

Image Approximation via Semi-Transparent Shape Evolution

Matteo Liotta

SM3800072

Optimization for Artificial Intelligence, 2025, UniTS - Final Project

Problem Introduction

Problem Introduction

This project is a revisit of the “Genetic-lisa” Peter Braden’s project, which aims to recreate images with genetic algorithms.,

It had different implementations over time, from Python to C

The base concept is to **evolve an image...**

- defined as a series of overlapping shapes
- /w (shape and color) mutation
- /w selection on image fitness
- /w crossover

... to reach a certain level of *similitude* with the original picture.



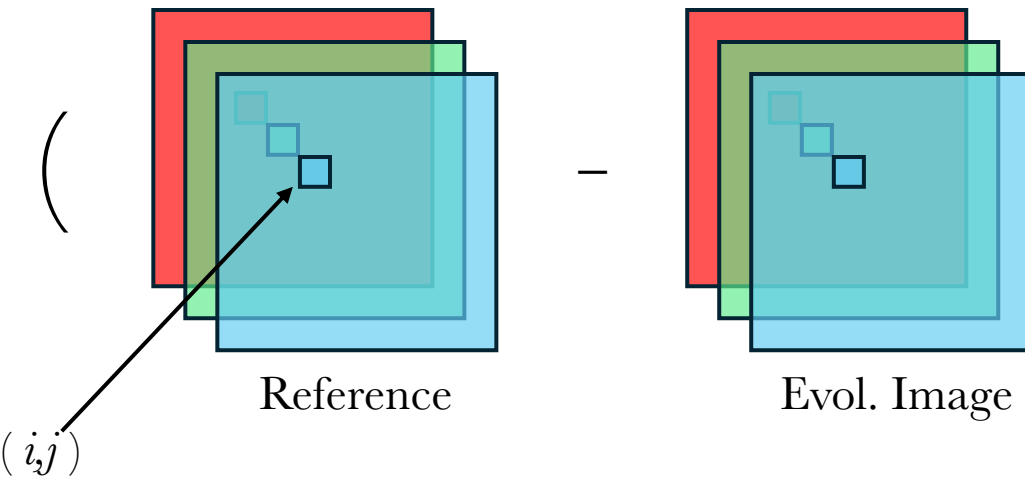
Problem Introduction

Similitude which is measured with defined objective function

$$\sum_{\substack{i=1,\dots,W \\ j=1,\dots,H}} \left(r_{i,j_{true}} - \widehat{r}_{i,j} \right)^2 + \left(g_{i,j_{true}} - \widehat{g}_{i,j} \right)^2 + \left(b_{i,j_{true}} - \widehat{b}_{i,j} \right)^2$$

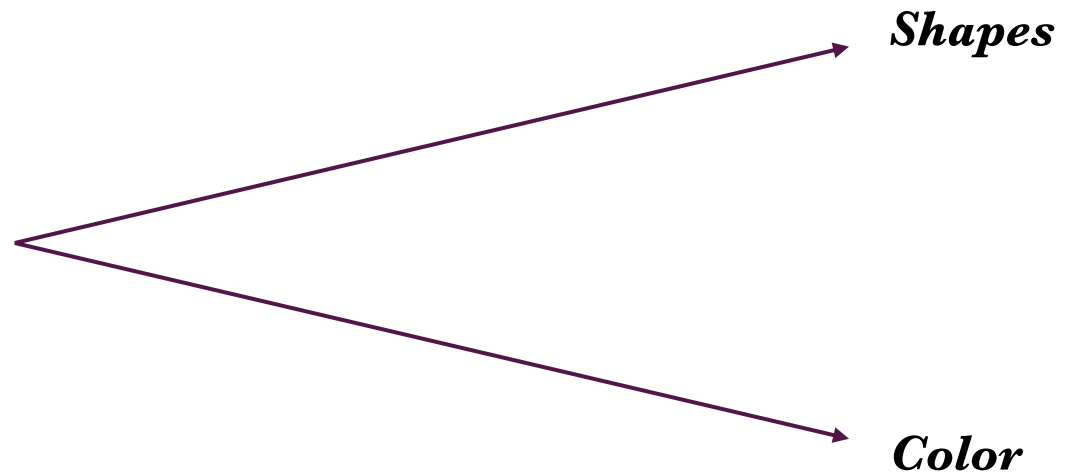
Problem Introduction

Similitude which is measured with defined objective function

$$\sum_{i,j} \left(\begin{array}{c} \text{Reference} \\ \text{Evol. Image} \end{array} \right)^2 \quad \begin{array}{l} \forall i = 1, \dots, W \\ \forall j = 1, \dots, H \end{array}$$


How are individuals defined?

How are individuals defined?



How are individuals defined?

Shape Definition

In the original code different shapes are proposed, but here we can focus on

- Ellipses
- Rectangle
- Triangles

defined as a dictionary of **name** and **coordinates**

```
{'type': 'triangle', 'coords': [44, 213, 93, 148, 163, 220]}
```


How are individuals defined?

Shape Definition

In the original code different shapes are proposed, but here we can focus on

- Ellipses
- Rectangle
- Triangles

defined as a dictionary of **name** and **coordinates**

```
{'type': 'triangle', 'coords': [44, 213, 93, 148, 163, 220]}
```

The diagram illustrates the mapping of the 'coords' list to three (x,y) coordinate pairs. The list [44, 213, 93, 148, 163, 220] is shown with three horizontal brackets underneath it. The first bracket, in blue, spans the first two elements (44, 213) and has a blue arrow pointing down to the text (x,y) in blue. The second bracket, in orange, spans the next two elements (93, 148) and has an orange arrow pointing down to the text (x,y) in orange. The third bracket, in purple, spans the last two elements (163, 220) and has a purple arrow pointing down to the text (x,y) in purple.

How are individuals defined?

Shape Definition

In the original code different shapes are proposed, but here we can focus on

- Ellipses
- Rectangle
- Triangles

defined as a dictionary of **name** and **coordinates**

```
{'type': 'rectangle', 'coords': [31, 136, 48, 160]}
```

```
{'type': 'ellispes', 'coords': [31, 136, 48, 160]}
```

How are individuals defined?

Shape Definition

In the original code different shapes are proposed, but here we can focus on

- Ellipses
- Rectangle
- Triangles

defined as a dictionary of **name** and **coordinates**

The diagram illustrates how the four coordinates in the 'coords' list of a shape dictionary are mapped to geometric parameters. It shows two identical dictionaries: `{'type': 'rectangle', 'coords': [31, 136, 48, 160]}` and `{'type': 'ellipse', 'coords': [31, 136, 48, 160]}`. For the rectangle, an orange arrow labeled **y** points to the second coordinate (136), and another orange arrow labeled **y + shape height** points to the fourth coordinate (160). For the ellipse, a blue arrow labeled **x** points to the first coordinate (31), and another blue arrow labeled **x + shape width** points to the third coordinate (48).

```
{'type': 'rectangle', 'coords': [31, 136, 48, 160]}
```

```
{'type': 'ellipse', 'coords': [31, 136, 48, 160]}
```

Shape Color Definition

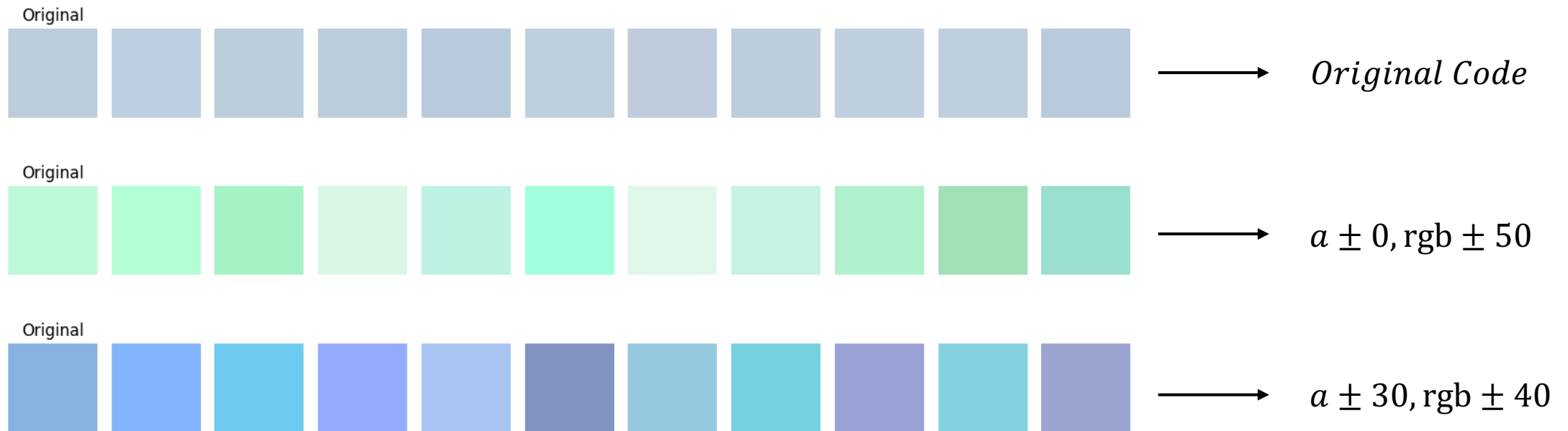
Also color could be generated, but the original code introduced (and didn't used) the **prev** input

```
def generate_color(prev = None, a_mutation = (-0x5,0x3), rgb_mutation = (-0x5,0x3)):
    if prev:
        return (prev[0] + random.randint(*a_mutation), # R
                prev[1] + random.randint(*rgb_mutation), # G
                prev[2] + random.randint(*rgb_mutation), # B
                prev[3] + random.randint(*rgb_mutation)) # A

    return (random.randint(0x33, 0x99), # R
            random.randint(0, 0xff), # G: between 0 and 255
            random.randint(0, 0xff), # B: between 0 and 255
            random.randint(0, 0xff)) # A: between 0 and 255
```

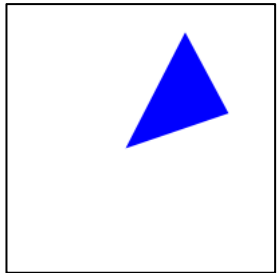
Shape Color Definition

This will be used inside the individual shape **mutation: using the *prev*** parameter we could *eventually* mutate the color avoiding random re-generation

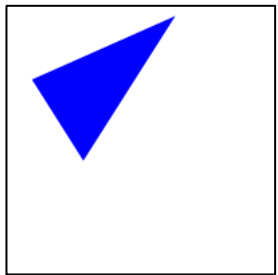


...Back to shape definition

This idea could be introduced in **shape mutation** too: it could avoid, eventually, random shape re-generation



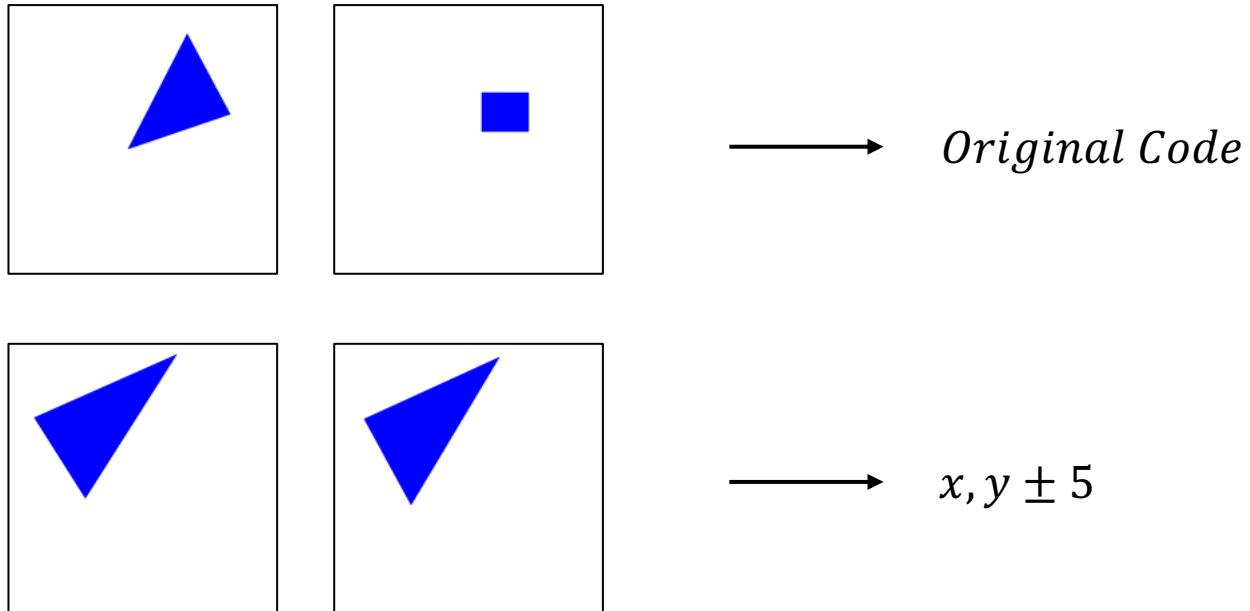
Original Code



$x, y \pm 5$

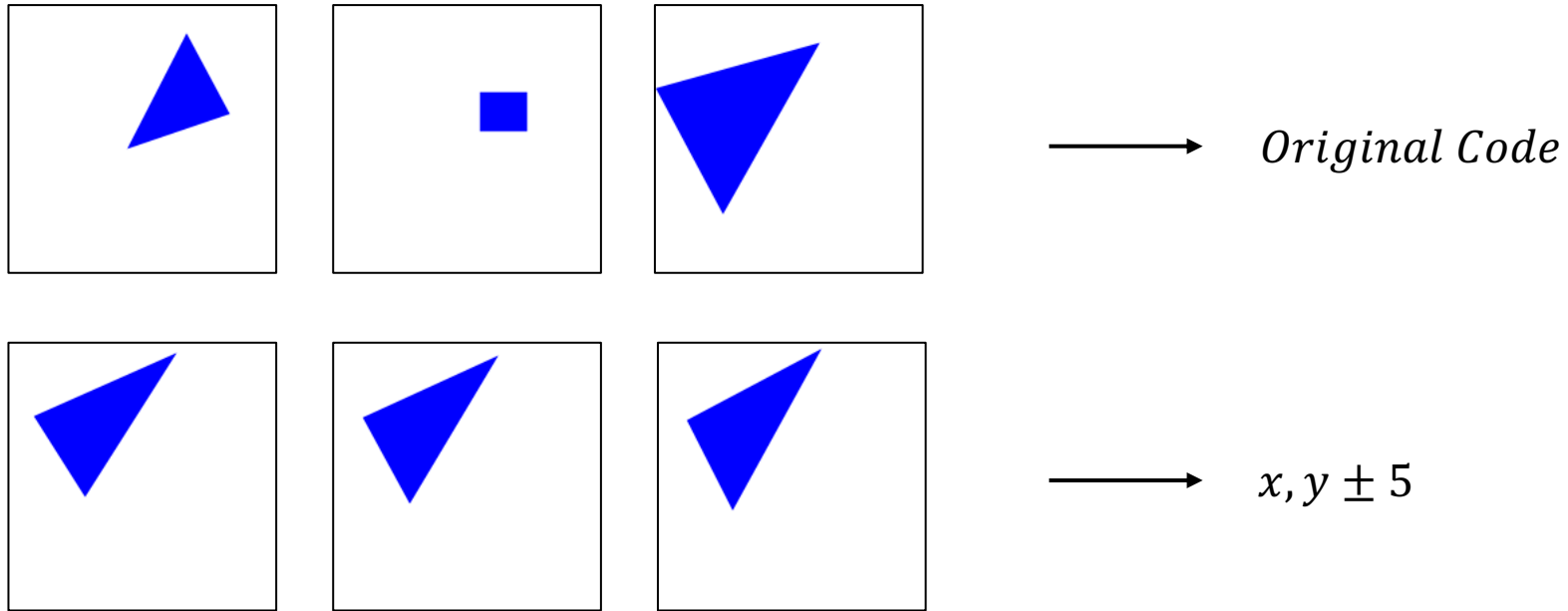
...Back to shape definition

This idea could be introduced in **shape mutation** too: it could avoid, eventually, random shape re-generation



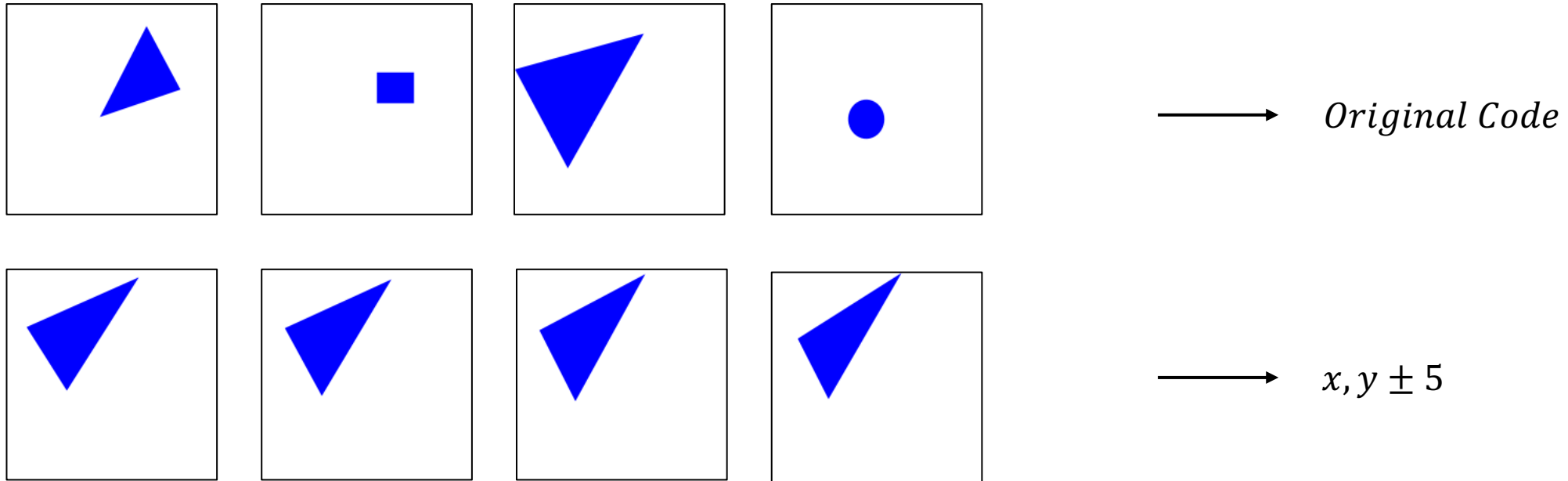
...Back to shape definition

This idea could be introduced in **shape mutation** too: it could avoid, eventually, random shape re-generation



...Back to shape definition

This idea could be introduced in **shape mutation** too: it could avoid, eventually, random shape re-generation



Individuals

The original code proposed a Strain **Class** to handle

- **Genotype** of individuals creation
- **Crossover** for individual creation from parents
- **Mutation**

Leading to a genotype...

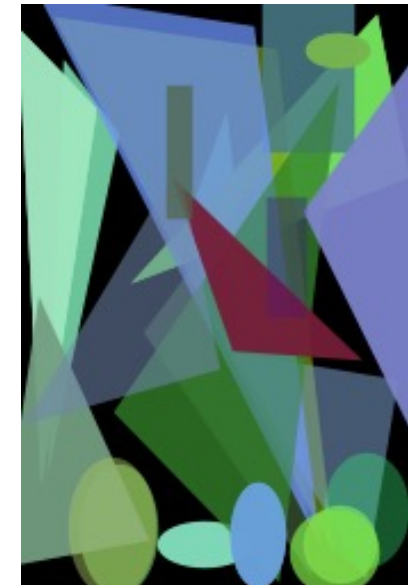
<i>Name</i>	<i>Dna</i>	<i>Fitness value</i>
<i>String</i>	<i>{shapes: {type, coordinates}, colors : color tuple}</i>	<i>Scalar</i>

Individuals

The original code proposed a Strain **Class** to handle

- **Genotype** of individuals creation
- **Crossover** for individual creation from parents
- **Mutation**

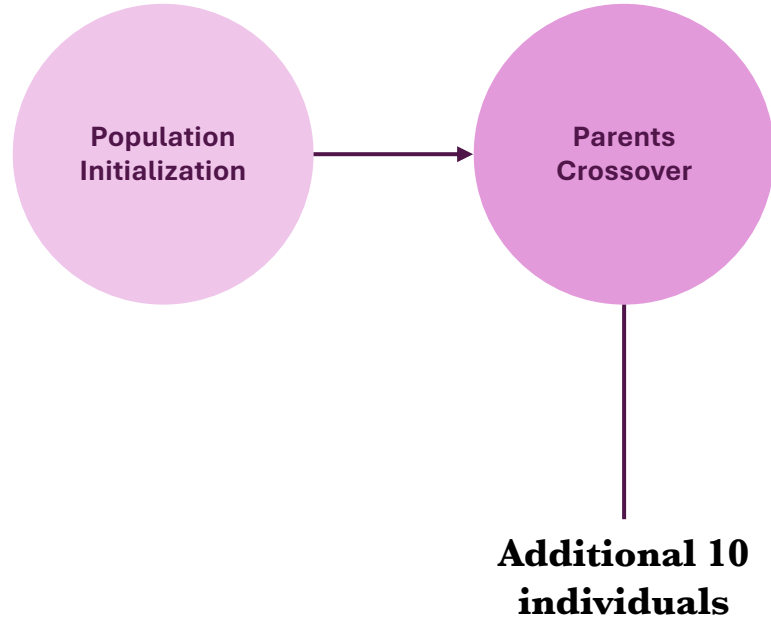
<i>Name</i>	<i>Dna</i>	<i>Fitness value</i>
<i>String</i>	<i>{shapes: {type, coordinates}, colors : color tuple}</i>	<i>Scalar</i>

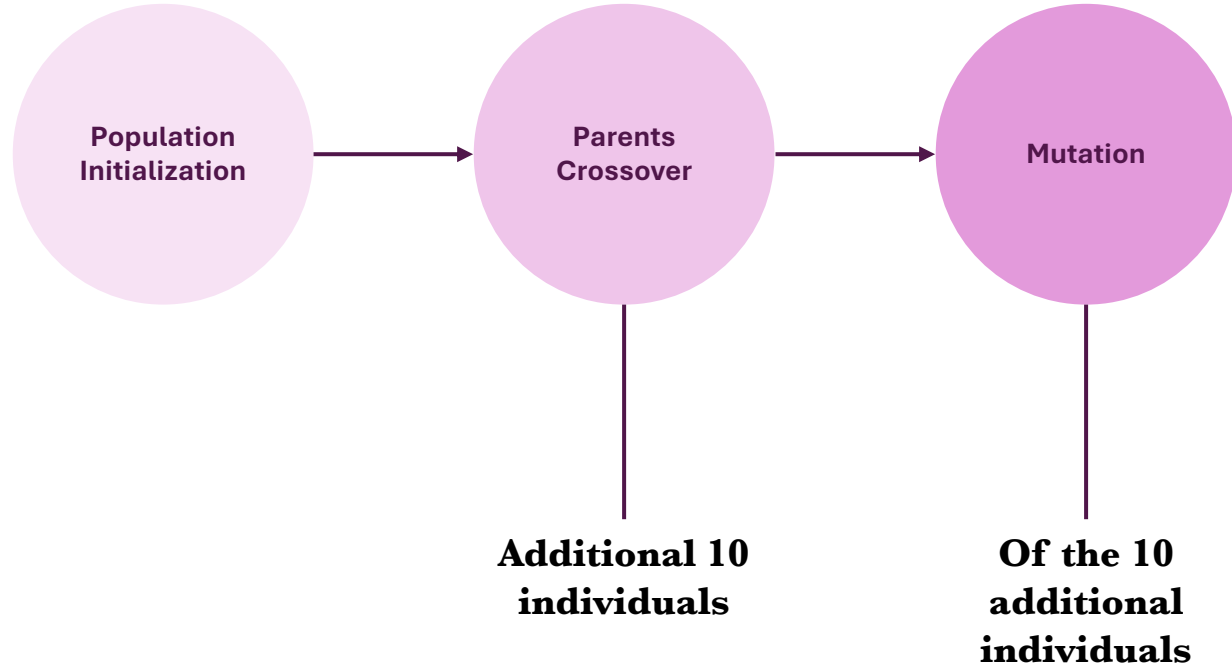


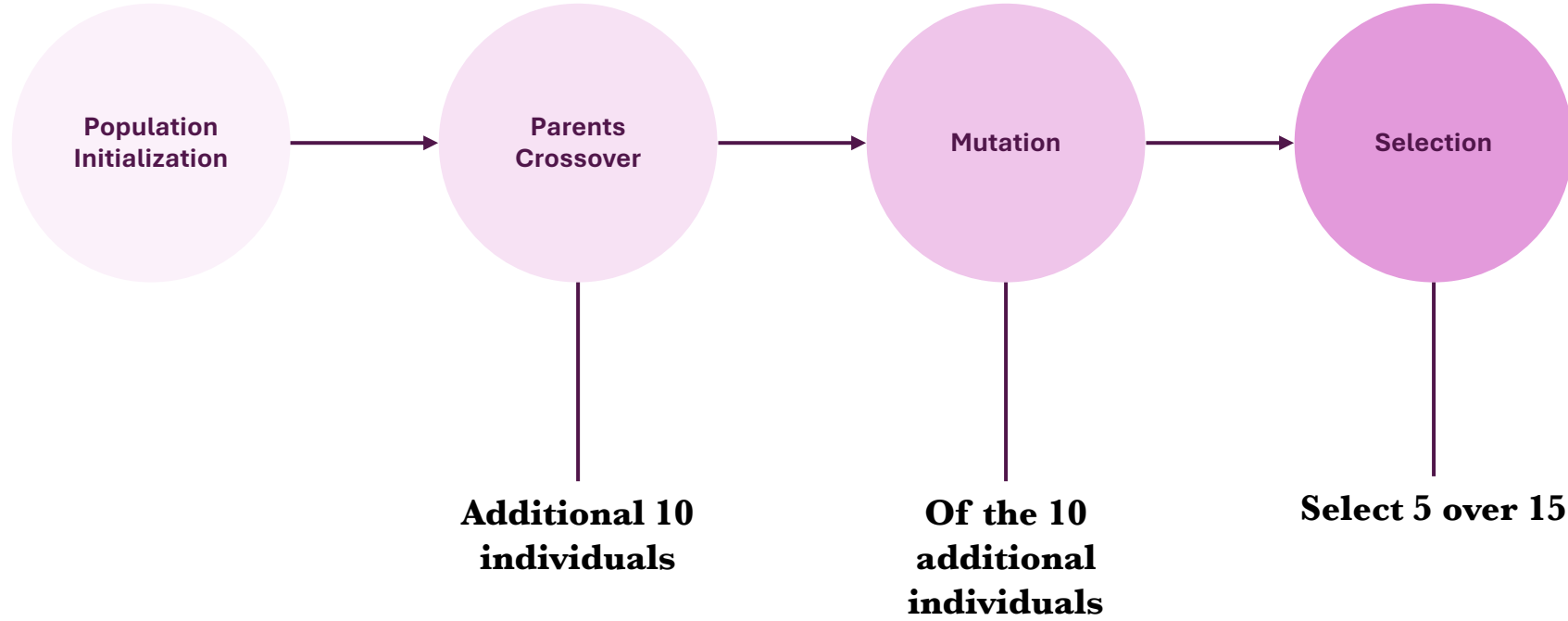
Evolutionary cycle

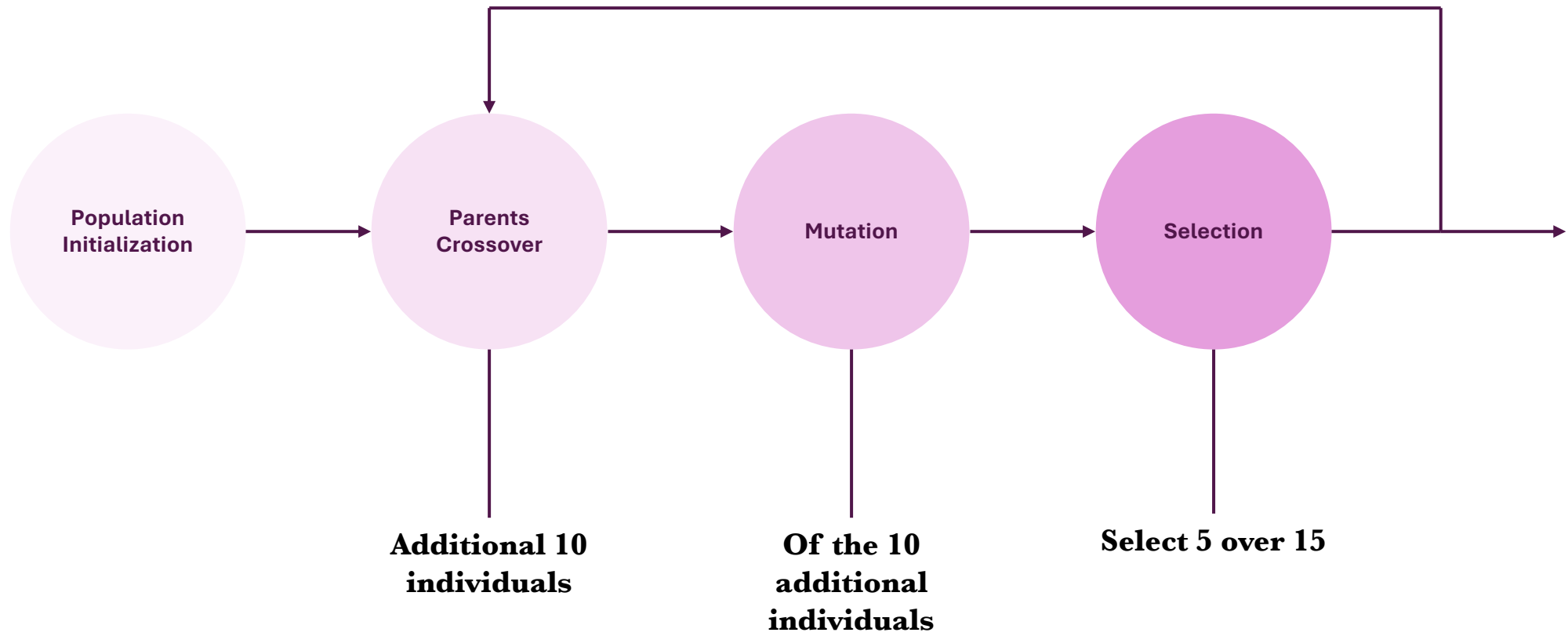


**Population
Initialization**







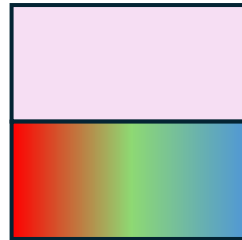


How is crossover defined?

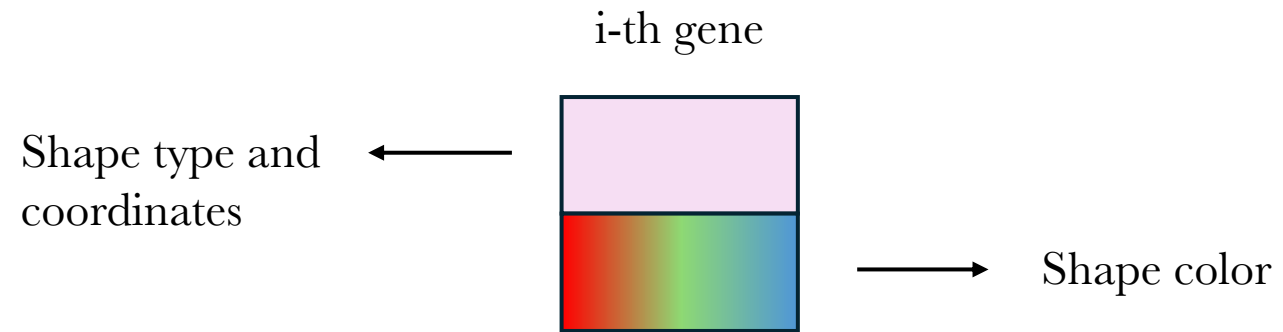
How is crossover defined?

Each individual has its own Dna, defined of atomic units: the genes

i-th gene



How is crossover defined?



How is crossover defined?

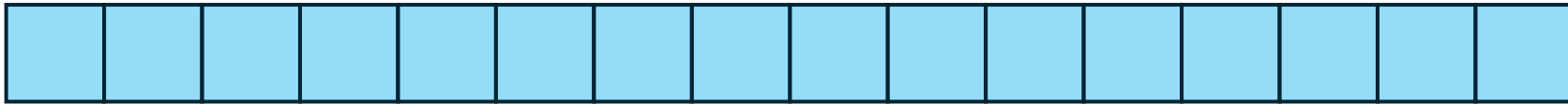
Individual dna



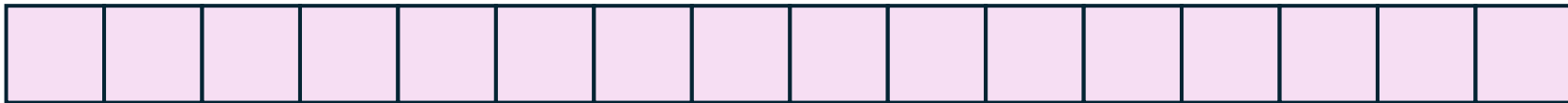
How is crossover defined?

We start with a parent population: each individual has its dna.

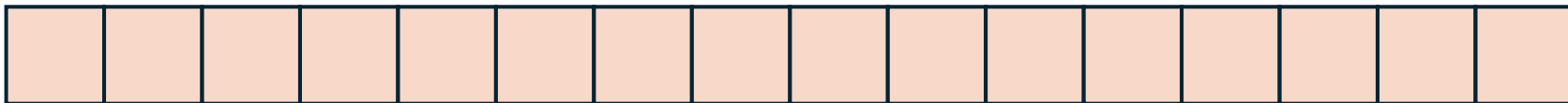
Parent 1



Parent 2

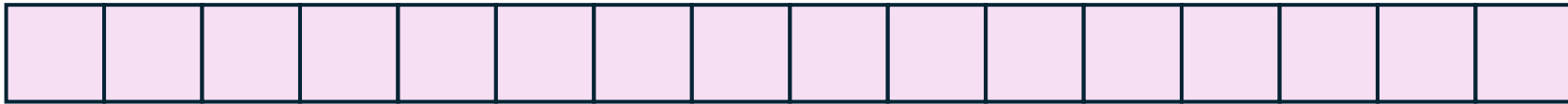


Parent 3



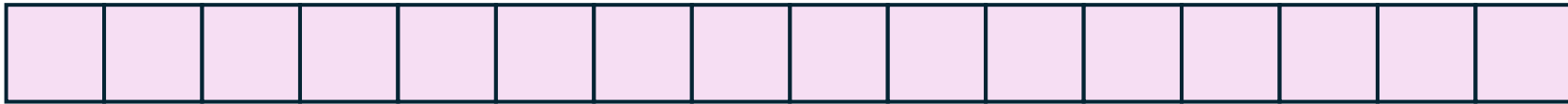
How is crossover defined?

To generate a new individual we select randomly a parent dna and deepcopy it.



How is crossover defined?

Then iterate on parents: change one random gene of in place of another of this offspring

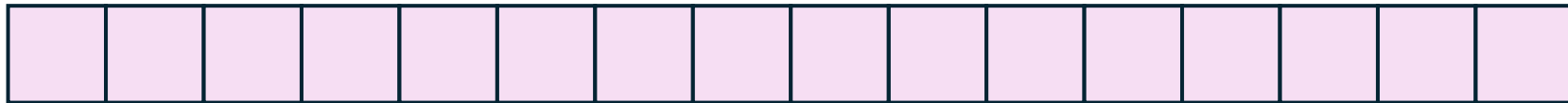


How is crossover defined?

Parent 1



Parent 2



How is crossover defined?

Parent 1



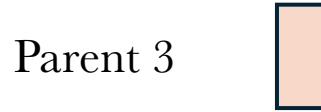
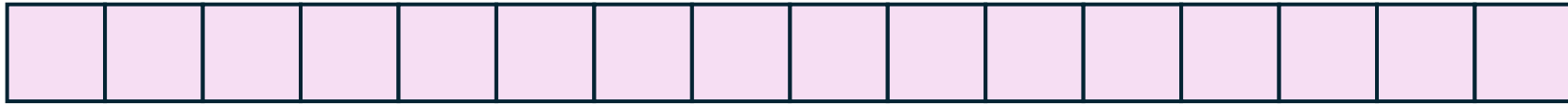
Parent 2



How is crossover defined?



Parent 2



Parent 3



How is crossover defined?



Parent 2



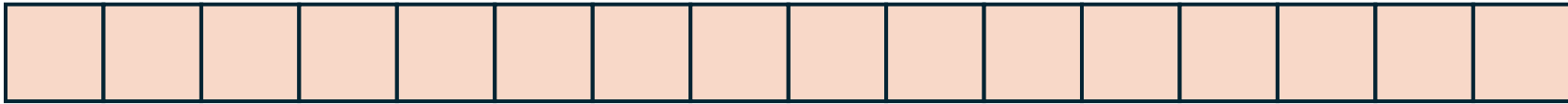
Parent 3



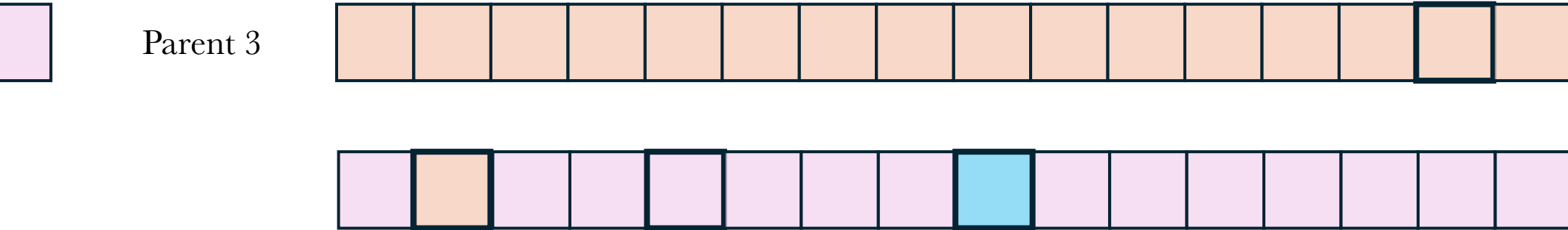
How is crossover defined?



Parent 3



How is crossover defined?



How is crossover defined?

After that, mutation will occur to each new offspring.



How is mutation defined?

Individuals

Three different actions:

- New random shape **appending** to offsprings DNA → *len<500 and 25% probability*
- Shape change and color **change** of a gene → *elif 75% probability*
- Random shape **removal** to offspring DNA → *else*

As introduced before, the function has been changed: now we can change a shape **not by deletion** and **random reinsertion**, but deletion and **conditionate reinsertion**.

(modified*) Original way: performances and results

* Changed mutation, reduced shape size, numpy fitness alternative

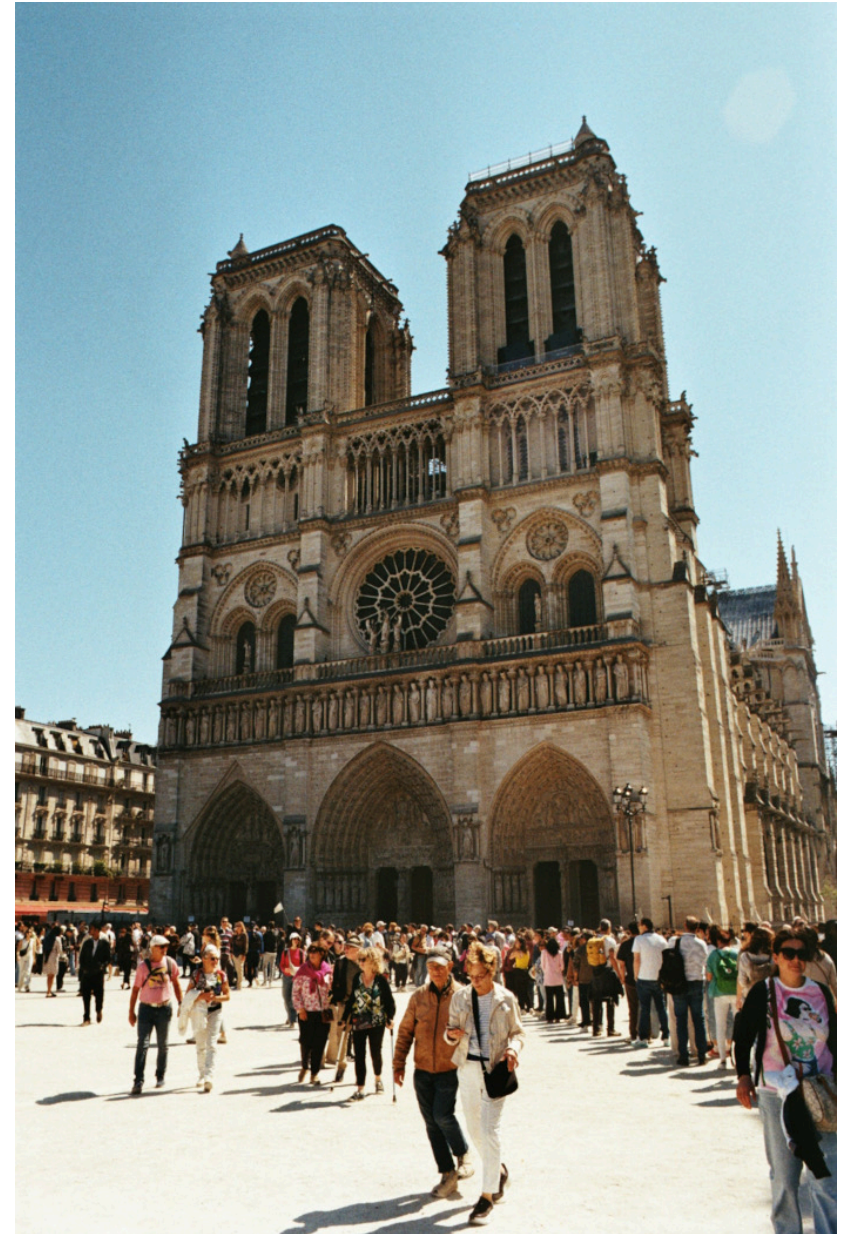
Example on Notre Dame

The example picture is a Notre Dame colored image I took this year in Paris.

The population initial parameters were

- Image_size: 170 x 256
- Generation_population: 10
- Crossover_population: 5

Over 30000 epochs.







The result isn't so good...

In addition, evaluation time is a problem

Why don't we change the approach?

How can we speed up evolution?

How can we speed up evolution?



***Multiprocessing
patches
evolution***

***Fitness
simplification***

Patches idea introduction

The main idea is to take advantage of multi-core processing.

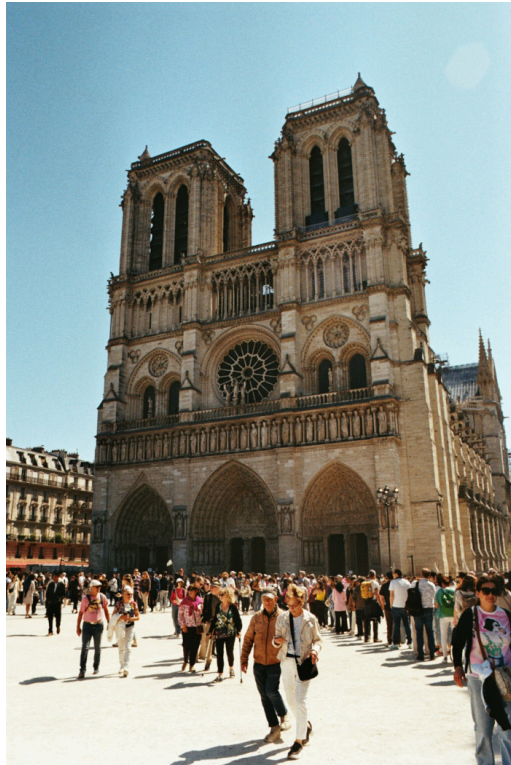
Notice this is related to the number of cores available

Considering that...

- The image must be big enough
- We cannot evolve on different nodes (evaluation problem)

So the idea is to break and cut the image... into smaller pieces...

Patches idea introduction



#processes=8



Patches idea introduction

... and evolve independently each piece.

We would have many advantages:

- Each core could handle evolution independently on a sub part of the image (patch)
- **Since shape sizes are canvas related, more precision should be present**
- We should notice a **speed increase** since fitness evaluations would be on smaller images, proportional to the number of cores
- Over same number of epochs we end up with core-number times more shapes
- **No assumptions** or reduced set of shapes and colors

+ Now we can measure shape sizes with a parameter

Fitness function revisited

+ we can define an alternative fitness which is the L1 norm:

```
def fitness(self):
    return self._fitness or self._fitness_func()
def _fitness_func(self):
    ref_img = self.reference_image.convert("RGBA")
    draw_img = np.array(self.draw().convert("RGBA"), dtype=np.int16)
    ref_img = np.array(ref_img, dtype=np.int16)
    diff = draw_img[:, :, :3] - ref_img[:, :, :3]
    fitness = np.sum(np.abs(diff))
    self._fitness = fitness
    return fitness
```

Modified way: (compared) performances and results

Time comparison

Original* Project

~**30000** Training Epoch

Evolution Time: ~ **1h 30 min**

Revisited Project

~ **40000** Training Epoch

Evolution Time: ~ **30 min**

Same parameters

8 processes on 8 core laptop

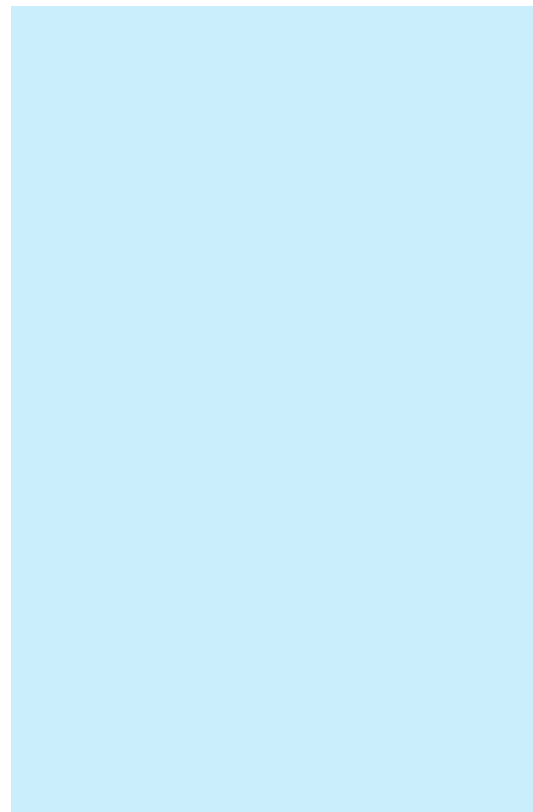
L1 approximated fitness



Original*



Reference



Revisited



Original*



Reference



Revisited



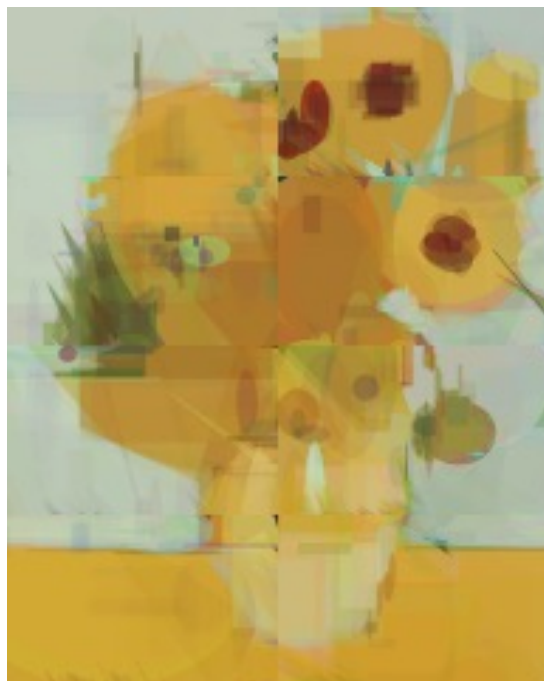
Can we do something more?

Can we do something more?  *Shape size
reduction
ratio**

* w.r.t. image size



Reference

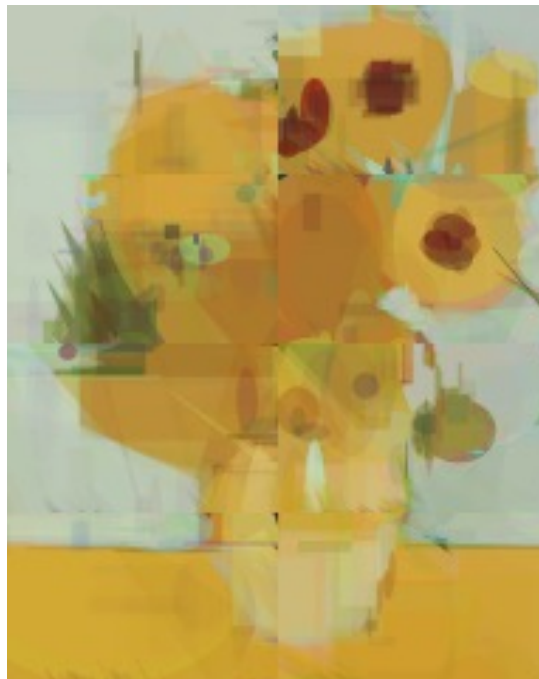


**Small Shapes Evolution
1000 epochs**



Big Shapes Evolution
1000 epochs

We see a great improvement with a **higher shape size reduction rate** on fixed number of patches (8)



Small Shapes



Big Shapes

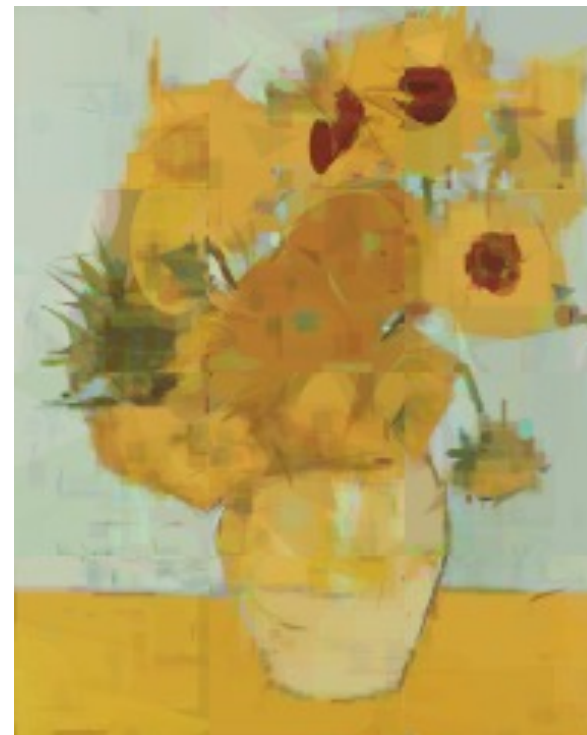
* The size is proportional to patch reference size

We can finally see results with:

- Patches and multiprocessing introduction
- More efficient loss
- Random re-generation avoidance for shapes and colors
- Better shape random generation
- Shape size ratio introduction



Reference



Small Shapes Evolution
50000 epochs



Reference

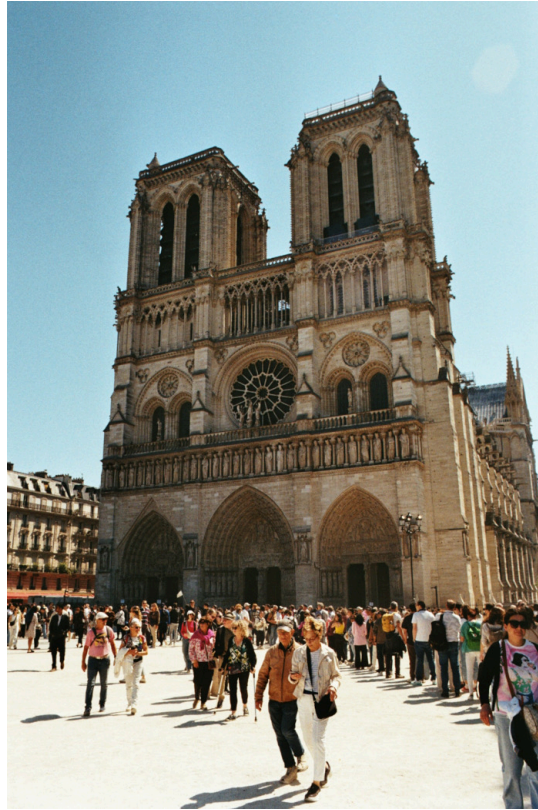


Small Shapes Evolution
50000 epochs

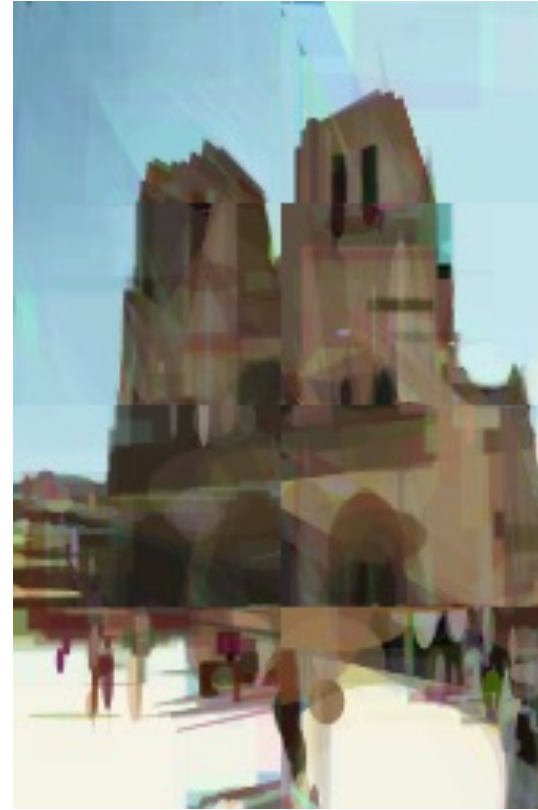
Final Notre Dame visual comparison



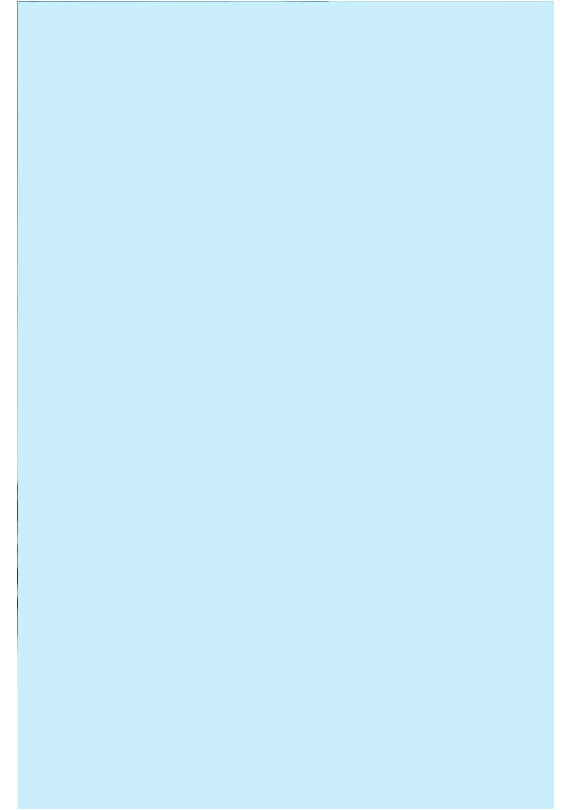
Original*



Reference



Revisited



Small shape revisited



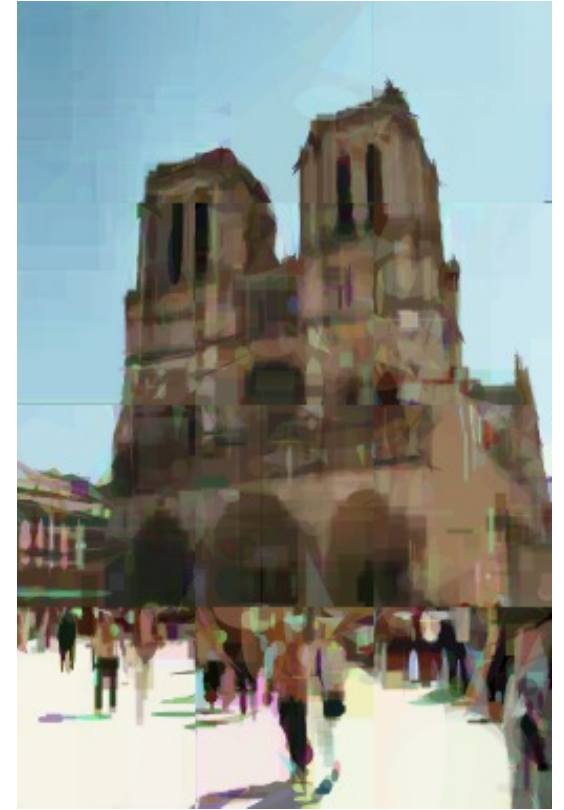
Original*



Reference



Revisited



Small shape revisited

Project References

- [1] The evolution of a Smile, Peter Braden: <https://github.com/peterbraden/genetic-lisa/>
- [2] Mona Lisa Gif Evolution: <https://github.com/peterbraden/genetic-lisa/blob/master/images/lisa-anim.gif>
- [3] Vase with Twelve Sunflowers (Arles, August 1888), Van Gogh. Neue Pinakothek, Munich: https://commons.wikimedia.org/wiki/File:Vincent_Willem_van_Gogh_128.jpg
- [4] La persistenza della memoria, Dalì: https://www.analisedellopera.it/wp-content/uploads/2018/10/Dali_La_persistenza_della_memoria-1.jpg