In This NB we work with different Metrics and Distances.

We will do so by working with Sierpinski triangles

Tarea: Generar un tríangulo de *Sierpinski* con N puntos. N está Dado por el número de iteraciones I. Considerar I = (1, 2, 3, 4, 5, 6, 7).

PARA CADA PUNTO:

- I. CALCULAR LA DISTANCIA ESPERADA A TODOS LOS DEMÁS PUNTOS.
- 2. CALCULAR LA DISTANCIA MÁXIMA. CALCULAR LA DISTANCIA MÍNIMA.



Let's start by importing the necessary tools

```
In [1]: import numpy as np
   import matplotlib.cm as cm
   import matplotlib.pyplot as plt
   import matplotlib.colors as mcolors
   import itertools
   from sklearn.metrics import pairwise_distances
   from IPython.display import display, clear_output
   import seaborn as sns
   import pandas as pd
   from random import randrange
```

Next we will define the number of generations as well as the initial triangle

We will also create a pandas DataFrame to keep our data

```
In [2]: # Define number of "point generations"
gens = 7

# Define initial triangle vertices (x,y)
a = (0, 0)
b = (1, 0)
c = (0.5, np.sqrt(3)/2)
vertices = (a, b, c)

df = pd.DataFrame(columns=['gen', 'coords'])
for point in vertices:
    df.loc[len(df)] = [0, point]
```

df

```
    Out [2]:
    gen
    coords

    0
    0
    (0, 0)

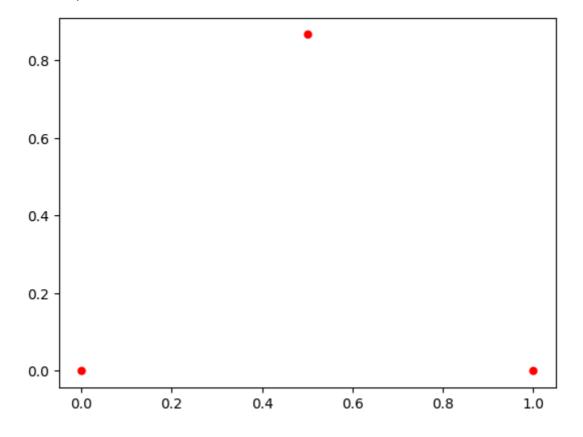
    1
    0
    (1, 0)

    2
    0
    (0.5, 0.8660254037844386)
```

Next we will plot the inital 3 points of the triangle

```
In [3]: #plot the first triangle
    fig, ax = plt.subplots()
    ax.plot(*a ,'o', color = 'red', ms= 5)
    ax.plot(*b ,'o', color = 'red', ms= 5)
    ax.plot(*c ,'o', color = 'red', ms= 5)
```

Out[3]: [<matplotlib.lines.Line2D at 0x17390b7a0>]



In this part we will define a midpoint function which we will use later on to create the fractals

```
In [4]: # def midpoint function for triangles, init triagles
def midpoint(a, b):
    ''' returns midpoints given 2 points of an equilateral triangle

    Parameters:
    a, b: tuple of x, y coordinates

    Returns:
    tuple of x, y coordinates of the midpoint
    '''
```

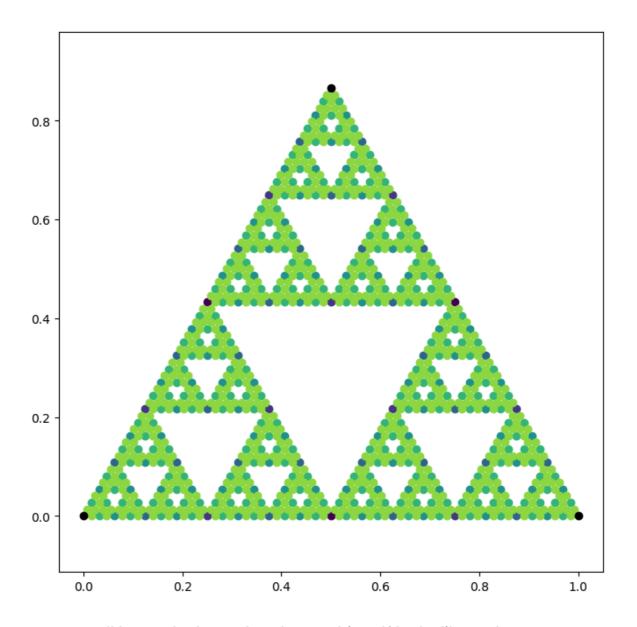
```
return ((a[0] + b[0]) / 2, (a[1] + b[1]) / 2)
mid = ((a[0] + b[0] + c[0]) / 3, (a[1] + b[1] + c[1]) / 3)
triangles = [vertices]
```

Actual creation of the fractals

In this part we iteratively create the fractal triangles.

We also plot the triangles (in different colors regarding the generation of each triangle generation)

```
In [5]: fig, ax = plt.subplots(figsize=(8, 8))
        for i in range(gens-1):
            new_triangles = []
            norm_val = i / (gens - 1)
            color = cm.viridis(norm_val)
            for triangle in triangles:
                A, B, C = triangle
                # Compute midpoints of each side
                AB_mid = midpoint(A, B)
                BC_mid = midpoint(B, C)
                CA_mid = midpoint(C, A)
                ax.scatter(*zip(*[AB_mid, BC_mid, CA_mid]), color=color, marker='
                new triangles.extend([
                    (A, AB_mid, CA_mid),
                    (AB_mid, B, BC_mid),
                    (CA_mid, BC_mid, C)
                ])
                # Add the points to df for distance calculations
                new_points = pd.DataFrame({'gen': [i + 1] * 3,'coords': [AB_mid,
                df = pd.concat([df, new_points], ignore_index=True)
            # Update the list of triangles for the next generation
            triangles = new_triangles
        ax.scatter(*zip(*vertices), color='black', marker='o')
        plt.axis('equal')
        plt.show()
```



Next we'll have a look on what the resulting df looks like and

In [6]:	<pre>print(df.shape) df.head()</pre>			
((1095, 2)			
Out[6]:		gen	coords	
	0	0	(0, 0)	
	1	0	(1, 0)	
	2	0	(0.5, 0.8660254037844386)	
	3	1	(0.5, 0.0)	
	4	1	(0.75, 0.4330127018922193)	

Calculation of Distances

As we have all points calculated it is now time to also calculate the distances between them.

We calculate the 4 given distances: Euclidian, Minkow, Manhatten and the "Generation-Distance"

```
In [7]: # Calculate all pairwise distances between all points
        euclid = pairwise distances(np.array(df['coords'].tolist()).reshape(-1, 2
        minkow = pairwise_distances(np.array(df['coords'].tolist()).reshape(-1, 2
        manhatten = pairwise_distances(np.array(df['coords'].tolist()).reshape(-1
        generation = pairwise distances(np.array(df['gen'].tolist()).reshape(-1,
        euclid
                         , 1.
Out[7]: array([[0.
                                    , 1.
                                                , ..., 0.97665625, 0.99227977,
               0.984375 ],
               [1.
                         , 0.
                                     , 1.
                                               , ..., 0.97665625, 0.984375 ,
               0.99227977],
               [1.
                                     , 0.
                                              , ..., 0.02706329, 0.015625 ,
                         , 1.
               0.015625 ],
               [0.97665625, 0.97665625, 0.02706329, ..., 0.
                                                               , 0.015625 ,
               0.015625 ],
               [0.99227977, 0.984375 , 0.015625 , ..., 0.015625 , 0.
               0.015625 ],
               [0.984375 , 0.99227977, 0.015625 , ..., 0.015625 , 0.015625 ,
```

Plotting the Distances

]])

0.

As we now have all the distances calculated, what we do next is plotting the distance matrizes

```
In [8]: # Create a figure with 1 row and 4 columns of subplots
        fig, axs = plt.subplots(1, 4, figsize=(20, 5))
        # Plot Euclidean distances
        im0 = axs[0].imshow(euclid, cmap='viridis')
        axs[0].set_title("Euclidean")
        fig.colorbar(im0, ax=axs[0])
        # Plot Minkowski distances
        im1 = axs[1].imshow(minkow, cmap='viridis')
        axs[1].set_title("Minkowski")
        fig.colorbar(im1, ax=axs[1])
        # Plot Manhattan distances
        im2 = axs[2].imshow(manhatten, cmap='viridis')
        axs[2].set_title("Manhattan")
        fig.colorbar(im2, ax=axs[2])
        # Plot Generation distances
        im3 = axs[3].imshow(generation, cmap='viridis')
        axs[3].set_title("Generation")
        fig.colorbar(im3, ax=axs[3])
```

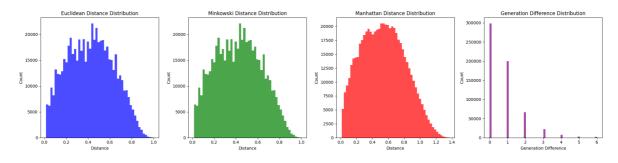
plt.show() Euclidean -0.8 200 -0.6 400 -0.6 400 -0.4 800 -0.

Although this gives some insights, it's hard to detect all the distances between the points and get a feeling for it.

So let's try something different.

We will plot the distances

```
In [9]: def get upper triangle values(matrix):
            # Get indices for the upper triangle (excluding the diagonal)
            triu_indices = np.triu_indices_from(matrix, k=1)
            return matrix[triu_indices]
        # Extract upper triangle values for each distance matrix
        euclid_values = get_upper_triangle_values(euclid)
        minkow_values = get_upper_triangle_values(minkow)
        manhatten_values = get_upper_triangle_values(manhatten)
        generation_values = get_upper_triangle_values(generation)
        # Create a figure with 1 row and 4 columns of subplots
        fig, axs = plt.subplots(1, 4, figsize=(20, 5))
        axs[0].hist(euclid_values, bins=50, color='blue', alpha=0.7)
        axs[0].set_title('Euclidean Distance Distribution')
        axs[0].set_xlabel('Distance')
        axs[0].set ylabel('Count')
        axs[1].hist(minkow_values, bins=50, color='green', alpha=0.7)
        axs[1].set_title('Minkowski Distance Distribution')
        axs[1].set_xlabel('Distance')
        axs[1].set_ylabel('Count')
        axs[2].hist(manhatten_values, bins=50, color='red', alpha=0.7)
        axs[2].set_title('Manhattan Distance Distribution')
        axs[2].set_xlabel('Distance')
        axs[2].set_ylabel('Count')
        axs[3].hist(generation_values, bins=50, color='purple', alpha=0.7)
        axs[3].set title('Generation Difference Distribution')
        axs[3].set_xlabel('Generation Difference')
        axs[3].set_ylabel('Count')
        plt.tight_layout()
        plt.show()
```



```
In [10]: #max of each distance
    max_euclid = euclid.max()
    max_minkow = minkow.max()
    max_manhatten = manhatten.max()
    max_generation = generation.max()

print(f"Max Euclidean distance: {max_euclid}")
    print(f"Max Minkowski distance: {max_minkow}")
    print(f"Max Manhattan distance: {max_manhatten}")
    print(f"Max Generation distance: {max_generation}")
```

Max Euclidean distance: 1.0 Max Minkowski distance: 1.0

Max Manhattan distance: 1.3660254037844386

Max Generation distance: 6.0

```
In [11]: #min of each distance
    min_euclid = euclid.min()
    min_minkow = minkow.min()
    min_manhatten = manhatten.min()
    min_generation = generation.min()

print(f"Min Euclidean distance: {min_euclid}")
    print(f"Min Minkowski distance: {min_minkow}")
    print(f"Min Manhattan distance: {min_manhatten}")
    print(f"Min Generation distance: {min_generation}")
```

Min Euclidean distance: 0.0 Min Minkowski distance: 0.0 Min Manhattan distance: 0.0 Min Generation distance: 0.0

Let's visualize this a bit better

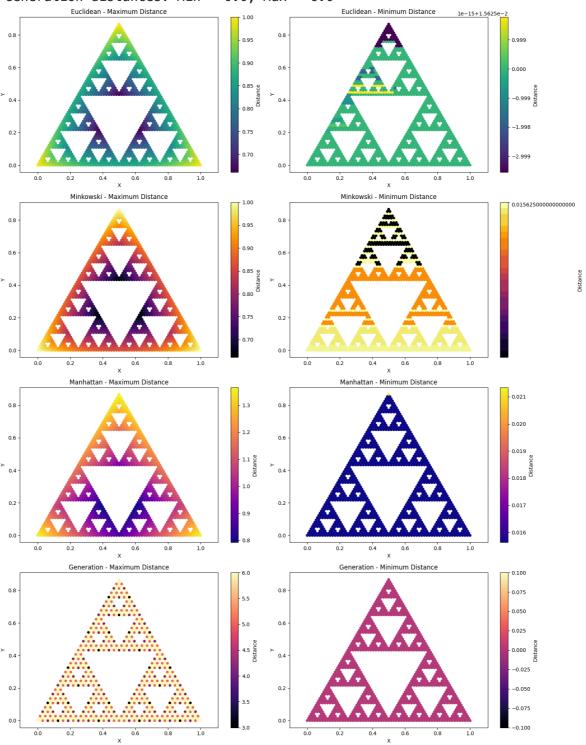
To do so we first plot the max and min values color-coded into the triangle. While doing this we will skip the diagonal values of the distance matrix to get a bit more insights (obviously the distance of a point to itself will be 0) we will also print the "real" max and min distances

```
# Exclude self-distance for max by setting the diagonal to -infinity.
    np.fill_diagonal(dmax_mat, -np.inf)
    d_min = np.min(dmin_mat, axis=1)
    d_max = np.max(dmax_mat, axis=1)
    return d_min, d_max
# Convert the coordinates from df['coords'] into a 2D array.
points = np.vstack(df['coords'].tolist())
# Define the metrics with the colormap to be used.
metrics = {
    'Euclidean': {'metric': 'euclidean', 'cmap': 'viridis'},
    'Minkowski': {'metric': 'minkowski', 'cmap': 'inferno'},
    'Manhattan': {'metric': 'manhattan', 'cmap': 'plasma'},
    'Generation': {'metric': 'generation', 'cmap': 'magma'}
}
# Create one row per metric and 2 columns (max and min plots).
n metrics = len(metrics)
fig, axes_array = plt.subplots(n_metrics, 2, figsize=(16, 5 * n_metrics))
axes_array = np.atleast_2d(axes_array)
for i, (name, params) in enumerate(metrics.items()):
    if name == 'Generation':
        # Compute distances using generation numbers.
        gen_values = np.array(df['gen'].tolist()).reshape(-1, 1)
        dist_matrix = pairwise_distances(gen_values)
    else:
        # Compute distances using spatial coordinates.
        dist_matrix = pairwise_distances(points, metric=params['metric'])
    # Compute the minimum and maximum distances (excluding self-distance)
    d_min, d_max = compute_min_max(dist_matrix)
    print(f"{name} distances: Min = {d_min.min()}, Max = {d_max.max()}")
    # Prepare normalized color scales.
    norm_min = mcolors.Normalize(vmin=d_min.min(), vmax=d_min.max())
    norm_max = mcolors.Normalize(vmin=d_max.min(), vmax=d_max.max())
    # Plot points colored by maximum distances first (left column).
    sc_max = axes_array[i, 0].scatter(points[:, 0], points[:, 1],
                                      c=d_max, cmap=params['cmap'],
                                      norm=norm_max, s=20)
    axes_array[i, 0].set_title(f'{name} - Maximum Distance')
    axes_array[i, 0].set_xlabel('X')
    axes_array[i, 0].set_ylabel('Y')
    axes_array[i, 0].axis('equal')
    fig.colorbar(sc_max, ax=axes_array[i, 0], label='Distance')
    # Plot points colored by minimum distances next (right column).
    sc_min = axes_array[i, 1].scatter(points[:, 0], points[:, 1],
                                      c=d_min, cmap=params['cmap'],
                                      norm=norm_min, s=20)
    axes_array[i, 1].set_title(f'{name} - Minimum Distance')
    axes_array[i, 1].set_xlabel('X')
    axes_array[i, 1].set_ylabel('Y')
    axes_array[i, 1].axis('equal')
    fig.colorbar(sc_min, ax=axes_array[i, 1], label='Distance')
```

```
plt.tight_layout()
plt.show()
```

```
Euclidean distances: Min = 0.015624999999994447, Max = 1.0 Minkowski distances: Min = 0.01562499999999936, Max = 1.0 Manhattan distances: Min = 0.015625, Max = 1.3660254037844386
```

Generation distances: Min = 0.0, Max = 6.0



Playground (don't mind this)

```
In [13]: #for each generation...
spielwiese = False

if spielwiese:
    for i in range(gens-1):
```

```
midpoints =[midpoint(p1,p2) for p1,p2 in itertools.combinations(d
    # Calculating new midpiints that are not already in the dataframe
    existing_points = set(df['coords'])
    unique_midpoints = [m for m in midpoints if m not in existing_poi
    unique_midpoints = list({m for m in unique_midpoints})
    new_points = pd.DataFrame({'gen': i + 1, 'coords': unique_midpoin
    print(new_points)
    #coloring in verdis style
    norm_val = i / (gens - 1)
    color = cm.viridis(norm_val)
    # plotting the new points
    ax.scatter(*zip(*unique_midpoints), color=(color), marker='o')
   #adding them to the df
   df = pd.concat([df, new_points], ignore_index=True)
display(fig)
df
```