219it [07:14, 2.21s/it]  
n\_combo #: 219  
combo : [3 4 7 9]  
220it [07:16, 2.17s/it]  
n\_combo #: 220  
combo : [3 4 8 9]  
221it [07:18, 2.17s/it]  
n\_combo #: 221  
combo : [3 5 6 7]  
222it [07:20, 2.14s/it]  
n\_combo #: 222  
combo : [3 5 6 8]  
223it [07:22, 2.12s/it]  
n\_combo #: 223  
combo : [3 5 6 9]  
224it [07:24, 2.11s/it]  
n\_combo #: 224  
combo : [3 5 7 8]  
225it [07:26, 2.10s/it]  
n\_combo #: 225  
combo : [3 5 7 9]  
226it [07:28, 2.09s/it]

n\_combo #: 226  
combo : [3 5 8 9]  
227it [07:30, 2.06s/it]  
n\_combo #: 227  
combo : [3 6 7 8]  
228it [07:32, 2.05s/it]  
n\_combo #: 228  
combo : [3 6 7 9]  
229it [07:34, 2.07s/it]  
n\_combo #: 229  
combo : [3 6 8 9]  
230it [07:37, 2.11s/it]  
n\_combo #: 230  
combo : [3 7 8 9]  
231it [07:39, 2.11s/it]  
n\_combo #: 231  
combo : [4 5 6 7]  
232it [07:41, 2.12s/it]  
n\_combo #: 232  
combo : [4 5 6 8]  
233it [07:43, 2.12s/it]  
n\_combo #: 233  
combo : [4 5 6 9]  
234it [07:46, 2.44s/it]  
n\_combo #: 234  
combo : [4 5 7 8]  
235it [07:48, 2.32s/it]  
n\_combo #: 235  
combo : [4 5 7 9]  
236it [07:50, 2.24s/it]  
n\_combo #: 236  
combo : [4 5 8 9]  
237it [07:52, 2.18s/it]  
n\_combo #: 237  
combo : [4 6 7 8]  
238it [07:54, 2.14s/it]  
n\_combo #: 238  
combo : [4 6 7 9]  
239it [07:56, 2.11s/it]  
n\_combo #: 239  
combo : [4 6 8 9]  
240it [07:58, 2.09s/it]  
n\_combo #: 240  
combo : [4 7 8 9]  
241it [08:00, 2.07s/it]  
n\_combo #: 241  
combo : [5 6 7 8]  
242it [08:03, 2.10s/it]



n\_combo #: 242  
combo : [5 6 7 9]  
243it [08:05, 2.09s/it]  
n\_combo #: 243  
combo : [5 6 8 9]  
244it [08:07, 2.08s/it]  
n\_combo #: 244  
combo : [5 7 8 9]  
245it [08:09, 2.07s/it]  
n\_combo #: 245  
combo : [6 7 8 9]  
246it [08:11, 2.06s/it]  
n\_combo #: 246  
combo : [0 2 3 4 5]  
247it [08:13, 2.24s/it]  
n\_combo #: 247  
combo : [0 2 3 4 6]  
248it [08:16, 2.33s/it]  
n\_combo #: 248  
combo : [0 2 3 4 7]  
249it [08:18, 2.38s/it]  
n\_combo #: 249  
combo : [0 2 3 4 8]  
250it [08:21, 2.42s/it]  
n\_combo #: 250  
combo : [0 2 3 4 9]  
251it [08:24, 2.48s/it]  
n\_combo #: 251  
combo : [0 2 3 5 6]  
252it [08:27, 2.81s/it]  
n\_combo #: 252  
combo : [0 2 3 5 7]  
253it [08:30, 2.74s/it]  
n\_combo #: 253  
combo : [0 2 3 5 8]  
254it [08:32, 2.69s/it]  
n\_combo #: 254  
combo : [0 2 3 5 9]  
255it [08:35, 2.67s/it]  
n\_combo #: 255  
combo : [0 2 3 6 7]  
256it [08:38, 2.64s/it]  
n\_combo #: 256  
combo : [0 2 3 6 8]  
257it [08:40, 2.60s/it]  
n\_combo #: 257  
combo : [0 2 3 6 9]  
258it [08:43, 2.58s/it]

n\_combo #: 258  
combo : [0 2 3 7 8]  
259it [08:45, 2.59s/it]  
n\_combo #: 259  
combo : [0 2 3 7 9]  
260it [08:48, 2.57s/it]  
n\_combo #: 260  
combo : [0 2 3 8 9]  
261it [08:50, 2.56s/it]  
n\_combo #: 261  
combo : [0 2 4 5 6]  
262it [08:53, 2.54s/it]  
n\_combo #: 262  
combo : [0 2 4 5 7]  
263it [08:55, 2.54s/it]  
n\_combo #: 263  
combo : [0 2 4 5 8]  
264it [08:58, 2.55s/it]  
n\_combo #: 264  
combo : [0 2 4 5 9]  
265it [09:01, 2.61s/it]  
n\_combo #: 265  
combo : [0 2 4 6 7]  
266it [09:03, 2.65s/it]  
n\_combo #: 266  
combo : [0 2 4 6 8]  
267it [09:06, 2.64s/it]  
n\_combo #: 267  
combo : [0 2 4 6 9]  
268it [09:09, 2.67s/it]  
n\_combo #: 268  
combo : [0 2 4 7 8]  
269it [09:11, 2.66s/it]  
n\_combo #: 269  
combo : [0 2 4 7 9]  
270it [09:14, 2.63s/it]  
n\_combo #: 270  
combo : [0 2 4 8 9]  
271it [09:18, 2.98s/it]  
n\_combo #: 271  
combo : [0 2 5 6 7]  
272it [09:20, 2.85s/it]  
n\_combo #: 272  
combo : [0 2 5 6 8]  
273it [09:23, 2.77s/it]  
n\_combo #: 273  
combo : [0 2 5 6 9]  
274it [09:25, 2.72s/it]

n\_combo #: 274  
combo : [0 2 5 7 8]  
275it [09:28, 2.80s/it]  
n\_combo #: 275  
combo : [0 2 5 7 9]  
276it [09:31, 2.83s/it]  
n\_combo #: 276  
combo : [0 2 5 8 9]  
277it [09:34, 2.82s/it]  
n\_combo #: 277  
combo : [0 2 6 7 8]  
278it [09:37, 2.81s/it]  
n\_combo #: 278  
combo : [0 2 6 7 9]  
279it [09:39, 2.74s/it]  
n\_combo #: 279  
combo : [0 2 6 8 9]  
280it [09:42, 2.71s/it]  
n\_combo #: 280  
combo : [0 2 7 8 9]  
281it [09:45, 2.75s/it]  
n\_combo #: 281  
combo : [0 3 4 5 6]  
282it [09:48, 2.69s/it]  
n\_combo #: 282  
combo : [0 3 4 5 7]  
283it [09:50, 2.64s/it]  
n\_combo #: 283  
combo : [0 3 4 5 8]  
284it [09:53, 2.61s/it]  
n\_combo #: 284  
combo : [0 3 4 5 9]  
285it [09:55, 2.61s/it]  
n\_combo #: 285  
combo : [0 3 4 6 7]  
286it [09:58, 2.73s/it]  
n\_combo #: 286  
combo : [0 3 4 6 8]  
287it [10:02, 2.94s/it]  
n\_combo #: 287  
combo : [0 3 4 6 9]  
288it [10:04, 2.89s/it]  
n\_combo #: 288  
combo : [0 3 4 7 8]  
289it [10:08, 2.97s/it]  
n\_combo #: 289  
combo : [0 3 4 7 9]  
290it [10:10, 2.96s/it]

n\_combo #: 290  
combo : [0 3 4 8 9]  
291it [10:15, 3.28s/it]  
n\_combo #: 291  
combo : [0 3 5 6 7]  
292it [10:17, 3.06s/it]  
n\_combo #: 292  
combo : [0 3 5 6 8]  
293it [10:20, 2.89s/it]  
n\_combo #: 293  
combo : [0 3 5 6 9]  
294it [10:22, 2.76s/it]  
n\_combo #: 294  
combo : [0 3 5 7 8]  
295it [10:24, 2.68s/it]  
n\_combo #: 295  
combo : [0 3 5 7 9]  
296it [10:27, 2.66s/it]  
n\_combo #: 296  
combo : [0 3 5 8 9]  
297it [10:30, 2.63s/it]  
n\_combo #: 297  
combo : [0 3 6 7 8]  
298it [10:32, 2.61s/it]  
n\_combo #: 298  
combo : [0 3 6 7 9]  
299it [10:35, 2.67s/it]  
n\_combo #: 299  
combo : [0 3 6 8 9]  
300it [10:38, 2.66s/it]  
n\_combo #: 300  
combo : [0 3 7 8 9]  
301it [10:40, 2.68s/it]  
n\_combo #: 301  
combo : [0 4 5 6 7]  
302it [10:43, 2.67s/it]  
n\_combo #: 302  
combo : [0 4 5 6 8]  
303it [10:46, 2.69s/it]  
n\_combo #: 303  
combo : [0 4 5 6 9]  
304it [10:49, 2.70s/it]  
n\_combo #: 304  
combo : [0 4 5 7 8]  
305it [10:51, 2.65s/it]  
n\_combo #: 305  
combo : [0 4 5 7 9]  
306it [10:54, 2.63s/it]

n\_combo #: 306  
combo : [0 4 5 8 9]  
307it [10:56, 2.63s/it]  
n\_combo #: 307  
combo : [0 4 6 7 8]  
308it [10:59, 2.67s/it]  
n\_combo #: 308  
combo : [0 4 6 7 9]  
309it [11:02, 2.71s/it]  
n\_combo #: 309  
combo : [0 4 6 8 9]  
310it [11:05, 2.76s/it]  
n\_combo #: 310  
combo : [0 4 7 8 9]  
311it [11:07, 2.77s/it]  
n\_combo #: 311  
combo : [0 5 6 7 8]  
312it [11:11, 3.12s/it]  
n\_combo #: 312  
combo : [0 5 6 7 9]  
313it [11:14, 2.93s/it]  
n\_combo #: 313  
combo : [0 5 6 8 9]  
314it [11:16, 2.81s/it]  
n\_combo #: 314  
combo : [0 5 7 8 9]  
315it [11:19, 2.75s/it]  
n\_combo #: 315  
combo : [0 6 7 8 9]  
316it [11:22, 2.67s/it]  
n\_combo #: 316  
combo : [2 3 4 5 6]  
317it [11:24, 2.63s/it]  
n\_combo #: 317  
combo : [2 3 4 5 7]  
318it [11:27, 2.59s/it]  
n\_combo #: 318  
combo : [2 3 4 5 8]  
319it [11:29, 2.59s/it]  
n\_combo #: 319  
combo : [2 3 4 5 9]  
320it [11:32, 2.57s/it]  
n\_combo #: 320  
combo : [2 3 4 6 7]  
321it [11:34, 2.57s/it]  
n\_combo #: 321  
combo : [2 3 4 6 8]  
322it [11:37, 2.58s/it]

n\_combo #: 322  
combo : [2 3 4 6 9]  
323it [11:39, 2.55s/it]  
n\_combo #: 323  
combo : [2 3 4 7 8]  
324it [11:42, 2.53s/it]  
n\_combo #: 324  
combo : [2 3 4 7 9]  
325it [11:44, 2.50s/it]  
n\_combo #: 325  
combo : [2 3 4 8 9]  
326it [11:47, 2.50s/it]  
n\_combo #: 326  
combo : [2 3 5 6 7]  
327it [11:49, 2.54s/it]  
n\_combo #: 327  
combo : [2 3 5 6 8]  
328it [11:52, 2.58s/it]  
n\_combo #: 328  
combo : [2 3 5 6 9]  
329it [11:55, 2.61s/it]  
n\_combo #: 329  
combo : [2 3 5 7 8]  
330it [11:57, 2.60s/it]  
n\_combo #: 330  
combo : [2 3 5 7 9]  
331it [12:00, 2.62s/it]  
n\_combo #: 331  
combo : [2 3 5 8 9]  
332it [12:02, 2.59s/it]  
n\_combo #: 332  
combo : [2 3 6 7 8]  
333it [12:05, 2.58s/it]  
n\_combo #: 333  
combo : [2 3 6 7 9]  
334it [12:09, 2.99s/it]  
n\_combo #: 334  
combo : [2 3 6 8 9]  
335it [12:12, 2.85s/it]  
n\_combo #: 335  
combo : [2 3 7 8 9]  
336it [12:14, 2.81s/it]  
n\_combo #: 336  
combo : [2 4 5 6 7]  
337it [12:17, 2.76s/it]  
n\_combo #: 337  
combo : [2 4 5 6 8]  
338it [12:20, 2.74s/it]

n\_combo #: 338  
combo : [2 4 5 6 9]  
339it [12:22, 2.67s/it]  
n\_combo #: 339  
combo : [2 4 5 7 8]  
340it [12:25, 2.63s/it]  
n\_combo #: 340  
combo : [2 4 5 7 9]  
341it [12:27, 2.58s/it]  
n\_combo #: 341  
combo : [2 4 5 8 9]  
342it [12:30, 2.54s/it]  
n\_combo #: 342  
combo : [2 4 6 7 8]  
343it [12:32, 2.63s/it]  
n\_combo #: 343  
combo : [2 4 6 7 9]  
344it [12:35, 2.73s/it]  
n\_combo #: 344  
combo : [2 4 6 8 9]  
345it [12:38, 2.76s/it]  
n\_combo #: 345  
combo : [2 4 7 8 9]  
346it [12:41, 2.80s/it]  
n\_combo #: 346  
combo : [2 5 6 7 8]  
347it [12:44, 2.80s/it]  
n\_combo #: 347  
combo : [2 5 6 7 9]  
348it [12:47, 2.86s/it]  
n\_combo #: 348  
combo : [2 5 6 8 9]  
349it [12:50, 2.95s/it]  
n\_combo #: 349  
combo : [2 5 7 8 9]  
350it [12:53, 2.92s/it]  
n\_combo #: 350  
combo : [2 6 7 8 9]  
351it [12:56, 2.88s/it]  
n\_combo #: 351  
combo : [3 4 5 6 7]  
352it [12:59, 2.88s/it]  
n\_combo #: 352  
combo : [3 4 5 6 8]  
353it [13:01, 2.84s/it]  
n\_combo #: 353  
combo : [3 4 5 6 9]  
354it [13:04, 2.82s/it]

n\_combo #: 354  
combo : [3 4 5 7 8]  
355it [13:07, 2.75s/it]  
n\_combo #: 355  
combo : [3 4 5 7 9]  
356it [13:11, 3.18s/it]  
n\_combo #: 356  
combo : [3 4 5 8 9]  
357it [13:13, 2.98s/it]  
n\_combo #: 357  
combo : [3 4 6 7 8]  
358it [13:16, 2.87s/it]  
n\_combo #: 358  
combo : [3 4 6 7 9]  
359it [13:18, 2.77s/it]  
n\_combo #: 359  
combo : [3 4 6 8 9]  
360it [13:21, 2.69s/it]  
n\_combo #: 360  
combo : [3 4 7 8 9]  
361it [13:23, 2.63s/it]  
n\_combo #: 361  
combo : [3 5 6 7 8]  
362it [13:26, 2.63s/it]  
n\_combo #: 362  
combo : [3 5 6 7 9]  
363it [13:29, 2.65s/it]  
n\_combo #: 363  
combo : [3 5 6 8 9]  
364it [13:31, 2.64s/it]  
n\_combo #: 364  
combo : [3 5 7 8 9]  
365it [13:34, 2.64s/it]  
n\_combo #: 365  
combo : [3 6 7 8 9]  
366it [13:37, 2.67s/it]  
n\_combo #: 366  
combo : [4 5 6 7 8]  
367it [13:40, 2.70s/it]  
n\_combo #: 367  
combo : [4 5 6 7 9]  
368it [13:42, 2.69s/it]  
n\_combo #: 368  
combo : [4 5 6 8 9]  
369it [13:45, 2.68s/it]  
n\_combo #: 369  
combo : [4 5 7 8 9]  
370it [13:48, 2.66s/it]



n\_combo #: 370  
combo : [4 6 7 8 9]  
371it [13:50, 2.63s/it]  
n\_combo #: 371  
combo : [5 6 7 8 9]  
372it [13:53, 2.58s/it]  
n\_combo #: 372  
combo : [0 2 3 4 5 6]  
373it [13:55, 2.68s/it]  
n\_combo #: 373  
combo : [0 2 3 4 5 7]  
374it [13:58, 2.75s/it]  
n\_combo #: 374  
combo : [0 2 3 4 5 8]  
375it [14:01, 2.83s/it]  
n\_combo #: 375  
combo : [0 2 3 4 5 9]  
376it [14:05, 2.99s/it]  
n\_combo #: 376  
combo : [0 2 3 4 6 7]  
377it [14:08, 3.12s/it]  
n\_combo #: 377  
combo : [0 2 3 4 6 8]  
378it [14:12, 3.19s/it]  
n\_combo #: 378  
combo : [0 2 3 4 6 9]  
379it [14:15, 3.20s/it]  
n\_combo #: 379  
combo : [0 2 3 4 7 8]  
380it [14:19, 3.65s/it]  
n\_combo #: 380  
combo : [0 2 3 4 7 9]  
381it [14:22, 3.46s/it]  
n\_combo #: 381  
combo : [0 2 3 4 8 9]  
382it [14:25, 3.32s/it]  
n\_combo #: 382  
combo : [0 2 3 5 6 7]  
383it [14:29, 3.26s/it]  
n\_combo #: 383  
combo : [0 2 3 5 6 8]  
384it [14:32, 3.16s/it]  
n\_combo #: 384  
combo : [0 2 3 5 6 9]  
385it [14:35, 3.11s/it]  
n\_combo #: 385  
combo : [0 2 3 5 7 8]  
386it [14:38, 3.17s/it]

n\_combo #: 386  
combo : [0 2 3 5 7 9]  
387it [14:41, 3.18s/it]  
n\_combo #: 387  
combo : [0 2 3 5 8 9]  
388it [14:44, 3.14s/it]  
n\_combo #: 388  
combo : [0 2 3 6 7 8]  
389it [14:47, 3.12s/it]  
n\_combo #: 389  
combo : [0 2 3 6 7 9]  
390it [14:50, 3.07s/it]  
n\_combo #: 390  
combo : [0 2 3 6 8 9]  
391it [14:53, 3.06s/it]  
n\_combo #: 391  
combo : [0 2 3 7 8 9]  
392it [14:57, 3.23s/it]  
n\_combo #: 392  
combo : [0 2 4 5 6 7]  
393it [15:01, 3.54s/it]  
n\_combo #: 393  
combo : [0 2 4 5 6 8]  
394it [15:06, 3.86s/it]  
n\_combo #: 394  
combo : [0 2 4 5 6 9]  
395it [15:10, 3.90s/it]  
n\_combo #: 395  
combo : [0 2 4 5 7 8]  
396it [15:13, 3.69s/it]  
n\_combo #: 396  
combo : [0 2 4 5 7 9]  
397it [15:16, 3.48s/it]  
n\_combo #: 397  
combo : [0 2 4 5 8 9]  
398it [15:19, 3.33s/it]  
n\_combo #: 398  
combo : [0 2 4 6 7 8]  
399it [15:22, 3.20s/it]  
n\_combo #: 399  
combo : [0 2 4 6 7 9]  
400it [15:25, 3.13s/it]  
n\_combo #: 400  
combo : [0 2 4 6 8 9]  
401it [15:28, 3.08s/it]  
n\_combo #: 401  
combo : [0 2 4 7 8 9]  
402it [15:31, 3.07s/it]

n\_combo #: 402  
combo : [0 2 5 6 7 8]  
403it [15:34, 3.03s/it]  
n\_combo #: 403  
combo : [0 2 5 6 7 9]  
404it [15:37, 3.02s/it]  
n\_combo #: 404  
combo : [0 2 5 6 8 9]  
405it [15:42, 3.63s/it]  
n\_combo #: 405  
combo : [0 2 5 7 8 9]  
406it [15:45, 3.53s/it]  
n\_combo #: 406  
combo : [0 2 6 7 8 9]  
407it [15:48, 3.45s/it]  
n\_combo #: 407  
combo : [0 3 4 5 6 7]  
408it [15:52, 3.44s/it]  
n\_combo #: 408  
combo : [0 3 4 5 6 8]  
409it [15:55, 3.44s/it]  
n\_combo #: 409  
combo : [0 3 4 5 6 9]  
410it [15:59, 3.51s/it]  
n\_combo #: 410  
combo : [0 3 4 5 7 8]  
411it [16:02, 3.50s/it]  
n\_combo #: 411  
combo : [0 3 4 5 7 9]  
412it [16:06, 3.49s/it]  
n\_combo #: 412  
combo : [0 3 4 5 8 9]  
413it [16:11, 4.14s/it]  
n\_combo #: 413  
combo : [0 3 4 6 7 8]  
414it [16:15, 4.11s/it]  
n\_combo #: 414  
combo : [0 3 4 6 7 9]  
415it [16:19, 3.95s/it]  
n\_combo #: 415  
combo : [0 3 4 6 8 9]  
416it [16:22, 3.74s/it]  
n\_combo #: 416  
combo : [0 3 4 7 8 9]  
417it [16:25, 3.54s/it]  
n\_combo #: 417  
combo : [0 3 5 6 7 8]  
418it [16:29, 3.46s/it]

n\_combo #: 418  
combo : [0 3 5 6 7 9]  
419it [16:32, 3.47s/it]  
n\_combo #: 419  
combo : [0 3 5 6 8 9]  
420it [16:36, 3.60s/it]  
n\_combo #: 420  
combo : [0 3 5 7 8 9]  
421it [16:40, 3.73s/it]  
n\_combo #: 421  
combo : [0 3 6 7 8 9]  
422it [16:44, 3.73s/it]  
n\_combo #: 422  
combo : [0 4 5 6 7 8]  
423it [16:47, 3.60s/it]  
n\_combo #: 423  
combo : [0 4 5 6 7 9]  
424it [16:50, 3.43s/it]  
n\_combo #: 424  
combo : [0 4 5 6 8 9]  
425it [16:53, 3.28s/it]  
n\_combo #: 425  
combo : [0 4 5 7 8 9]  
426it [16:56, 3.21s/it]  
n\_combo #: 426  
combo : [0 4 6 7 8 9]  
427it [16:59, 3.14s/it]  
n\_combo #: 427  
combo : [0 5 6 7 8 9]  
428it [17:02, 3.10s/it]  
n\_combo #: 428  
combo : [2 3 4 5 6 7]  
429it [17:05, 3.08s/it]  
n\_combo #: 429  
combo : [2 3 4 5 6 8]  
430it [17:08, 3.03s/it]  
n\_combo #: 430  
combo : [2 3 4 5 6 9]  
431it [17:12, 3.47s/it]  
n\_combo #: 431  
combo : [2 3 4 5 7 8]  
432it [17:16, 3.44s/it]  
n\_combo #: 432  
combo : [2 3 4 5 7 9]  
433it [17:19, 3.43s/it]  
n\_combo #: 433  
combo : [2 3 4 5 8 9]  
434it [17:22, 3.29s/it]

n\_combo #: 434  
combo : [2 3 4 6 7 8]  
435it [17:25, 3.22s/it]  
n\_combo #: 435  
combo : [2 3 4 6 7 9]  
436it [17:28, 3.13s/it]  
n\_combo #: 436  
combo : [2 3 4 6 8 9]  
437it [17:31, 3.07s/it]  
n\_combo #: 437  
combo : [2 3 4 7 8 9]  
438it [17:34, 3.00s/it]  
n\_combo #: 438  
combo : [2 3 5 6 7 8]  
439it [17:37, 2.97s/it]  
n\_combo #: 439  
combo : [2 3 5 6 7 9]  
440it [17:40, 2.95s/it]  
n\_combo #: 440  
combo : [2 3 5 6 8 9]  
441it [17:43, 2.95s/it]  
n\_combo #: 441  
combo : [2 3 5 7 8 9]  
442it [17:46, 2.92s/it]  
n\_combo #: 442  
combo : [2 3 6 7 8 9]  
443it [17:49, 3.03s/it]  
n\_combo #: 443  
combo : [2 4 5 6 7 8]  
444it [17:53, 3.27s/it]  
n\_combo #: 444  
combo : [2 4 5 6 7 9]  
445it [17:56, 3.27s/it]  
n\_combo #: 445  
combo : [2 4 5 6 8 9]  
446it [17:59, 3.17s/it]  
n\_combo #: 446  
combo : [2 4 5 7 8 9]  
447it [18:02, 3.17s/it]  
n\_combo #: 447  
combo : [2 4 6 7 8 9]  
448it [18:05, 3.11s/it]  
n\_combo #: 448  
combo : [2 5 6 7 8 9]  
449it [18:08, 3.10s/it]  
n\_combo #: 449  
combo : [3 4 5 6 7 8]  
450it [18:11, 3.07s/it]

n\_combo #: 450  
combo : [3 4 5 6 7 9]  
451it [18:14, 3.14s/it]  
n\_combo #: 451  
combo : [3 4 5 6 8 9]  
452it [18:17, 3.10s/it]  
n\_combo #: 452  
combo : [3 4 5 7 8 9]  
453it [18:20, 3.08s/it]  
n\_combo #: 453  
combo : [3 4 6 7 8 9]  
454it [18:25, 3.38s/it]  
n\_combo #: 454  
combo : [3 5 6 7 8 9]  
455it [18:28, 3.34s/it]  
n\_combo #: 455  
combo : [4 5 6 7 8 9]  
456it [18:31, 3.26s/it]  
n\_combo #: 456  
combo : [0 2 3 4 5 6 7]  
457it [18:37, 4.04s/it]  
n\_combo #: 457  
combo : [0 2 3 4 5 6 8]  
458it [18:42, 4.35s/it]  
n\_combo #: 458  
combo : [0 2 3 4 5 6 9]  
459it [18:45, 4.15s/it]  
n\_combo #: 459  
combo : [0 2 3 4 5 7 8]  
460it [18:49, 4.01s/it]  
n\_combo #: 460  
combo : [0 2 3 4 5 7 9]  
461it [18:53, 3.93s/it]  
n\_combo #: 461  
combo : [0 2 3 4 5 8 9]  
462it [18:57, 3.87s/it]  
n\_combo #: 462  
combo : [0 2 3 4 6 7 8]  
463it [19:00, 3.78s/it]  
n\_combo #: 463  
combo : [0 2 3 4 6 7 9]  
464it [19:04, 3.82s/it]  
n\_combo #: 464  
combo : [0 2 3 4 6 8 9]  
465it [19:08, 3.95s/it]  
n\_combo #: 465  
combo : [0 2 3 4 7 8 9]  
466it [19:13, 4.28s/it]

n\_combo #: 466  
combo : [0 2 3 5 6 7 8]  
467it [19:20, 4.87s/it]  
n\_combo #: 467  
combo : [0 2 3 5 6 7 9]  
468it [19:26, 5.37s/it]  
n\_combo #: 468  
combo : [0 2 3 5 6 8 9]  
469it [19:32, 5.38s/it]  
n\_combo #: 469  
combo : [0 2 3 5 7 8 9]  
470it [19:37, 5.32s/it]  
n\_combo #: 470  
combo : [0 2 3 6 7 8 9]  
471it [19:41, 5.05s/it]  
n\_combo #: 471  
combo : [0 2 4 5 6 7 8]  
472it [19:45, 4.73s/it]  
n\_combo #: 472  
combo : [0 2 4 5 6 7 9]  
473it [19:49, 4.41s/it]  
n\_combo #: 473  
combo : [0 2 4 5 6 8 9]  
474it [19:53, 4.19s/it]  
n\_combo #: 474  
combo : [0 2 4 5 7 8 9]  
475it [19:56, 4.02s/it]  
n\_combo #: 475  
combo : [0 2 4 6 7 8 9]  
476it [20:00, 3.96s/it]  
n\_combo #: 476  
combo : [0 2 5 6 7 8 9]  
477it [20:04, 4.10s/it]  
n\_combo #: 477  
combo : [0 3 4 5 6 7 8]  
478it [20:08, 4.02s/it]  
n\_combo #: 478  
combo : [0 3 4 5 6 7 9]  
479it [20:12, 3.98s/it]  
n\_combo #: 479  
combo : [0 3 4 5 6 8 9]  
480it [20:16, 3.95s/it]  
n\_combo #: 480  
combo : [0 3 4 5 7 8 9]  
481it [20:20, 3.88s/it]  
n\_combo #: 481  
combo : [0 3 4 6 7 8 9]  
482it [20:23, 3.82s/it]

n\_combo #: 482  
combo : [0 3 5 6 7 8 9]  
483it [20:27, 3.84s/it]  
n\_combo #: 483  
combo : [0 4 5 6 7 8 9]  
484it [20:31, 3.88s/it]  
n\_combo #: 484  
combo : [2 3 4 5 6 7 8]  
485it [20:37, 4.38s/it]  
n\_combo #: 485  
combo : [2 3 4 5 6 7 9]  
486it [20:41, 4.19s/it]  
n\_combo #: 486  
combo : [2 3 4 5 6 8 9]  
487it [20:44, 4.01s/it]  
n\_combo #: 487  
combo : [2 3 4 5 7 8 9]  
488it [20:48, 3.87s/it]  
n\_combo #: 488  
combo : [2 3 4 6 7 8 9]  
489it [20:51, 3.83s/it]  
n\_combo #: 489  
combo : [2 3 5 6 7 8 9]  
490it [20:55, 3.78s/it]  
n\_combo #: 490  
combo : [2 4 5 6 7 8 9]  
491it [20:59, 3.73s/it]  
n\_combo #: 491  
combo : [3 4 5 6 7 8 9]  
492it [21:02, 3.67s/it]  
n\_combo #: 492  
combo : [0 2 3 4 5 6 7 8]  
493it [21:07, 3.88s/it]  
n\_combo #: 493  
combo : [0 2 3 4 5 6 7 9]  
494it [21:11, 3.99s/it]  
n\_combo #: 494  
combo : [0 2 3 4 5 6 8 9]  
495it [21:15, 4.06s/it]  
n\_combo #: 495  
combo : [0 2 3 4 5 7 8 9]  
496it [21:19, 4.08s/it]  
n\_combo #: 496  
combo : [0 2 3 4 6 7 8 9]  
497it [21:23, 4.12s/it]  
n\_combo #: 497  
combo : [0 2 3 5 6 7 8 9]  
498it [21:28, 4.13s/it]



```

n_combo #: 498
combo : [0 2 4 5 6 7 8 9]
499it [21:32, 4.13s/it]
n_combo #: 499
combo : [0 3 4 5 6 7 8 9]
500it [21:36, 4.17s/it]
n_combo #: 500
combo : [2 3 4 5 6 7 8 9]
501it [21:40, 4.26s/it]
n_combo #: 501
combo : [0 2 3 4 5 6 7 8 9]
502it [21:46, 2.60s/it]
502it [21:46, 2.60s/it]

```

```

In [16]: # Store the combination matrix in a csv file
        combo_df = pd.DataFrame.from_dict(combo_embedding)
        combo_df.to_csv(results_path + 'combo_dataframe.csv', index=True)

```

```

In [17]: # Making a readable dictionary of the combo_embeddings to later store in
        readable_distance_dict = {
            'combination': [],
            'pair': [],
            'distance': []
        }

        # For every combination, for every test pair, store the distance
        for nc, combo in enumerate(combo_embedding['combination']):
            for pair in all_pair_combinations:
                i = pair[0]
                j = pair[1]

                if i < j:
                    dist = combo_embedding['distance_matrix'][nc][i, j]
                    readable_distance_dict['combination'].append(combo)
                    readable_distance_dict['pair'].append(pair)
                    readable_distance_dict['distance'].append(dist)

        # Store the distance matrix in a csv file
        distance_df = pd.DataFrame.from_dict(readable_distance_dict)
        distance_df.to_csv(results_path + 'distance_dataframe.csv', index=True)

```

```

In [ ]:

```

## Analyses

Plotting the pairwise distance b/w a given pair across the several combinations

```

In [18]: # Plot distances from all combinations for each pair of digit clusters

```

```

fig, ax = plt.subplots(1, figsize=(20, 4))
x_ticklabels = []

n_combos = len(combo_embedding['combination'])

# Iterate over all pairs of digits
for n_pair, test_pair in enumerate(all_pair_combinations):
    i = test_pair[0]
    j = test_pair[1]

    if i < j:
        # Fetch the pairwise digit for all combinations
        distances = [combo_embedding['distance_matrix'][combo_index][i, j]

        # Discard distances = 0 => pair is not present in combo
        valid_distances = [d for d in distances if d != 0]
        n_valid_distances = len(valid_distances)

        # combo_indices = [combo_index for combo_index in np.arange(n_com

        print('test_pair: ', test_pair)
        print('n_valid_distances: ', n_valid_distances)

        # Plot the pairwise distances at a given x-coordinate
        ax.scatter(np.zeros((n_valid_distances))+n_pair, valid_distances,
        # im=ax.scatter(np.zeros((n_valid_distances))+n_pair, valid_dista

        # Add a boxplot of the distances of the test pair in different co
        ax.boxplot(valid_distances,
                    patch_artist=False, # fill with color
                    positions = [n_pair],
                    boxprops=dict(color='lightgrey'),
                    whiskerprops=dict(color='lightgrey'),
                    showfliers = False,
                    medianprops = dict(color='black')
                    )

        # Add the x-ticklabels
        tl = str(i) + '-' + str(j)
        x_ticklabels.append(tl)

# Plot formatting
ax.set_xticklabels(x_ticklabels, rotation=45);
ax.set_ylabel('Euclidean distance\nb/w test pair in diff combinations')
ax.set_xlabel('Test pair')

ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
# ax.spines['bottom'].set_visible(False)
# ax.spines['left'].set_visible(False)

```

```
ax.set_ylim(-.1, 1.5)
```

```
test_pair: [0 2]
n_valid_distances: 128
test_pair: [0 3]
n_valid_distances: 128
test_pair: [0 4]
n_valid_distances: 128
test_pair: [0 5]
n_valid_distances: 128
test_pair: [0 6]
n_valid_distances: 128
test_pair: [0 7]
n_valid_distances: 128
test_pair: [0 8]
n_valid_distances: 128
test_pair: [0 9]
n_valid_distances: 128
test_pair: [2 3]
n_valid_distances: 128
test_pair: [2 4]
n_valid_distances: 128
test_pair: [2 5]
n_valid_distances: 128
test_pair: [2 6]
n_valid_distances: 128
test_pair: [2 7]
n_valid_distances: 128
test_pair: [2 8]
n_valid_distances: 128
test_pair: [2 9]
n_valid_distances: 128
test_pair: [3 4]
n_valid_distances: 128
test_pair: [3 5]
n_valid_distances: 128
test_pair: [3 6]
n_valid_distances: 128
test_pair: [3 7]
n_valid_distances: 128
test_pair: [3 8]
n_valid_distances: 128
test_pair: [3 9]
n_valid_distances: 128
test_pair: [4 5]
n_valid_distances: 128
test_pair: [4 6]
n_valid_distances: 128
test_pair: [4 7]
n_valid_distances: 128
test_pair: [4 8]
n_valid_distances: 128
test_pair: [4 9]
```

```

n_valid_distances: 128
test_pair: [5 6]
n_valid_distances: 128
test_pair: [5 7]
n_valid_distances: 128
test_pair: [5 8]
n_valid_distances: 128
test_pair: [5 9]
n_valid_distances: 128
test_pair: [6 7]
n_valid_distances: 128
test_pair: [6 8]
n_valid_distances: 128
test_pair: [6 9]
n_valid_distances: 128
test_pair: [7 8]
n_valid_distances: 128
test_pair: [7 9]
n_valid_distances: 128
test_pair: [8 9]
n_valid_distances: 128

```

```
Out[18]: (-0.1, 1.5)
```

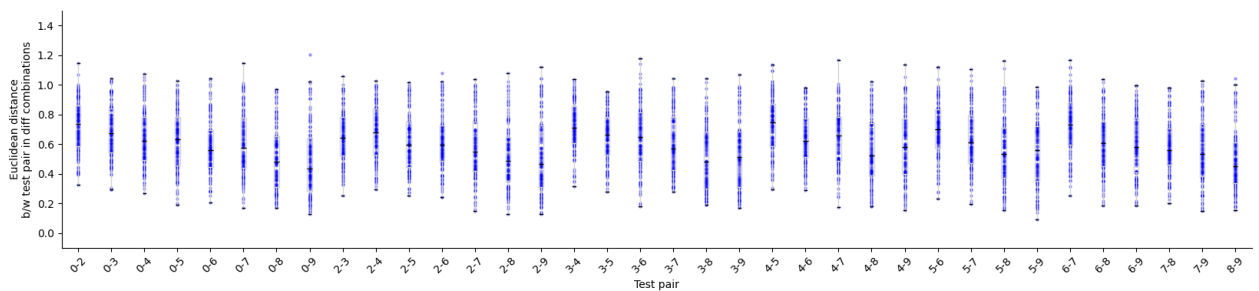


Fig: The x axis indicates the pair of digits being tested. The blue point shows the euclidean distance b/w the clusters of the test pair, in the UMAP representation of one combination. The box plot describes the distribution of pairwise distances for a given test pair across all valid combinations.

```
In [19]: # Saving the figure
fig.savefig(results_path + 'pairwise_distances_across_pairs.png', bbox_in
```

```
In [22]:
```

```
In [31]: # Plot distances for each pair of digit clusters across all combinations

fig, ax = plt.subplots(n_pairs, figsize=(20, 60), sharex=True)
x_ticklabels = []

# Iterate over all pairs of digits
for n_pair, test_pair in enumerate(all_pair_combinations):
    i = test_pair[0]
    j = test_pair[1]
```

```

if i<j:
    # Fetch the pairwise digit for all combinations
    distances = np.array([combo_embedding['distance_matrix'][combo_in

    # Make x axis with the combinations
    x_combo = np.arange(n_combos)

    # Discard where distances = 0 => pair is not present in combo
    non_zero_indices = np.where(distances != 0)
    x_combo = x_combo[non_zero_indices]
    distances = distances[non_zero_indices]

    # Plot the pairwise distances across all combinations for a given
    ax[n_pair].plot(x_combo, distances, alpha=0.5, lw=0.1, label=str(

    # tl = str(i) + '-' + str(j)

    # Plot formatting
    ax[n_pair].set_title(str(test_pair), loc='right', color='blue', alpha

    ax[n_pair].set_ylim(-.1, 1.5)
    ax[n_pair].set_xticks([])
    ax[n_pair].tick_params(axis='x', which='both', bottom=False)

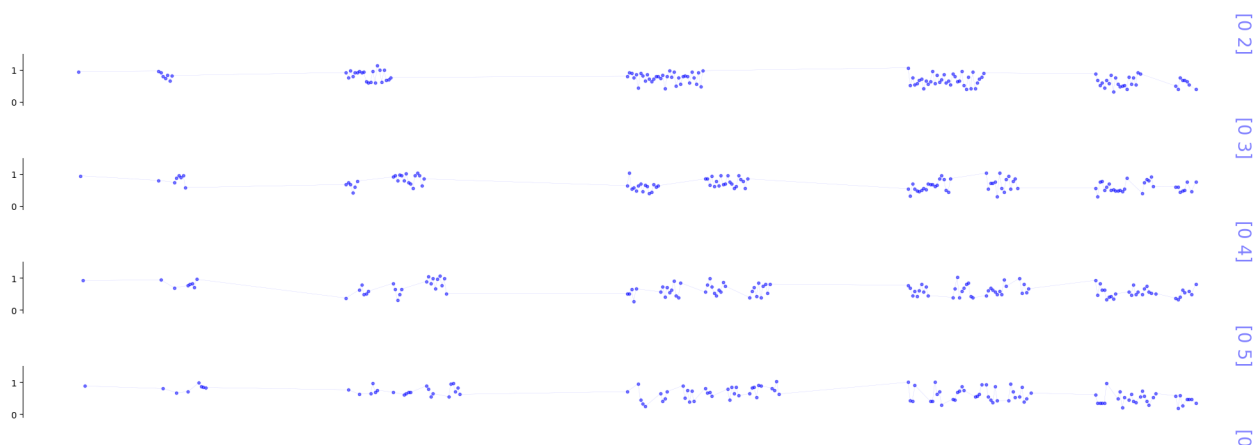
    ax[n_pair].spines['top'].set_visible(False)
    ax[n_pair].spines['right'].set_visible(False)
    ax[n_pair].spines['bottom'].set_visible(False)

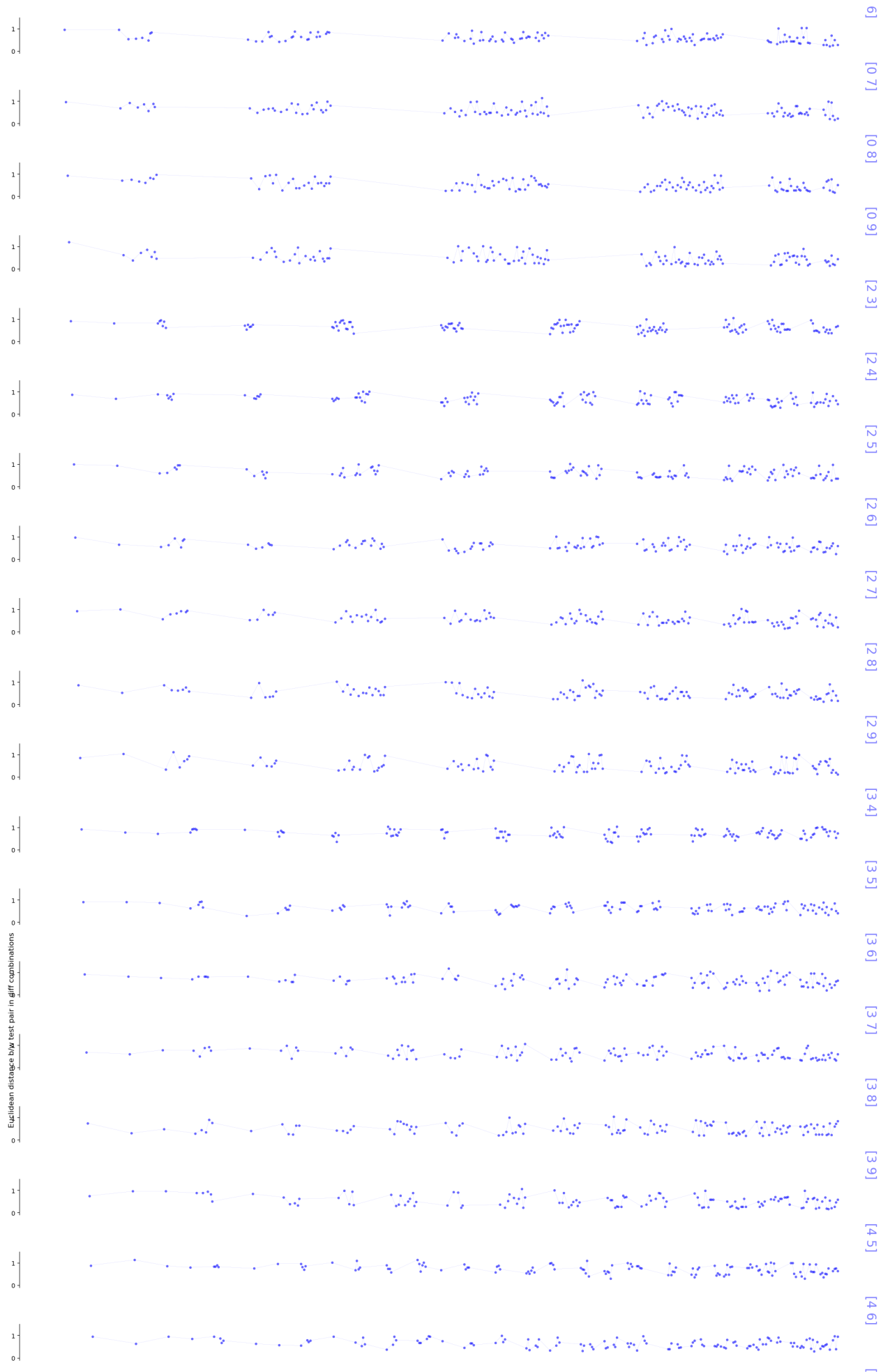
if n_pair == n_pairs-1:
    x_ticklabels = combo_embedding['combination']
    ax[n_pair].spines['bottom'].set_visible(True)
    ax[n_pair].tick_params(axis='x', which='both', bottom=True)
    ax[n_pair].set_xticks(np.arange(n_combos)[:20])
    ax[n_pair].set_xticklabels(x_ticklabels[:20], rotation=45, ha="right")

fig.supylabel('Euclidean distance b/w test pair in diff combinations')
fig.supxlabel('Combination')

fig.tight_layout()

```





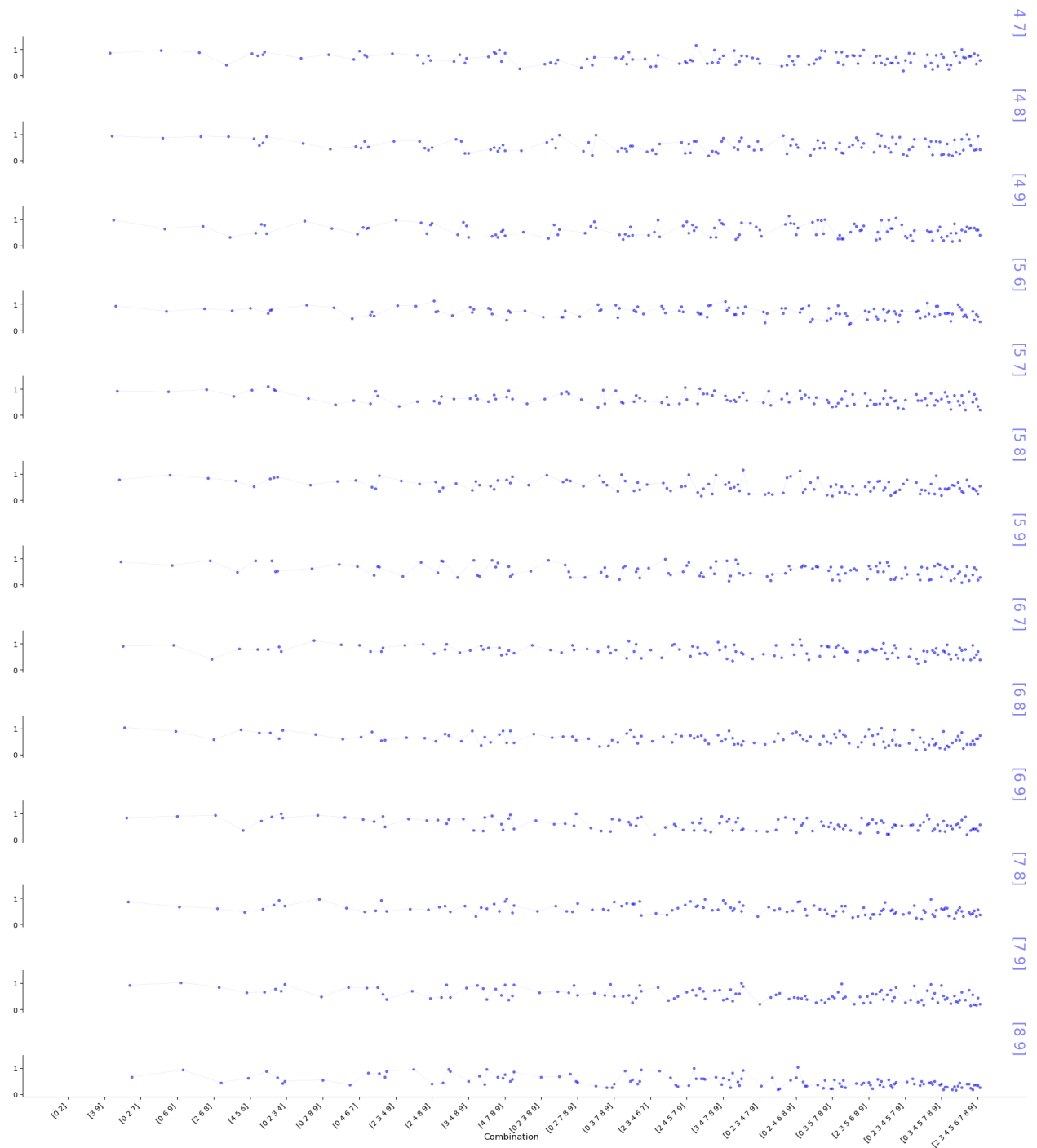


Fig: The x axis indicates the combination of digits being used to make the UMAP representation. The tested pair of digits is written in blue on the right edge of each subplot. The blue point shows the euclidean distance b/w the clusters of the test pair in the UMAP representation of the indicated combination. The blue line connects the pairwise distances of the same test pair in diff combinations.

```
In [32]: # Saving the figure
fig.savefig('Figures/wo1_digits/exclusion/pairwise_distances_across_combo
```

```
In [ ]:
```