

Diffusion Limited Aggregation

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1 Introduction

Diffusion limited aggregation (DLA) is a growth mechanism where particles move randomly and attach to a structure as soon as they collide with it. They then grow into branched structures, much like dendrites. The difference here is that dendritic growth is somewhat deterministic i.e. the particles in the system follow a certain path due to a driving force, while DLA is occurring due to the random motion of particles.

This concept was first introduced in 1981 by Witten and Sandler [1] and it is their work that has been the instruction manual for this coding project. The code has been implemented in the python programming language. The following sections will explore this model and how it can be used.

2 Code manual

A model of a DLA process is built in the Python programming language. The python packages used are numpy and matplotlib. In short, a grid of a certain size is built. An initial seed is added to the center of the grid and a walker is randomly added at a certain distance from the center. This walker randomly moves randomly in the grid, until it either reaches the seed and attaches to it or touches the boundaries in which it leaves the

system. Another walker is then introduced, and this continues until an irregular dendritic shape starts taking form.

2.1 Build grid

The grid is built using numpy.meshgrid, 1D arrays representing the coordinates of a grid are used as input. This return three coordinate matrices; one with x values, one with y values and one with the values of the combined coordinate points. The x and y matrices are used to plot the system, while the value matrice is used as the lattice on which the random walk is taking place.

An outer circle with the radius of half the box size is defined. This is the outer boundary of the system. An inner circle of a used defined radius is set, it is at the interface of the inner circle that the walkers are introduced. By giving these gridpoints certain values (now set as 0.2 and 0.5 for a nice colormap contrast), one can easily keep track of when the walker has approached the limits.

```
def set_outer_circle(matrix_points):
                                        circle_limit = np.shape(matrix_points)[0]/2
12
                                       for i in range(np.shape(matrix_points)[0]):
14
                                                       for j in range(np.shape(matrix_points)[1]):
16
                                                                       \  \  \, \text{if np.sqrt((i-circle\_limit)**2+(j-circle\_limit)**2)} \  \, \text{>= circle\_limit:} \\
18
                                                                                        matrix_points[i][j] = 0.5
19
20
                                        return matrix_points
21
22
                       def set_inner_circle(matrix_points):
\frac{23}{24}
                                       circle_limit = np.shape(matrix_points)[0]/2.2
25
                                       center = np.shape(matrix_points)[0]/2 - circle_limit
26
27
                                       for i in range(np.shape(matrix_points)[0]):
29
                                                      for j in range(np.shape(matrix_points)[1]):
                                                                       if \ np.sqrt((i-circle\_limit-center)**2+(j-circle\_limit-center)**2) >= circle\_limit \ and \ matrix\_points[i][j] \ != 0.5: | (i-circle\_limit-center)**2 | (i-ci
                                                                                      matrix_points[i][j] = 0.2
33
                                       return matrix_points
```

2.2 Add seed

A seed is added randomly close to the central of the box. How close it is to the central is determined by a limit the that user sets themselves. This is so that the nucleation point of our structure is randomized.

2.3 Random walk

The process can be described in five simple steps:

• A walker is introduced at the inner circle

```
def release_walker(matrix_points): #releases walker from the inner sphere vertix
release = False

while release == False:
random_point = [np.random.choice(np.shape(matrix_points)[0],1, replace=False)[0],
np.random.choice(np.shape(matrix_points)[0],1, replace=False)[0]]

try:
grannar = neighbours(matrix_points, random_point)
occurency = int(np.count_nonzero(np.array(grannar) == 0.2))
if 0.0 in grannar and (occurency == 2 or occurency == 1):
release = True
except:
continue
return random_point
```

• There are four alternative steps, either moving up one step, moving down one step, moving to the left or to the right. The step is picked randomly.

```
def random_step(random_point):

#there are four movements the walker can take

scenarios = ["step_forward_x", "step_backward_x",

"step_up_y", "step_down_y"]

which_scenario = np.random.choice(np.shape(scenarios)[0])

if scenarios[which_scenario] == "step_forward_x":

random_point[0] +=1

if scenarios[which_scenario] == "step_backward_x":

random_point[0] -=1

if scenarios[which_scenario] == "step_up_y":

random_point[1] +=1

if scenarios[which_scenario] == "step_up_y":

random_point[1] -=1

return random_point
```

- If the new position in the neighbouring sites are empty, then the walker is allowed to move. If there is a neighbour, then it settles
- If the walker settles, a new one is released. Otherwise it continues until it reaches a neighbour and settles there.

• If the new positions is out of the limit, i.e. within the inner and outer circle then, the process starts over with releasing a new walker.

```
\frac{157}{158}
         for i in range(N):
              random_point = release_walker(matrix_points)
159
160
              try:
while matrix_points[random_point[0]][random_point[1]] == 0.0:
    grannar = neighbours(matrix_points, random_point)
162
163
                        if 1.0 in grannar or 0.8 in grannar: #checks if there is a neighbour == 1 or the seed == 0.8
164
165
166
                             #now we reached our neighbour.
                                                                    lets settle down
                             matrix_points[random_point[0]][random_point[1]] = 1.0
                             particles += 1
167
168
169
170
                             random_point = random_step(random_point)
#inner circle limit
                             if matrix_points[random_point[0]][random_point[1]] == 0.2:
                                  #we're now out of bounds
raise Exception("out!")
              except Exception:
                   continue
```

This process can be described by the following flowchart.

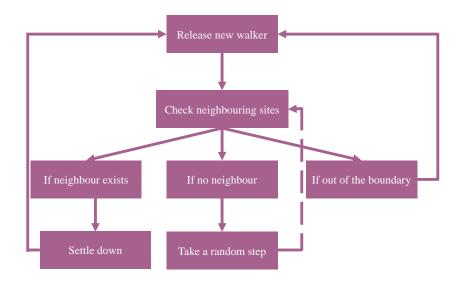


Figure 1: Flow chart of the diffusion limited aggregation algorithm.

3 Calculate fractal dimension

The fractal dimension can be calculated according to the equation given in reference [2],

$$D = \frac{\log(N(\delta))}{\log(1/\delta)} \tag{1}$$

, where δ is the size of the subgrids and $N(\delta)$ is the number of subgrids that are covered by the fractal. By plotting these values for different subgrid sizes, one can then then take the slope to be the fractal dimension.

```
def fractal_dimension(k, matrix_points):
    div = []
\frac{106}{107}
108
              for i in range(2,k+1):
109
                    div.append(2**i)
               #the pixels are in the array matrix_points
\begin{array}{c} 110 \\ 111 \end{array}
              cover = np.zeros(np.shape(div)[0])
112
               inverse_delta = np.zeros(np.shape(div)[0])
               def view_as_blocks(arr, BSZ):
               # reference: https://stackoverflow.com/questions/44782476/split-a-numpy-array-both-horizontally-and-vertically
    # arr is input array, BSZ is block-size
    m,n = arr.shape
118
119
120
                    return arr.reshape(m//M, M, n//N, N).swapaxes(1,2).reshape(-1,M,N)
              for i in range(np.shape(div)[0]):
123
124
                     inverse_delta[i] += 1/div[i]
                    boxes = view_as_blocks(matrix_points,(int(div[i]),int(div[i])))
125
126
                    for j in range(np.shape(boxes)[0]): #loop over all boxes
    occupied = np.count_nonzero(boxes[j] == 1.0) #is the pixels in the grid occupied?
    if int(occupied) > 0: #if box is occupied count it as one
\frac{127}{128}
               \texttt{D = (np.log(cover)[1]-np.log(cover)[len(cover)-1])/(np.log(inverse\_delta)[1]-np.log(inverse\_delta)[len(inverse\_delta)-1]) }
```

4 Results

Diffusion limited growth was simulated using the algorithm described in the previous section. Here, one such growth is given in Figure 2.

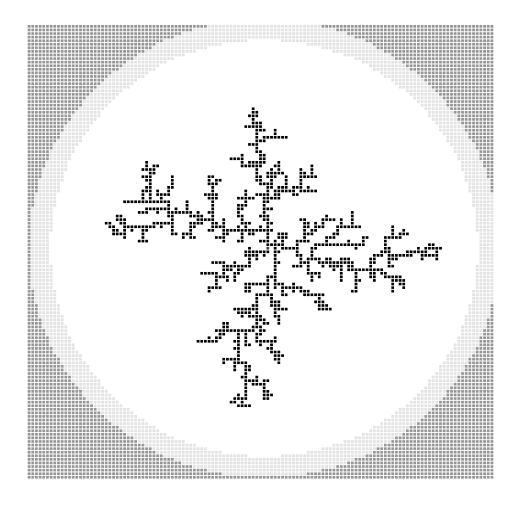


Figure 2: DLA simulation with 911 particles showing the outer and inner circle is light grey.

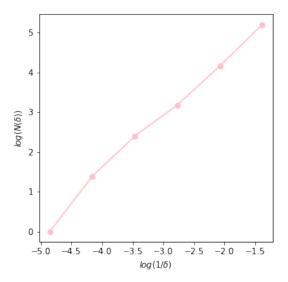


Figure 3: The logarithm of the number of covered subgrids $N(\delta)$ vs. the logarithm of the inverse subgrid size δ .

The first point is excluded, as that one is for the subgrid size of NxN which des not represent the fractal dimension. A rough estimate of the slope is calculated by taing the second and last point. This gives a fractal dimension with the exact value of 1.5. The code runs again with the same settings generating another fractal, see Figure 4.

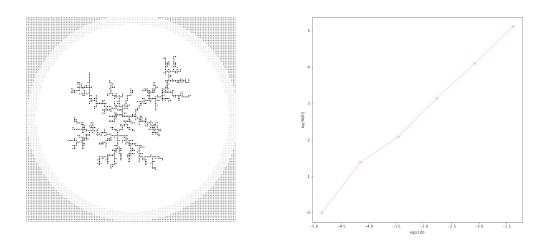


Figure 4: Another simulation using the same settings.

Using the second and last points give the dimension of 1.48. However by looking at the points in the graph, a more representative slope would be between point two and the last and this gives a value of 1.51.

5 Outlook

It took approximately 5 minutes to run the simulation that produced the fractal in Figure 2. The code is quite hard-coded and could be made more efficient for faster results and larger systems.

One could also improve the code further by properly fitting the datapoints of the box counting and thus obtaining a more exact value for the slope.

6 References

- [1] Witten Jr, T. A., Sander, L. M. (1981). Diffusion-limited aggregation, a kinetic critical phenomenon. Physical review letters, 47(19), 1400.
- [2] So, G. B., So, H. R., Jin, G. G. (2017). Enhancement of the box-counting algorithm for fractal dimension estimation. Pattern Recognition Letters, 98, 53-58.

7 Code

```
import numpy as np
        import matplotlib.pyplot as plt
 4
        def set_grid(size,step):
            x = np.arange(0,size+step,step)
 6
7
             y = np.arange(0,size+step,step)
xx, yy = np.meshgrid(x, y)
             matrix_points = np.zeros((np.shape(yy)[0],np.shape(xx)[0]))
return xx, yy, matrix_points
10
        def set_outer_circle(matrix_points):
12
             circle_limit = np.shape(matrix_points)[0]/2
             for i in range(np.shape(matrix_points)[0]):
14
                   for j in range(np.shape(matrix_points)[1]):
16
                         if np.sqrt((i-circle_limit)**2+(j-circle_limit)**2) >= circle_limit:
18
                              matrix_points[i][j] = 0.5
20
             return matrix_points
21
        def set_inner_circle(matrix_points):
22
23
24
             circle_limit = np.shape(matrix_points)[0]/2.2
25
26
             center = np.shape(matrix points)[0]/2 - circle limit
27
28
             for i in range(np.shape(matrix_points)[0]):
    for j in range(np.shape(matrix_points)[1]):
29
30
                         if np.sqrt((i-circle_limit-center)**2+(j-circle_limit-center)**2) >= circle_limit and matrix_points[i][j] != 0.5:
    matrix_points[i][j] = 0.2
31
32
33
34
             return matrix_points
35
        def add_initial_seed(matrix_points, size, step):
36
             #sets the initial seed, puts it at random sommhere close to the central
random_point = [np.random.choice(np.shape(matrix_points)[0],1, replace=False)[0],
37
38
39
             np.random.choice(np.shape(matrix_points)[0],1, replace=False)[0]]
x_seed = xx[random_point[0]][random_point[1]]
\frac{41}{42}
             y_seed = yy[random_point[0]][random_point[1]]
             seed_limit_1 = (size/2)-(step*2)
seed_limit_2 = (size/2)+(step*2)
43
45
             if seed_limit_2>x_seed>seed_limit_1 and seed_limit_2>y_seed>seed_limit_1:
    matrix_points[random_point[0]][random_point[1]] = 0.8
47
                   while (x_seed>seed_limit_2 or x_seed<seed_limit_1) or (y_seed>seed_limit_2 or y_seed<seed_limit_1):
    random_point = [np.random.choice(np.shape(matrix_points)[0],1, replace=False)[0],
49
                         np.random.choice(np.shape(matrix_points)[0],1, replace=False)[0]]
x_seed = xx[random_point[0]][random_point[1]]
51
                   y_seed = yy[random_point[0]][random_point[1]]
matrix_points[random_point[0]][random_point[1]] = 0.8
53
55
             return matrix_points, random_point
        def release walker(matrix points): #releases walker from the inner sphere vertix
57
58
             release = False
59
60
             while release == False:
                   random_point = [np.random.choice(np.shape(matrix_points)[0],1, replace=False)[0],
61
                                          np.random.choice(np.shape(matrix_points)[0],1, replace=False)[0]]
63
                         grannar = neighbours(matrix_points, random_point)
occurency = int(np.count_nonzero(np.array(grannar) == 0.2))
if 0.0 in grannar and (occurency == 2 or occurency == 1):
\frac{64}{65}
66
                   release = True except:
67
68
69
                         continue
70
71
              return random_point
        def random_step(random_point):
    #there are four movements the walker can take
    scenarios = ["step_forward_x", "step_backward_x",
    "step_up_y", "step_down_y"]
\frac{74}{75}
             which_scenario = np.random.choice(np.shape(scenarios)[0])
if scenarios[which_scenario] == "step_forward_x":
76
77
78
79
             random_point[0] +=1
if scenarios[which_scenario] == "step_backward_x":
             random_point[0] -=1
if scenarios[which_scenario] == "step_up_y":
80
             random_point[1] +=1
if scenarios[which_scenario] == "step_down_y":
82
             random_point[1] -=1
return random_point
84
86
        def neighbours(matrix_points, random_point):
             a = int(random_point[0]-1)
b = int(random_point[0]+1)
c = int(random_point[1]-1)
88
             d = int(random_point[1]+1)
```

```
92
                     out = int(np.shape(matrix_points[0])[0])-1
 93
94
                    if a < 0 or a > out or b < 0 or b > out or c < 0 or c > out or d < 0 or d > out:
    raise Exception("outside")
 95
 96
                     right = matrix_points[random_point[0]][random_point[1]+1]
                    left = matrix_points[random_point[0]][random_point[1]-1]
bottom = matrix_points[random_point[0]+1][random_point[1]]
 97
 98
 99
                    top = matrix_points[random_point[0]-1][random_point[1]]
100
101
                     grannar = [right, left, top, bottom]
102
103
                    return grannar
104
            def fractal_dimension(k, matrix_points):
    div = []
105
107
                    for i in range(2,k+1):
109
                           div.append(2**i)
                     #the pixels are in the array matrix_points
111
                     cover = np.zeros(np.shape(div)[0])
113
                    inverse_delta = np.zeros(np.shape(div)[0])
                    def view as blocks(arr, BSZ):
115
116
                     # reference: https://stackoverflow.com/questions/44782476/split-a-numpy-array-both-horizontally-and-vertically
                           # arr is input array, BSZ is block-size
117
                           m,n = arr.shape
M,N = BSZ
119
120
                           return arr.reshape(m//M, M, n//N, N).swapaxes(1,2).reshape(-1,M,N)
121
122
                    for i in range(np.shape(div)[0]):
123
                            inverse_delta[i] += 1/div[i]
boxes = view_as_blocks(matrix_points,(int(div[i]),int(div[i])))
124
125
                            for j in range(np.shape(boxes)[0]): #loop over all boxes
    occupied = np.count_nonzero(boxes[j] == 1.0) #is the pixels in the grid occupied?
126
127
128
                                   if int(occupied) > 0: #if box is occupied count it as one
    cover[i] += 1
129
130
                    D = (np.log(cover)[1]-np.log(cover)[len(cover)-1])/(np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delta)[1]-np.log(inverse_delt
131
132
133
                    print("The dimension of the fractal is:", D)
134
135
136
137
             #-----DETERMINES THE SIZE OF OUR GRID SYSTEM-----
138
            k = 7
140
             N = 2**k
            step = 1/N

size = 1 - step
142
144
145
            xx, yy, matrix_points = set_grid(size, step)
146
            matrix_points, random_point = add_initial_seed(matrix_points,size,step)
148
149
            matrix_points = set_outer_circle(matrix_points)
150
151
            matrix_points = set_inner_circle(matrix_points)
152
153
            N = 95000
154
            particles = 0
155
156
157
            for i in range(N):
    random_point = release_walker(matrix_points)
158
                    159
160
161
                                   grannar = neighbours(matrix_points, random_point)
162
163
                                   if 1.0 in grannar or 0.8 in grannar: #checks if there is a neighbour == 1 or the seed == 0.8
                                                                                                      lets settle
                                           #now we reached our neighbour, lets settle down
matrix_points[random_point[0]][random_point[1]] = 1.0
164
165
                                           particles += 1
166
167
168
                                   else:
                                           random_point = random_step(random_point)
#inner circle limit
169
170
                                           if matrix_points[random_point[0]][random_point[1]] == 0.2:
171
                                                  #we're now out of bounds
raise Exception("out!")
173
174
175
                    except Exception:
177
            plt.pcolormesh(xx, yy, matrix_points,cmap='Greys', edgecolors="white")
            plt.axis("off")
plt.rcParams["figure.figsize"] = (10,10)
179
181
182
            print(particles)
183
184
            plt.show()
185
            fractal_dimension(k, matrix_points)
```