Preparations

In [124…

```
## IMPORTS ##
import numpy as np
import scipy as sc
from scipy.signal import convolve2d
import matplotlib.pylab as plt
from matplotlib import animation
from copy import deepcopy
import csv
from matplotlib import rc
from IPython.display import HTML, Image
import IPython
import pandas as pd

# Silence warnings
np.warnings.filterwarnings("ignore", category=np.VisibleDeprecationWarning)  # Silence wa
# Visualisation functions
def figure_world(A, cmap="viridis"):
    """Set up basic graphics of unpopulated, unsized world"""
    global img  # make final image global
    fig = plt.figure()  # Initiate figure
    img = plt.imshow(A, cmap=cmap, interpolation="nearest", vmin=0)  # Set image
    plt.title = ("World A")
    plt.close()
    return fig
def figure_asset(K, growth, cmap="viridis", K_sum=1, bar_K=False):
    """ Return graphical representation of input kernel and growth function.
    Subplot 1: Graph of Kernel in matrix form
    Subplot 2: Cross section of Kernel around center. Y: gives values of cell in row, X: g
    Subplot 3: Growth function according to values of U (Y: growth value, X: values in U)
    """
    global R
    K_size = K.shape[0];
    K_mid = K_size // 2  # Get size and middle of Kernel
    fig, ax = plt.subplots(1, 3, figsize=(14, 2),
                           gridspec_kw={"width_ratios": [1, 1, 2]})  # Initiate figures wi

    ax[0].imshow(K, cmap=cmap, interpolation="nearest", vmin=0)
    ax[0].title.set_text("Kernel_K")

    if bar_K:
        ax[1].bar(range(K_size), K[K_mid, :], width=1)  # make bar plot
    else:
        ax[1].plot(range(K_size), K[K_mid, :])  # otherwise, plot normally
    ax[1].title.set_text("K cross-section")
    ax[1].set_xlim([K_mid - R - 3, K_mid + R + 3])

    if K_sum <= 1:
        x = np.linspace(0, K_sum, 1000)
        ax[2].plot(x, growth(x))
    else:
        x = np.arange(K_sum + 1)
        ax[2].step(x, growth(x))
    ax[2].axhline(y=0, color="grey", linestyle="dotted")
    ax[2].title.set_text("Growth G")
    return fig

def get_parameters(dict):
    """Get list of parameters from dictionary"""
    return [dict[i] for i in ["R", "T", "m", "s", "b"]]
```

```python
def save_parameters(parameters, filename, cells):
    ### NEED TO FIGURE OUT A SOLUTION TO B
    dict = {}
    keys = ["R", "T", "m", "s", "b"]
    for i in range(len(parameters)):
        dict[keys[i]] = parameters[i]

    with open("parameters_"+filename+".csv", "w") as f:
        csvwrite = csv.writer(f)
        for k in dict:
                csvwrite.writerow([k, dict[k]])
    with open("cells_"+filename+".csv", "w") as f:
        csvwrite = csv.writer(f)
        for i in cells:
            csvwrite.writerow(i)

    return dict

def load_parameters(filename):
    """Load parameters from csv"""
    dict = {}
    with open("../sandbox/Lenia/results/parameters/parameters_" + filename + ".csv", "r")
        csvread = csv.reader(f)
        for row in csvread:
            if row[0] == "b":
                dict[row[0]] = [float(i) for i in row[1].strip("[]").split(",")]
            else:
                dict[row[0]] = float(row[1])
    cells = []
    with open("../sandbox/Lenia/results/parameters/cells_" + filename + ".csv", "r") as f:
        csvread = csv.reader(f)
        for i in csvread:
            cells.append([float(s) for s in i])
    dict["cells"] = cells
    return dict
```

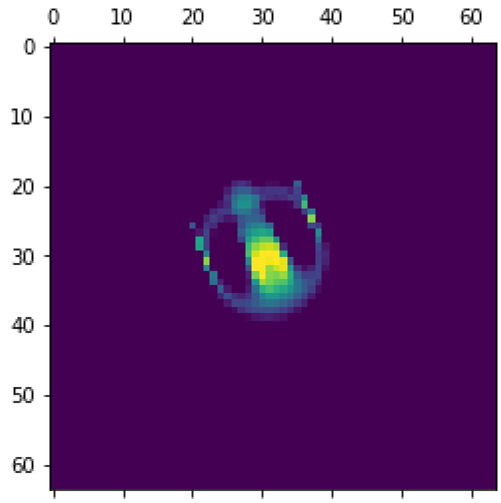
In [114…

```python
## Set constants
orbium = {"name": "Orbium", "R": 13, "T": 10, "m": 0.15, "s": 0.015, "b": [1],
          "cells": [[0, 0, 0, 0, 0, 0, 0.1, 0.14, 0.1, 0, 0, 0.03, 0.03, 0, 0, 0.3, 0, 0,
                    [0, 0, 0, 0, 0, 0.08, 0.24, 0.3, 0.3, 0.18, 0.14, 0.15, 0.16, 0.15, 0.
                    [0, 0, 0, 0, 0, 0.15, 0.34, 0.44, 0.46, 0.38, 0.18, 0.14, 0.11, 0.13,
                    [0, 0, 0, 0, 0.06, 0.13, 0.39, 0.5, 0.5, 0.37, 0.06, 0, 0, 0, 0.02, 0.
                    [0, 0, 0, 0.11, 0.17, 0.17, 0.33, 0.4, 0.38, 0.28, 0.14, 0, 0, 0, 0, 0
                    [0, 0, 0.09, 0.18, 0.13, 0.06, 0.08, 0.26, 0.32, 0.32, 0.27, 0, 0, 0,
                    [0.27, 0, 0.16, 0.12, 0, 0, 0, 0.25, 0.38, 0.44, 0.45, 0.34, 0, 0, 0,
                    [0, 0.07, 0.2, 0.02, 0, 0, 0, 0.31, 0.48, 0.57, 0.6, 0.57, 0, 0, 0, 0,
                    [0, 0.59, 0.19, 0, 0, 0, 0, 0.2, 0.57, 0.69, 0.76, 0.76, 0.49, 0, 0, 0
                    [0, 0.58, 0.19, 0, 0, 0, 0, 0, 0.67, 0.83, 0.9, 0.92, 0.87, 0.12, 0, 0
                    [0, 0, 0.46, 0, 0, 0, 0, 0, 0.7, 0.93, 1, 1, 1, 0.61, 0, 0, 0, 0, 0.18
                    [0, 0, 0.82, 0, 0, 0, 0, 0, 0.47, 1, 1, 0.98, 1, 0.96, 0.27, 0, 0, 0,
                    [0, 0, 0.46, 0, 0, 0, 0, 0, 0.25, 1, 1, 0.84, 0.92, 0.97, 0.54, 0.14,
                    [0, 0, 0, 0.4, 0, 0, 0, 0, 0.09, 0.8, 1, 0.82, 0.8, 0.85, 0.63, 0.31,
                    [0, 0, 0, 0.36, 0.1, 0, 0, 0, 0.05, 0.54, 0.86, 0.79, 0.74, 0.72, 0.6,
                    [0, 0, 0, 0.01, 0.3, 0.07, 0, 0, 0.08, 0.36, 0.64, 0.7, 0.64, 0.6, 0.5
                    [0, 0, 0, 0, 0.1, 0.24, 0.14, 0.1, 0.15, 0.29, 0.45, 0.53, 0.52, 0.46,
                    [0, 0, 0, 0, 0, 0.08, 0.21, 0.21, 0.22, 0.29, 0.36, 0.39, 0.37, 0.33,
                    [0, 0, 0, 0, 0, 0, 0.03, 0.13, 0.19, 0.22, 0.24, 0.24, 0.23, 0.18, 0.1
                    [0, 0, 0, 0, 0, 0, 0, 0, 0.02, 0.06, 0.08, 0.09, 0.07, 0.05, 0.01, 0,
          }  # load orbium
theta = [orbium[i] for i in ["R", "T", "m", "s", "b"]]  # save paramters
size = 64
mid = size // 2
cx, cy = 20, 20
C = np.asarray(orbium["cells"])  # Initial configuration of cells
```

```
"""Load learning channel, A"""
A = np.zeros([size, size])  # Initialise learning channel, A
A[cx:cx + C.shape[0], cy:cy + C.shape[1]] = C  # Load initial configurations into learning
plt.matshow(A)

# Take care NOT to edit A
```

Out[114…

```
<matplotlib.image.AxesImage at 0x7f890c162580>
```



In [115…

```
# DEFINE RELEVANT FUNCTIONS
def load_obstacles(n, r=5, size=size, use_seed=False, seed=0):
    """Load obstacle channel with random configuration
    of n obstacles with radius r"""
    # Sample center point coordinates a, b
    #np.random.seed(seed)
    if use_seed:
        np.random.seed(seed)
    O = np.zeros([size, size])
    for i in range(n):
        mid_point = tuple(np.random.randint(0, size - 1, 2))
        O[mid_point[0]:mid_point[0] + r, mid_point[1]:mid_point[1] + r] = 1  # load obstac
    return O

def learning_kernel(R, mid=mid, fourier=True):
    """Create and return learning Kernel"""
    D = np.linalg.norm(np.ogrid[-mid:mid, -mid:mid])/R
    K = (D < 1) * bell(D, 0.5, 0.15)  ## Transform all distances within radius 1 along smo
    K = K / np.sum(K)  # Normalise between 0:1
    if fourier:
        fK = np.fft.fft2(np.fft.fftshift(K))  # fourier transform kernel
        return fK
    else:
        return K

### GROWTH FUNCTIONS ####
bell = lambda x, m, s: np.exp(-((x - m) / s) ** 2 / 2)  # Gaussian function

def growth_render(U):
    """Growth function specifically for render-check.
    This function does not take mean and std as arguments, since they
    are set as globals when rendering"""
    return bell(U, m, s) * 2 - 1


def growth(U, m, s):
    """Growth function to use in manual simulation"""
    return bell(U, m, s) * 2 - 1
```

```python
def obstacle_growth(U):
    """Defines how creatures grow (shrink) with obstacles"""
    return -10 * np.maximum(0, (U - 0.001))

def update(i):
    """Update function for rendering. All properties made global beforehand"""
    global As, img
    U1 = np.real(np.fft.ifft2(fK*np.fft.fft2(As[0])))
    #U1 = convolve2d(As[0], K, mode="same", boundary="wrap")
    """Update learning channel with growth from both obstacle and
    growth channel"""
    As[0] = np.clip(As[0] + 1 / T * (growth_render(U1) + obstacle_growth(As[1])), 0, 1)
    img.set_array(sum(As))  # Sum two channels to create one channel
    return img,


def make_dict(parameters):
    """Take list of parameters and convert to dictionary"""
    dict = {}
    keys = ["R", "T", "m", "s", "b"]
    for i in range(len(parameters)):
        dict[keys[i]] = parameters[i]
    return dict

def render(parameters, A=A, obstacles=5, r=8, seed=0, kernel_only = False):
    """Render Lenia animation for cross check from input set of parameters"""
    #parameters = make_dict(parameters)
    globals().update(parameters)  # set as globals

    # Load assets
    O = load_obstacles(n=obstacles, r=r, seed=seed, use_seed=True)
    K = learning_kernel(R, fourier=False)
    global fK, As
    fK = learning_kernel(R)
    As = deepcopy([A, O])

    figure_asset(K, growth_render)
    plt.show()

def render_without_obstacles(parameters, A=A):
    globals().update(parameters)
    global K, As
    K = learning_kernel(R, fourier=True)
    As = deepcopy(A)

def update_without_obstacles(i):
    """Update function for rendering. All properties made global beforehand"""
    global As, img
    U1 = np.real(np.fft.ifft2(fK*np.fft.fft2(As)))
    #U1 = convolve2d(As[0], K, mode="same", boundary="wrap")
    """Update learning channel with growth from both obstacle and
    growth channel"""
    As = np.clip(As + 1 / T * (growth_render(U1)), 0, 1) #+ obstacle_growth(As[1])), 0, 1)
    img.set_array(As)  # Sum two channels to create one channel
    return img,


def update_man(grid, obstacle, fK, T, m, s, t=0, show = False):
    """Update one time step of Lenia growth.
    grid = A
    obstacle = o"""
    U1 = np.real(np.fft.ifft2(fK*np.fft.fft2(grid)))
    """Update learning channel with growth from both obstacle and
    growth channel"""
    grid = np.clip(grid + 1 / T * (growth(U1, m, s) + obstacle_growth(obstacle)), 0, 1)
```

```
    if show & (t == 5):  # Feature for cross check
        As = [grid, o]
        plt.matshow(sum(As))
    return grid
```

Evolving Orbium: First trial

First attempt at code inspired by Godany, Khatri, Goldstein 2017. Orbium creatures are optimised in a stochastic environment of solid obstacles. Optimisation is performed through random mutation of a single mutation, then selection. Winning parameters are passed on, and losing ones are lost entirely. In this first attempt, single orbiums are evolved linearly- there is no population consideration.

Classic orbium parameters are defined as follows: R (radius), T (time), m (mean), s (standard deviation), b (kernel peaks)

$$\theta = [R : 13, T : 10, m : 0.15, s = 0.015, b = [1]]$$

Set up

Each round of **mutation and selection** is performed as follows:

1. A parameter from theta is chosen at random, and mutated using the following formula from Godany et al., where x is the sampled parameter and r is sampled from a Uniform distribution (-0.2, 0.2)

$$f(x) = e^{in(x)+r}$$

2. Subsequently, mutant parameters (M) and wild*type parameters (W) are run over the same ten random obstacle configurations. The number of timesteps they survive for, $t*{m},t_{w}
$, is summed over all configurations, and used to compute a selection coefficients: $s = \frac{t_m - t_w}{t_w}$ $
3. Probability of fixation is calculated: $pfix = 2s$
4. Lastly, a random number, n is drawn between zero and one: $$ if $pfix$ >=
   - If $pfix >= n$ mutation is accepted
   - If $pfix < n$ the mutation is rejected.
5. The winning set of parameters is returned.

In [116…

```
### First trial: Mutation and selection ###
def mutate(p):
    """Mutate input parameter"""
    return np.exp(np.log(p) + np.random.uniform(low=-0.2, high = 0.2))


def prob_fixation(wild_time, mutant_time):
    """Return probability of mutant fixing given time survived
    by mutant and wild type"""
    s = (mutant_time-wild_time)/wild_time  # selection coefficient
    return s*2

def run_one(grid, O, K, parameters):
    """Run creature of input parameters and kernel in given obstacle configuration.
    Return timesteps taken before creature dissolves.

    Grid = learning channel
    O = obstacle channel
    K = kernel (loaded from same set of parameters)"""
```

```python
    status = np.sum(grid)  # Survival calculated by presence of living cells in learning c
    t = 0  # set timer
    """While there are living cells in the learning channel, run another timestep"""
    while status > 0:
        t += 1  # count one timestep
        if t >10000:  # Max out
            return t
        grid = update_man(grid, obstacle=O, fK=K, T=parameters[1], m = parameters[2], s=pa
        status = np.sum(grid)
    return t

def select_one(parameters, A=A, show_time=False):
    """Run one instance of mutation of parameters and select solution best fit for surviva
    Return winning parameter set"""
    # Load wild and mutant types
    wild_type = parameters[:]  # deep copy
    mutant_type = parameters[:]
    x = np.random.randint(0, len(parameters)-1)  # Choose random index from parameter list
    mutant_type[x] = mutate(mutant_type[x])  # Mutant chosen parameter

    # Load kernels for mutant and wild type
    fK_wild = learning_kernel(R=wild_type[0])
    fK_mutant = learning_kernel(R = mutant_type[0])

    """Run mutant and wild type over 10 random obstacle configurations and sum survival ti
    t_wild, t_mutant = 0, 0  # initiate survival timers
    for i in range(10):
        O = load_obstacles(n=5, r=8)  # load obstacle configuration at random
        t_wild += run_one(grid = A, O=O, K=fK_wild, parameters = wild_type)
        t_mutant += run_one(grid = A, O=O, K=fK_mutant, parameters= mutant_type)
    if show_time:
        print("Total time for wild type", t_wild)
        print("Total time for mutant", t_mutant)

    # Calculate probability of fixation
    p_fix = prob_fixation(wild_time = t_wild, mutant_time = t_mutant)
    n = np.random.uniform(0, 1)

    if p_fix >= x:
        print("Accept mutation")
        return mutant_type
    else:
        print("Reject mutation")
        return wild_type


select_one(theta, show_time=True)  # Run selection process with Orbium parameters
```

```
Total time for wild type 2068
Total time for mutant 990
Reject mutation
```

Out[116…

```
[13, 10, 0.15, 0.015, [1]]
```

Parameter solutions are **optimised** by running the above selection and mutation process repeatedly, each time feeding the winning set of parameters back into the selection function. Optimisation is run until the parameter solution becomes fixed over x number of generations

In [117…

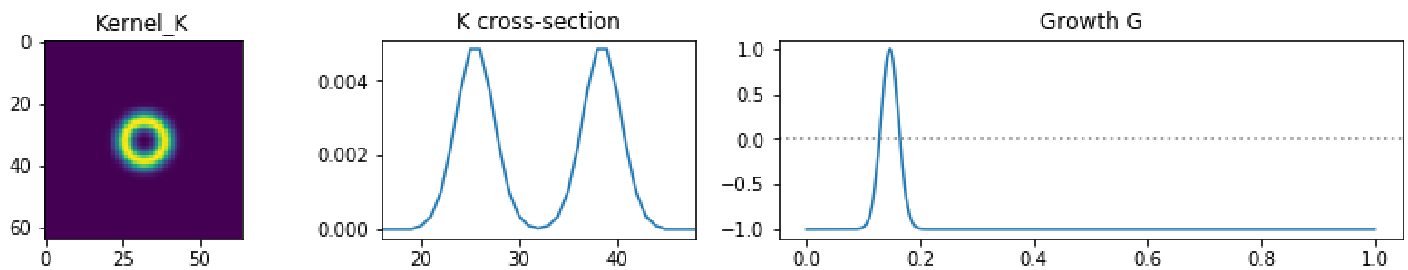
```python
def optimise(parameters, fixation):
    """Run selection and mutation until parameter solution achieves defined fixation
    (number of wins in a row). Return optimised parameter solution"""
    fix = 0  # initiate fixation count
    par_in = parameters[:] # shallow copy
```

```
    while fix < fixation:
        par_out = select_one(par_in)
        if par_out != par_in:  # if mutation wins, feed mutated parameters into function
            par_in = deepcopy(par_out)
            fix = 0  # reset fixation
        else:
            fix += 1  # if wild type wins, add to fix count

    save_parameters(par_out, "fixation_"+str(fixation), C)  # save parameters to file
    return par_out

# Bracketed out since will take too long to re-load:
#np.random.seed(0)
#trial_one = optimise(theta, fixation = 10)  # extremely short fixation trial
```

Results

In [118…

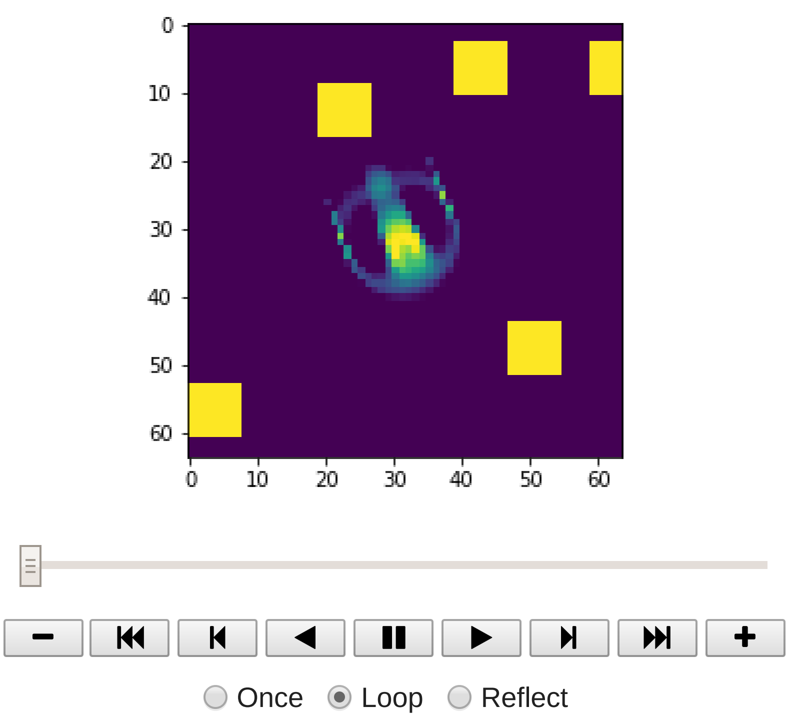
```
trial_one = load_parameters("fixation_10_seed_0")  # Load above run of optimised parameter
render(trial_one, kernel_only=True)
```



In [119…

```
# Render animation of discovered parameters (fig 1)
np.random.seed(0)
fig = figure_world(sum(As))
IPython.display.HTML(animation.FuncAnimation(fig, update, frames=200, interval=20).to_jsht
```

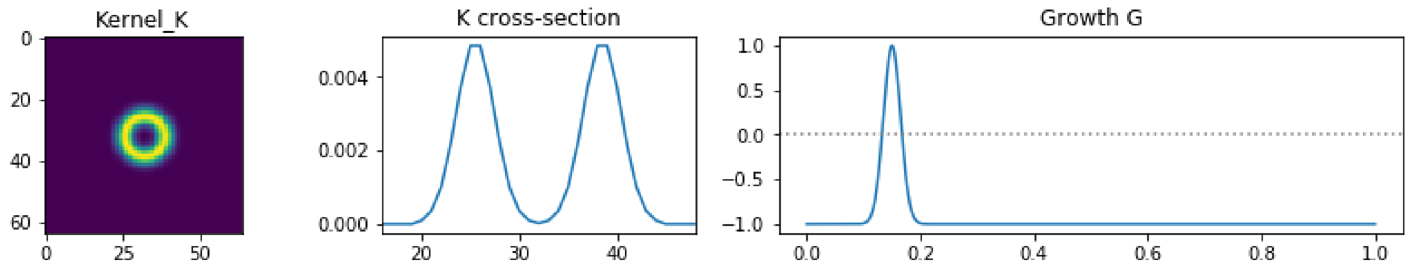
Out[119…



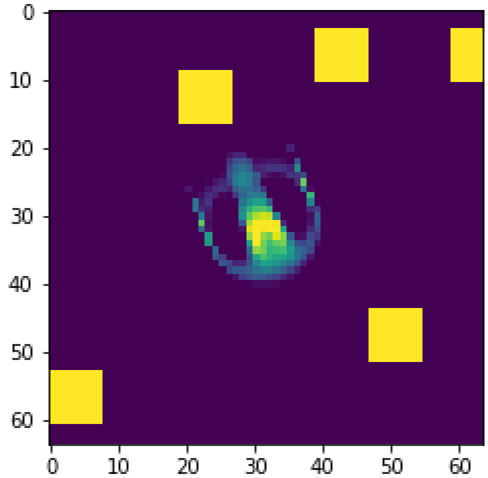
In [120…

```
# fig 2
np.random.seed(0)
```

```
render(orbium)
fig = figure_world(sum(As))
IPython.display.HTML(animation.FuncAnimation(fig, update, frames=200, interval=20).to_jsht
```



Out[120…

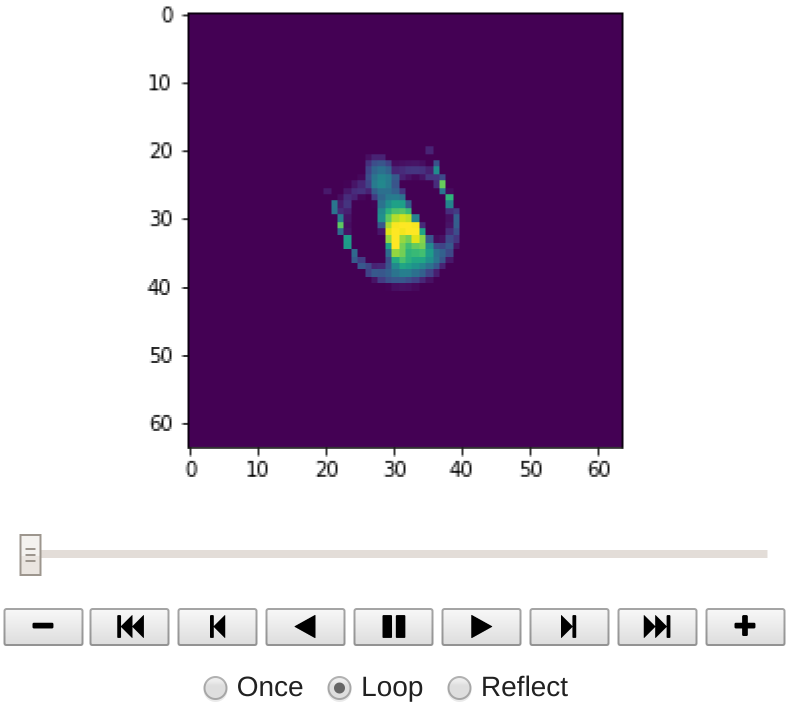


Once Loop Reflect

In [121…

```
# Fig 3
render_without_obstacles(orbium)
fig = figure_world(As)
IPython.display.HTML(animation.FuncAnimation(fig, update_without_obstacles, frames=200, ir
```

Out[121…



Analysis

Figure 3 above shows the swimming patterns of Lenia in a completely neutral environment (no obstacles). The orbium swim in a near-straight trajectory with slight biases to the right. Figure two demonstrates the same unevolved orbium parameters in our obstacles environment. In the top right-hand corner of the grid, the orbium quickly catches itself on a first obstacle and dissolves. Note, even unevolved, the orbium does not naively swim over the obstacle. Instead we see a slight tilt of trajectory as the orbium first catches the obstacles corner. The configuration has some robustness to obstacles prior to evolution.

Figure 3 shows our evolved orbium, (orbium 2.0). Despite a relatively short evoltionary time, orbium 2.0's behaviour demonstrates the following improvements:

1. More robust to obstacle perturbation: When navigating between the two obstacles in the top right corner, while our unevolved orbium finally dissolved after both wings made contact with the obstacles, orbium 2.0 glided through unaffected, and were able to maintain their wings afterwards.
2. Greater sensitivity to obstacles: Orbium 2.0 appears to turn more quickly upon first contact with the obstacles in the top right corner, allow it to avoid greater overlap. The unevolved orbium on the other hand (though it does turn) is slower to turn and resultantly collides more clumsily on the edge.
3. Improved turning abilities: In the last few timesteps, we can see orbium 2.0 turn at a near 90 degree angle upon head on collision with the obstacle.

Further Questions

1. How long will it run for?
2. How will it fair with different obstacle configurations (ie. different numbers or shapes)
3. How different is it from Orbium parameters?
4. What happens if we let the evolution run on (plug these parameters back into optimisation)

In [144…

```
# How long will it run for
```

```python
def get_t(parameters, obstacle_seed, n=5, r=8):
    """Get survival time for input parameters"""
    k = learning_kernel(R=parameters[0])
    o = load_obstacles(n=n, r=r, use_seed=True, seed=obstacle_seed)
    return run_one(grid=A, O=o, K=k, parameters=parameters)

theta2 = get_parameters(trial_one)
print("Mutant time: ", get_t(theta2, 0))
print("Original orbium:", get_t(theta, 0))
```

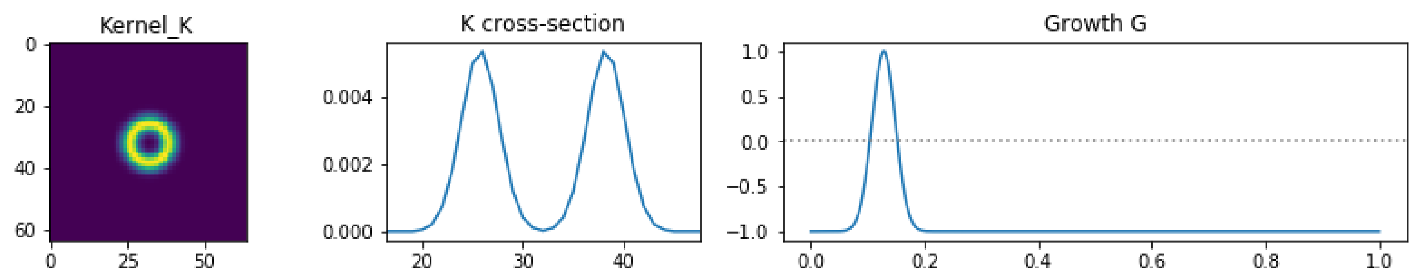
```
Mutant time:  331
Original orbium: 124
```

Let the evolution run on

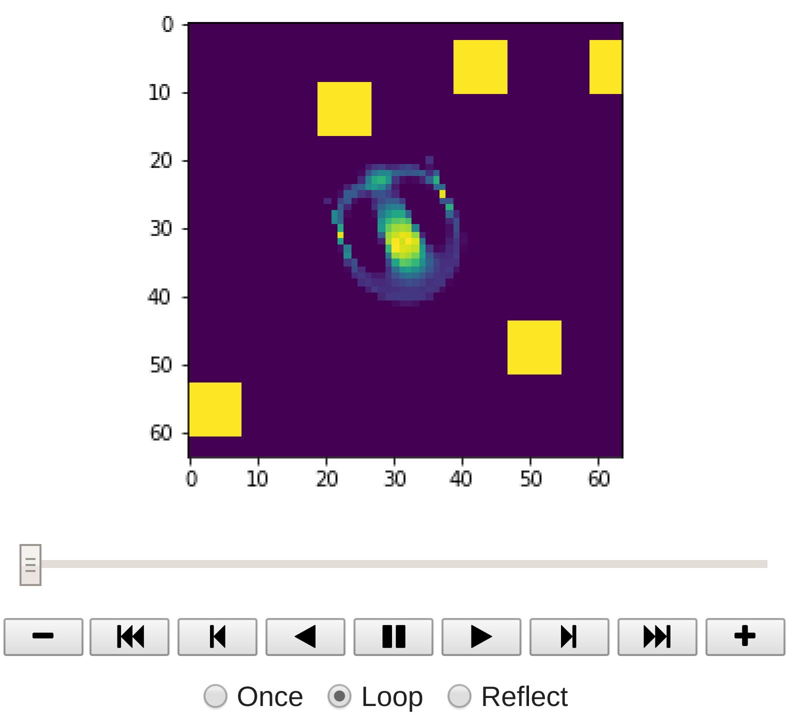
Using the same seed (0), I now allow it to run until it fixes over twenty five mutation/selection trials. While fixation of ten took roughly five minutes to run, this took hours.

In [123…

```python
# Let the evolution run on
# Fixation = 20

fix_20 = load_parameters("fixation_25_seed_0")
np.random.seed(0)
render(fix_20)
fig = figure_world(sum(As))
IPython.display.HTML(animation.FuncAnimation(fig, update, frames=500, interval=20).to_jsht
```



Out[123…



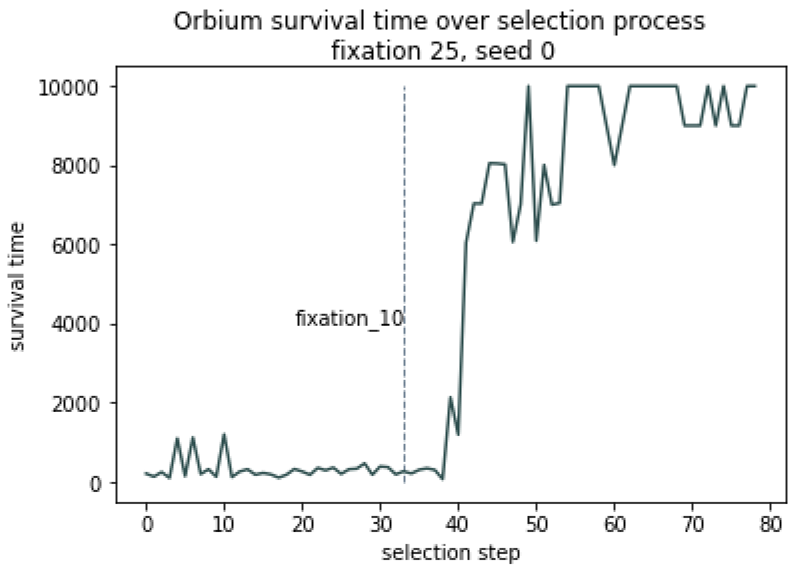
Overtime, the optimisation favours an explosion into many local, static rings. This will be because of our survival criteria, which only searches for living cells in the learning channel. Taking a look at the survival times below, we can see where this net-like distribution of localised patterns takes off, and the living cells live until the maximum time of 10,000 timesteps.

In [131…

```
dat = pd.read_csv("../sandbox/Lenia/results/time_logs/fixation_25_seed_0_times.csv")
plt.plot(np.arange(len(dat)), dat["wild"], color="darkslategrey")
plt.xlabel("selection step")
plt.ylabel("survival time")
plt.suptitle("Orbium survival time over selection process\n fixation 25, seed 0")
#plt.title("fixation 20, seed 0", fontsize = 10)
plt.vlines(33, ymin=0, ymax = 10000, colors="lightslategray", linestyles="dashed", linewic
plt.annotate("fixation_10", xy=(19, 4000), xytext=(19, 4000), fontsize=10)
```

Out[131…

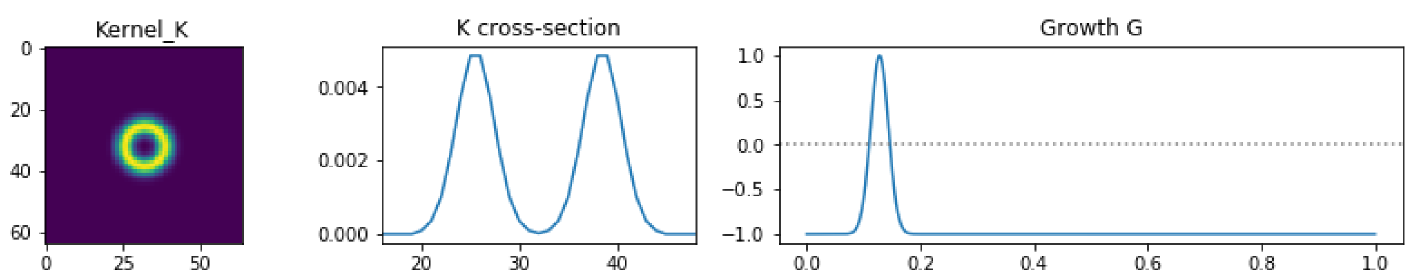
```
Text(19, 4000, 'fixation_10')
```



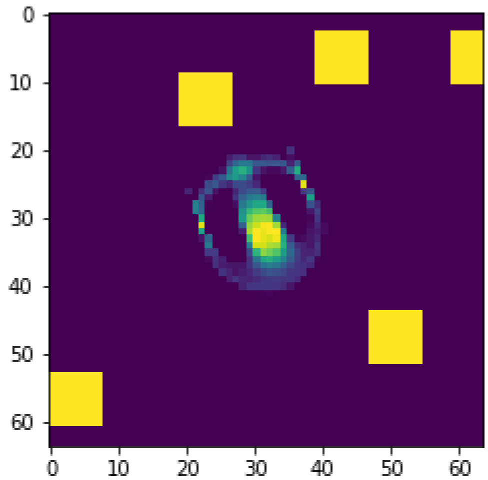
The dotted line above shows where selection ended in our fixation_10 results. We can see in one selection step (40/41) the survival time jumps up.

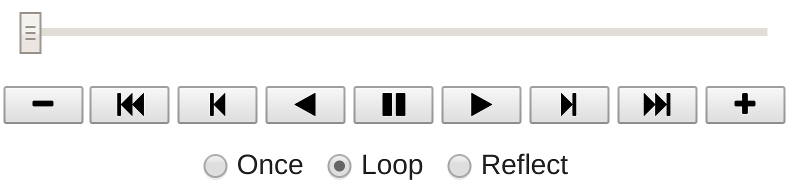
In [133…

```
## Render selection step 40
t40 = load_parameters("trials_40_seed_0")
render(t40)
np.random.seed(0)
fig = figure_world(sum(As))
IPython.display.HTML(animation.FuncAnimation(fig, update, frames=200, interval=20).to_jsht
```



Out[133…





Oddly it is not able to survive very long in this set of obstacles.

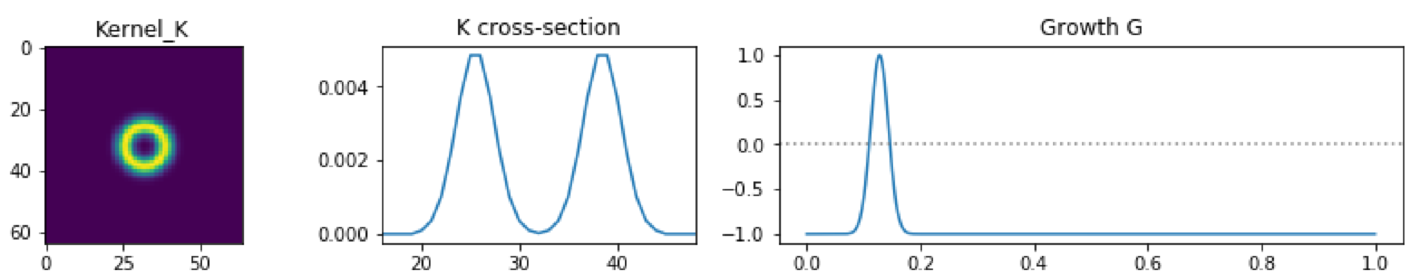
In [155…

```
print("obstacles seed 1: ", get_t(get_parameters(t40), 0))
print("obstacles seed 10: ", get_t(get_parameters(t40), 10))
print("obstacles seed 11: ", get_t(get_parameters(t40), 11))
```

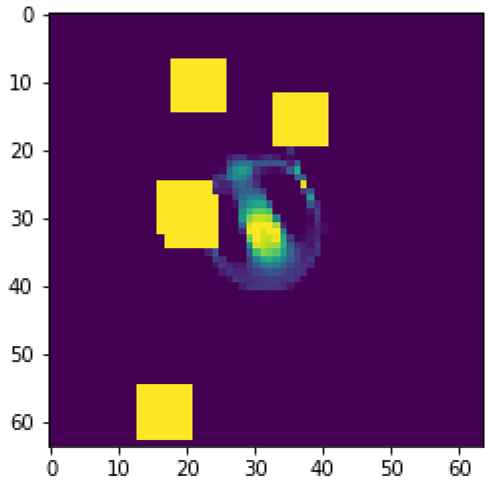
```
obstacles seed 1:  114
obstacles seed 10:  14
obstacles seed 11:  10001
```

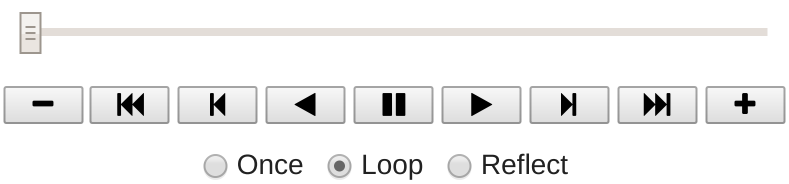
In [148…

```
render(t40, seed=11)
fig = figure_world(sum(As))
IPython.display.HTML(animation.FuncAnimation(fig, update, frames=200, interval=20).to_jsht
```



Out[148…

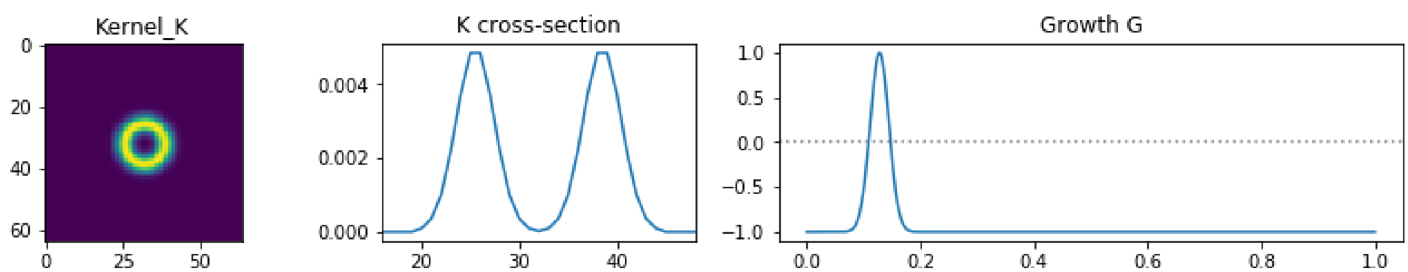




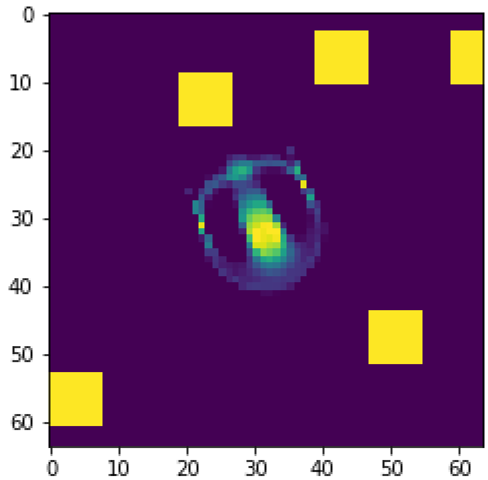
The right obstacle contacts throws it out into a new equilibrium of many localised, stable states. Allowing the "creature" to survive over many timesteps.

In [157…

```
t41 = load_parameters("trials_41_seed_0")
render(t41)
np.random.seed(0)
fig = figure_world(sum(As))
IPython.display.HTML(animation.FuncAnimation(fig, update, frames=500, interval=20).to_jsht
```



Out[157…



Once Loop Reflect

One timstep later, it appears to more ready to combust into lots of localised patterns.

How do we overcome this? One solution would be to make the "survival" criteria more specific. Rather than simply living cells, we check for living cells in a specific configuration... or of a specific size. This is similat to the machine learning methods used by the Flowers lab, which specifically aimed at training the creature to move in a localised shape from A to B through a field of obstacles.

However, imposing any outter constraints would be ad hoc, and would not show how a swimmer is more favourable than simply localised patterns spread out. Sense making/navigation needs to be selected for.

One possible solution is to introduce moving obstacles that will kills off any stable local patterns.

```
In [ ]:
```