University of Antwerp

Image painting using Genetic Algorithms and Classifiers

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Table of contents

- Introduction
- Initial goal
- Project
  - Genetic Algorithm
  - CNN Classifier
  - First Integration
  - Siamese Networks
  - Second Integration
- Conclusion

Introduction

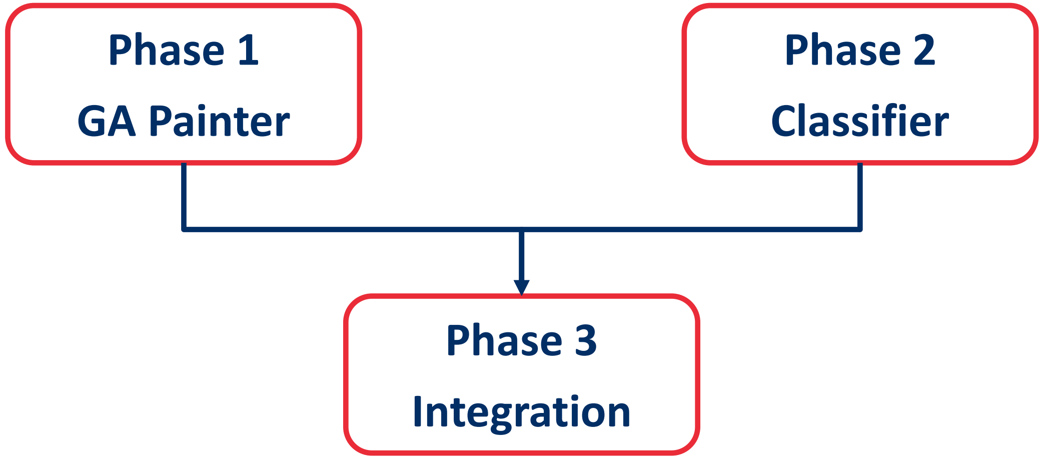
Introduction

- **Genetic algorithms project**
- **Professor Oramas and Ms. Haidar**
- **Weekly meeting**
- **Milestones**

Initial goal

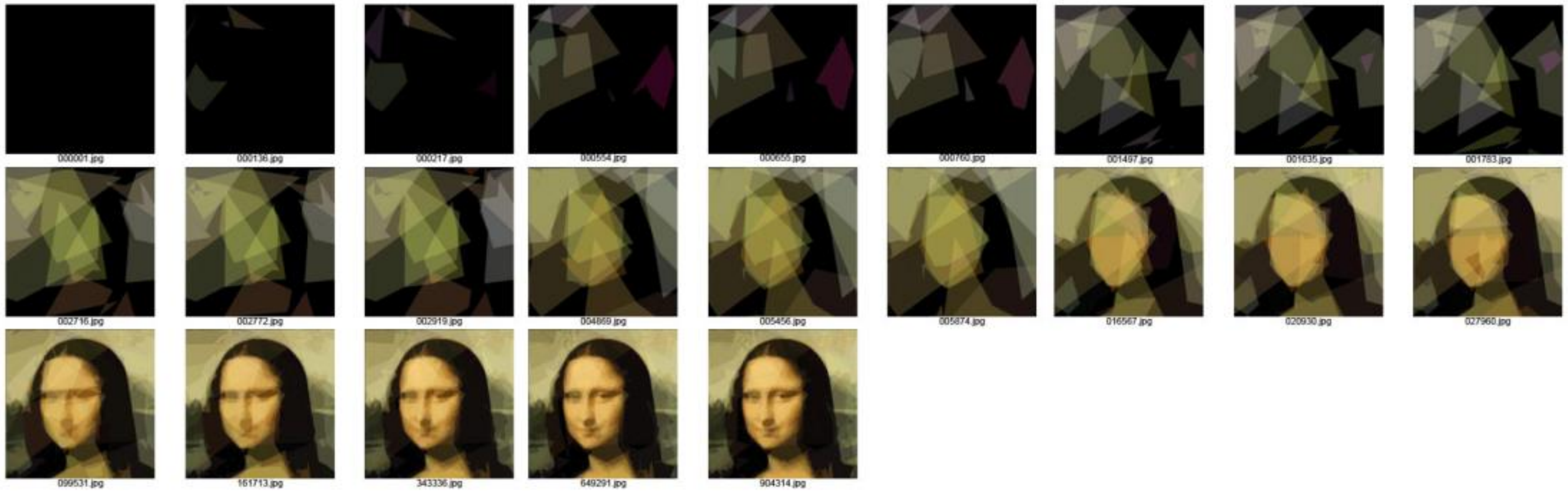
The plan

- Divide and conquer
- Three phase plan
- First two phases simultaneously



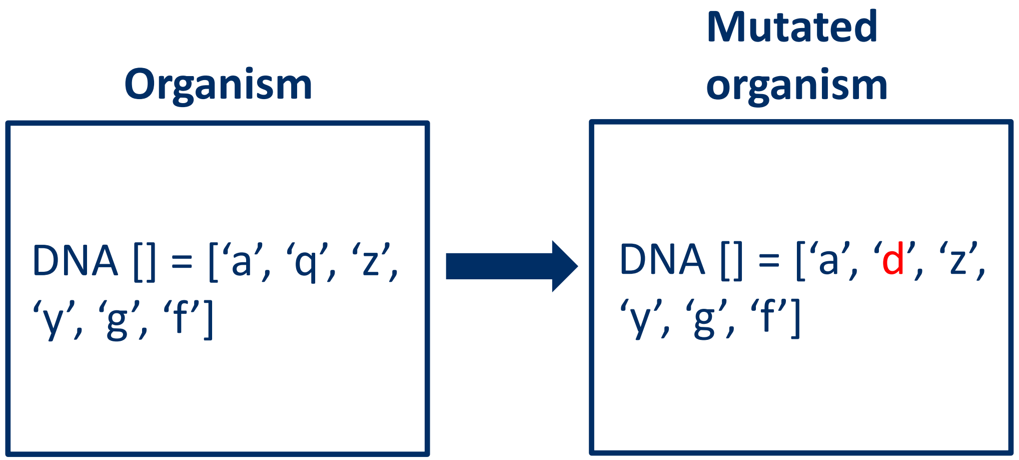
Phase 1 - The painter

- **Approximating a reference image**



Phase 1 - the painter

- **Approximating a reference image**



Organism

DNA [] = [‘a’, ‘q’, ‘z’, ‘y’, ‘g’, ‘f’]

Mutated organism

DNA [] = [‘a’, ‘d’, ‘z’, ‘y’, ‘g’, ‘f’]

Phase 2 – The classifier

- Fitness function for genetic algorithm
- Training to recognize
- Evolve

INPUT

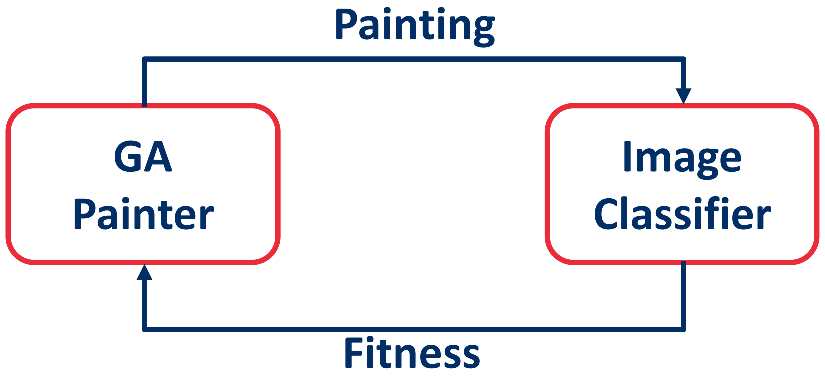
. . .

Predicted: American Lizard
Confidence: 95%

OUTPUT

Phase 3 – Integrating the parts

- **Combine classifier and genetic algorithm painter**



Project progress

Genetic algorithm

Genetic algorithm - practical considerations

- **Giorgi, Ilias & Viktor**
- **Constraints:**
  - Greyscale
  - Low resolution images
  - Simple dataset
- **Orientation**

Genetic algorithm - Pipeline

Organism

DNA [] = list of genes

Example

DNA [] =
[‘a’, ‘q’, ‘z’, ‘y’, ‘g’, ‘f’]

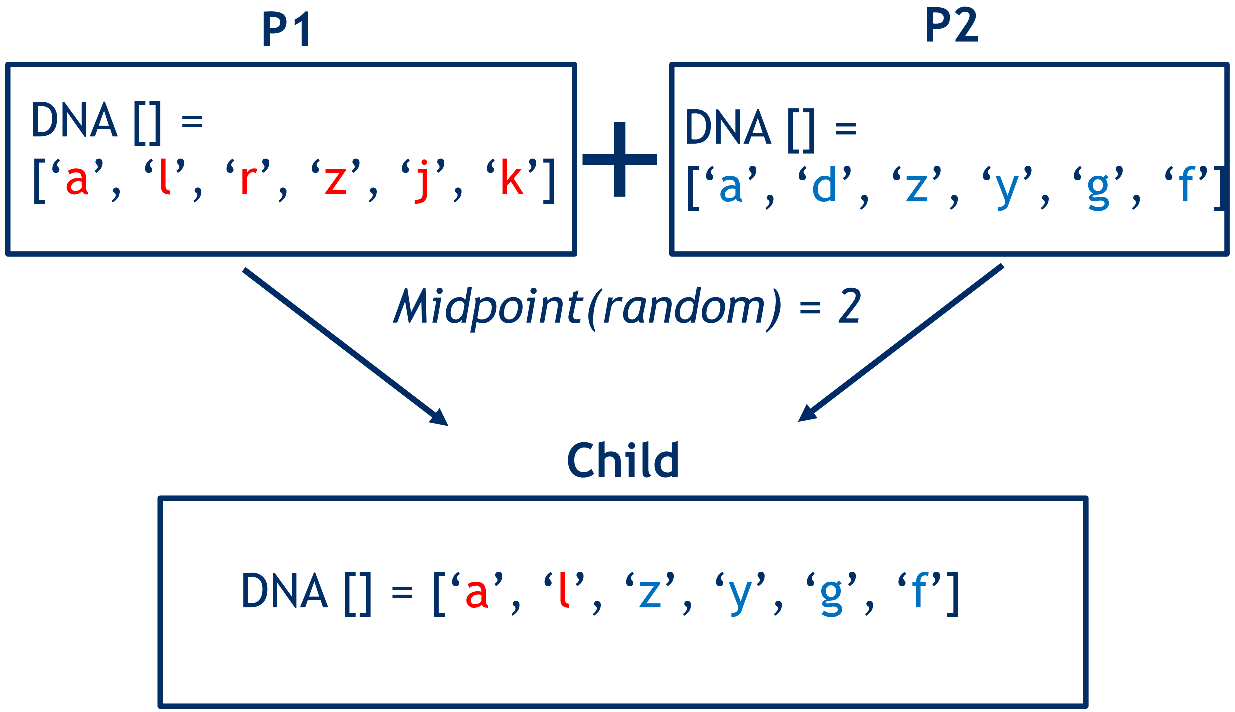
Mutation phase

Organism

DNA [] =
[‘a’, ‘d’, ‘z’, ‘y’, ‘g’, ‘f’]

*Each gene has a {**mutationRate**} % chance to mutate*

Crossover phase



P1

DNA [] =
[‘a’, ‘l’, ‘r’, ‘z’, ‘j’, ‘k’]

+

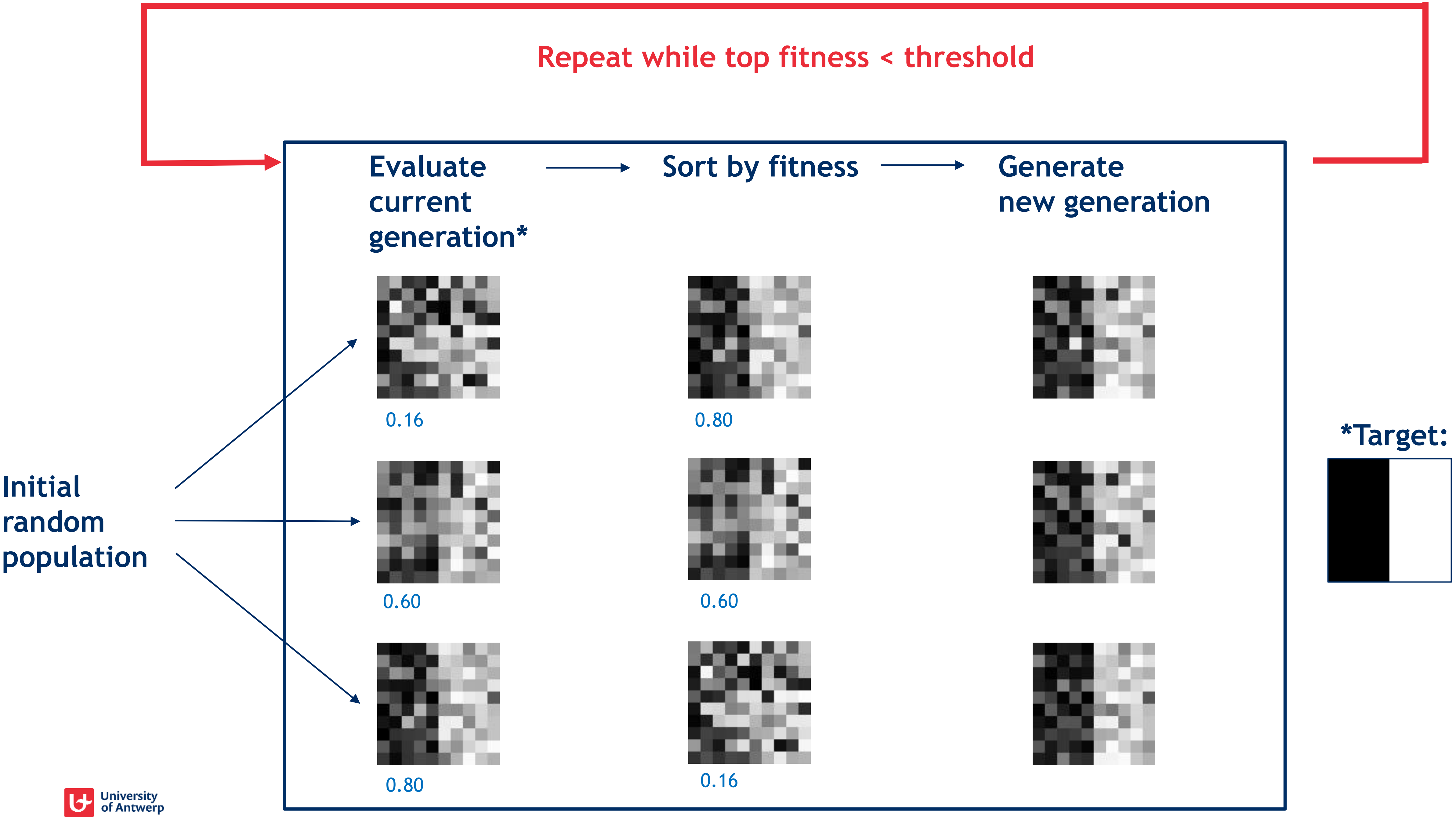
P2

DNA [] =
[‘a’, ‘d’, ‘z’, ‘y’, ‘g’, ‘f’]

Midpoint(random) = 2

Child

DNA [] = [‘a’, ‘l’, ‘z’, ‘y’, ‘g’, ‘f’]



Repeat while top fitness < threshold

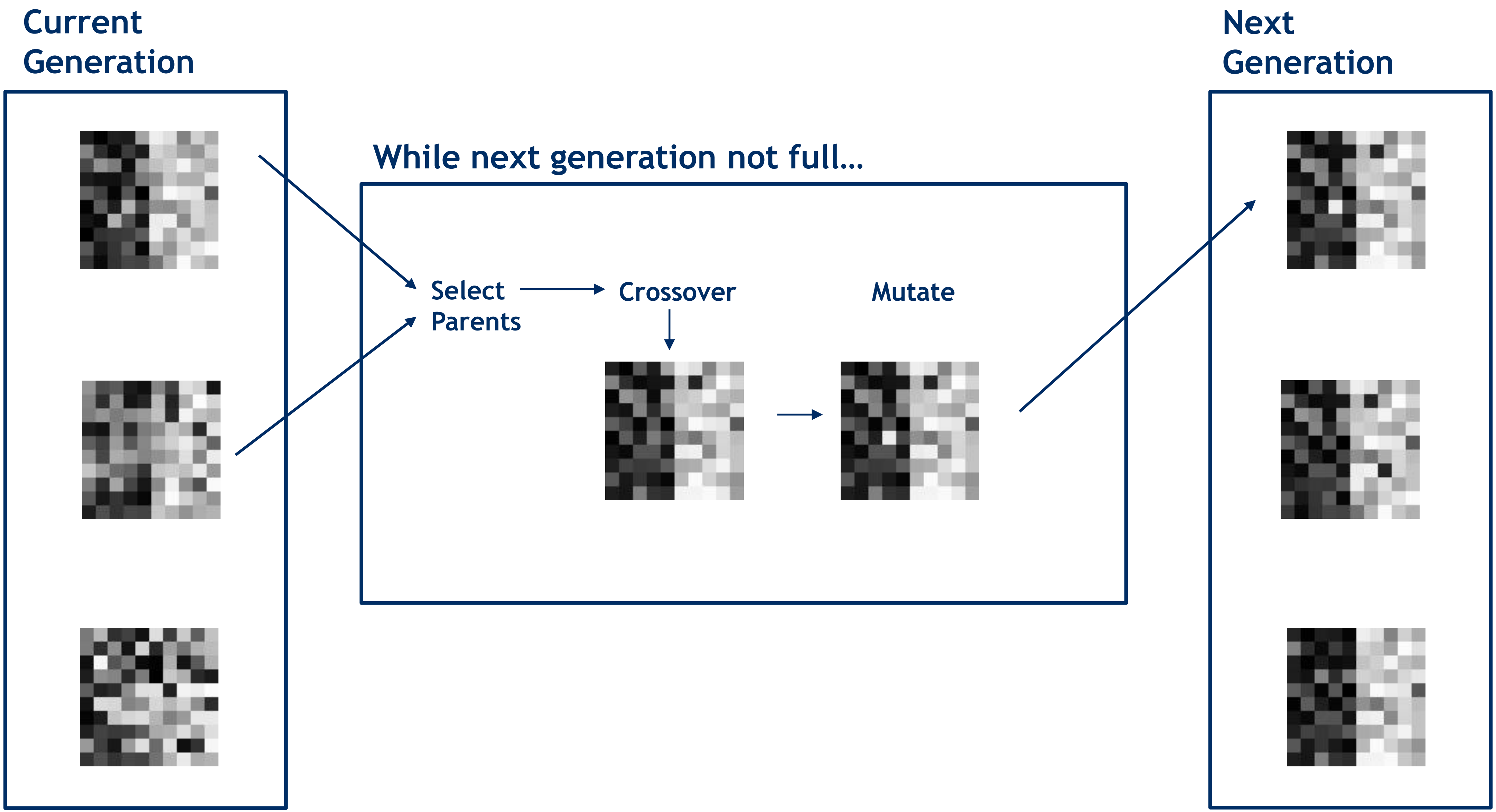
Initial random population

Evaluate current generation*

Sort by fitness

Generate new generation

*Target:



Current Generation

While next generation not full...

Select Parents

Crossover

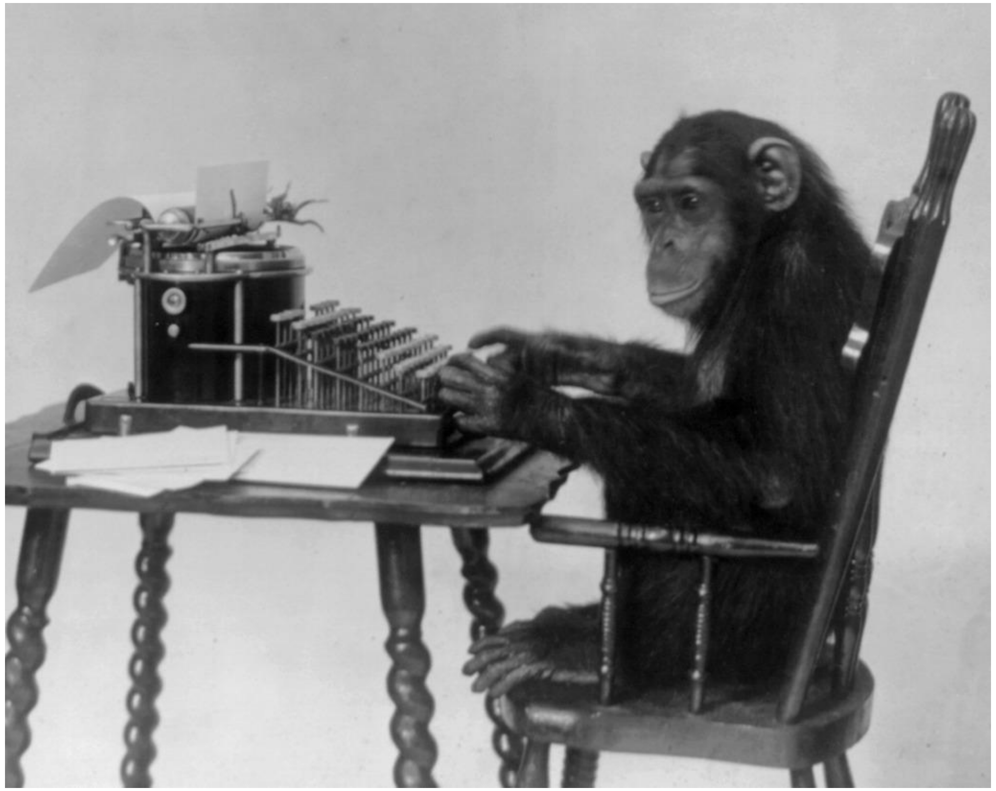
Mutate

Next Generation

Genetic algorithm – basic implementation

- **Implemented with strings**
- **Infinite Monkey Theorem**

```
DNA [] =
[‘t’, ‘o’, ‘b’, ‘e’, ‘o’, ‘r’, ‘n’, ‘o’, ‘t’, ‘t’, ‘o’, ‘b’, ‘e’]
```



Genetic algorithm – basic implementation

- **Ref Target:** to be or not to be

GENERATION	AVERAGE FITNESS	BEST FITNESS	BEST ORGANISM
0	0.033889	0.222222	`trybpuolsjlgjwpcue`
1	0.081667	0.222222	`trybpuolsjlevfgree`
2	0.130556	0.277778	`trybpuo  dzvsnc tn`
3	0.176111	0.333333	`trybe eoxmmy   cue`
4	0.222222	0.388889	`trybpuolsjsr ty je`
5	0.270278	0.444444	`tr drlmn ndr ty bf`
6	0.320556	0.5	`trybe obngotxwe te`
7	0.366667	0.555556	`trybe ovwnolaty te`
8	0.416111	0.555556	`trybe ovwnolaoo je`
9	0.455556	0.666667	`trybe objzot ty be`
10	0.503889	0.666667	`trybe objzot ty be`
11	0.55	0.722222	`tocbe ohynotety be`
12	0.592778	0.722222	`tocbe objzot ty be`
13	0.632222	0.722222	`trybe objzot to be`
14	0.663611	0.777778	`toybe ovwnot ty be`
15	0.690833	0.833333	`toybe oh vot to be`
16	0.726667	0.833333	`toybe ab not to be`
17	0.754722	0.888889	`torbe oh not to be`
18	0.792222	0.888889	`tocbe ob not to be`
19	0.822222	0.944444	`toybe or not to be`
20	0.853611	0.944444	`tocbe or not to be`
21	0.880556	1	`to be or not to be`

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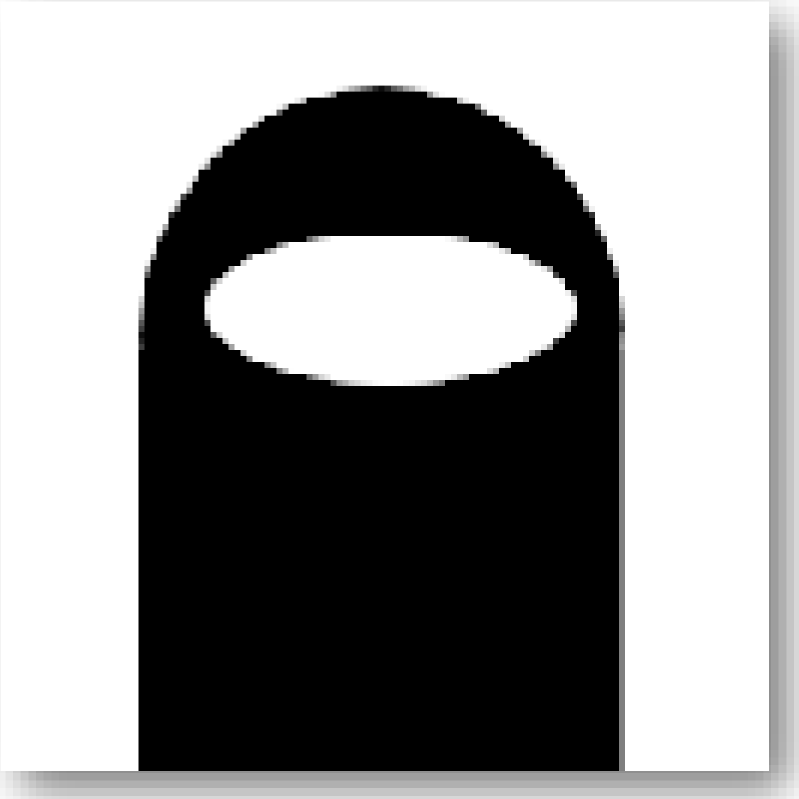
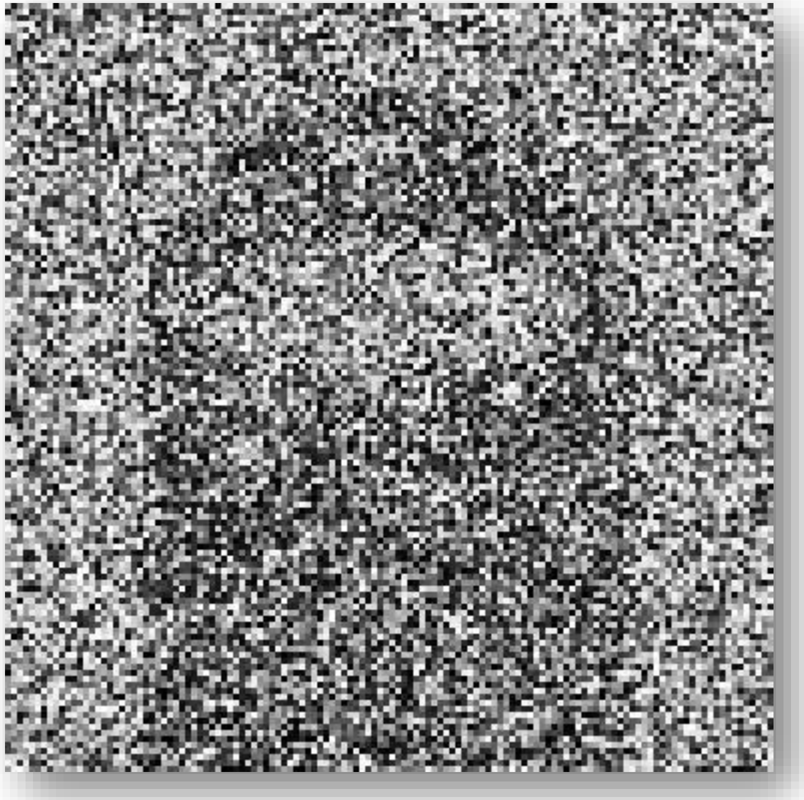
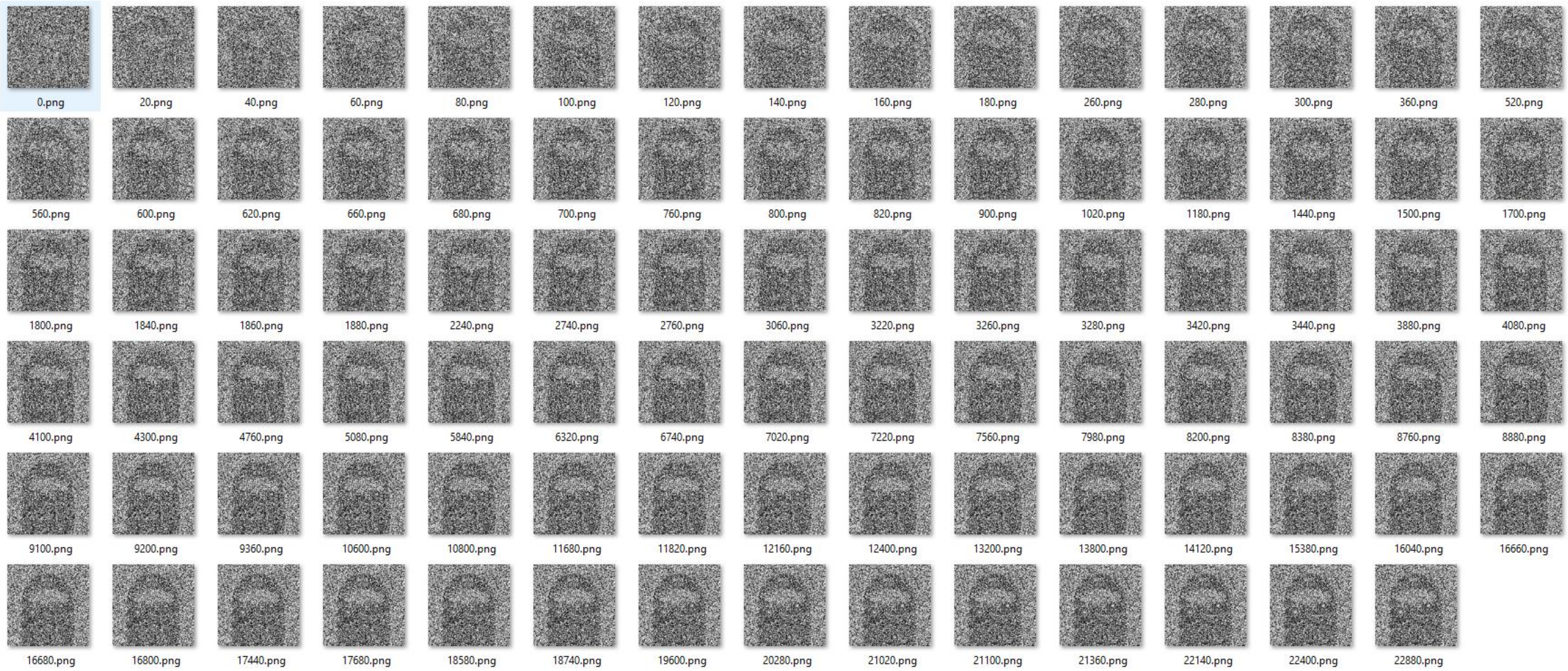
Genetic algorithm – basic implementation

- **First pixel test**
- **It’s getting there, but suffers *Premature Convergence***



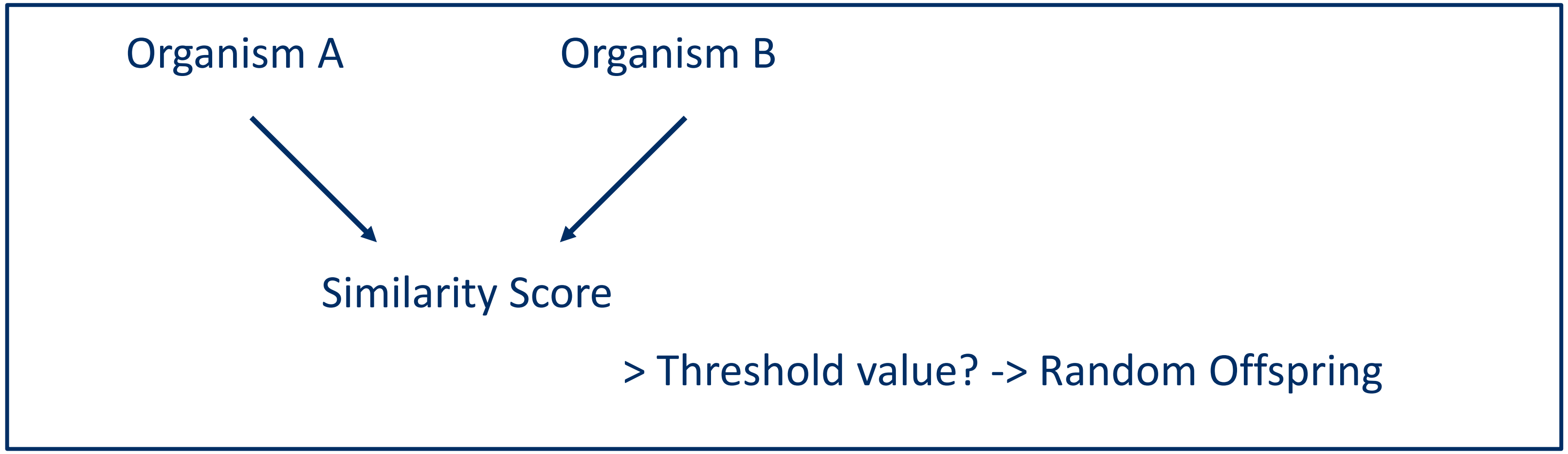


Genetic algorithm – basic implementation



Genetic algorithm – basic implementation

- **Preventing Premature Convergence:**
    - Adding special algorithms to counteract the problem
        - Random Offspring Generation (ROG)



Organism A

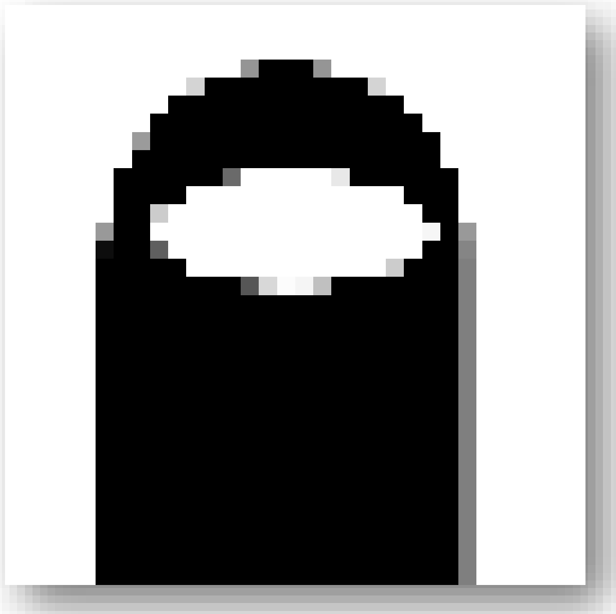
Organism B

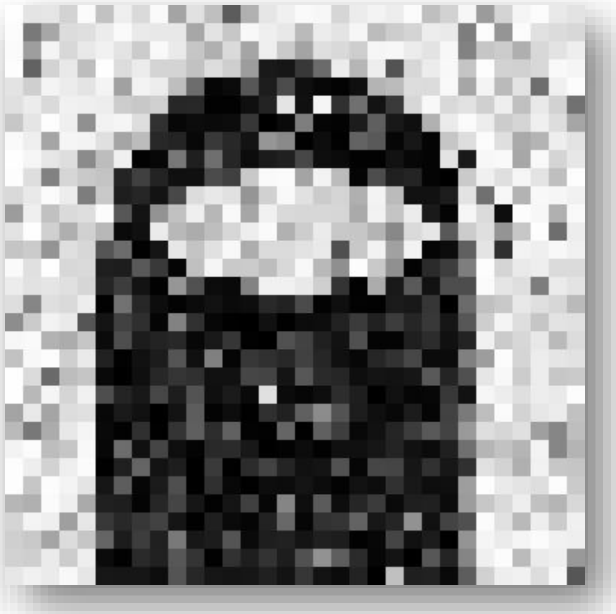
Similarity Score

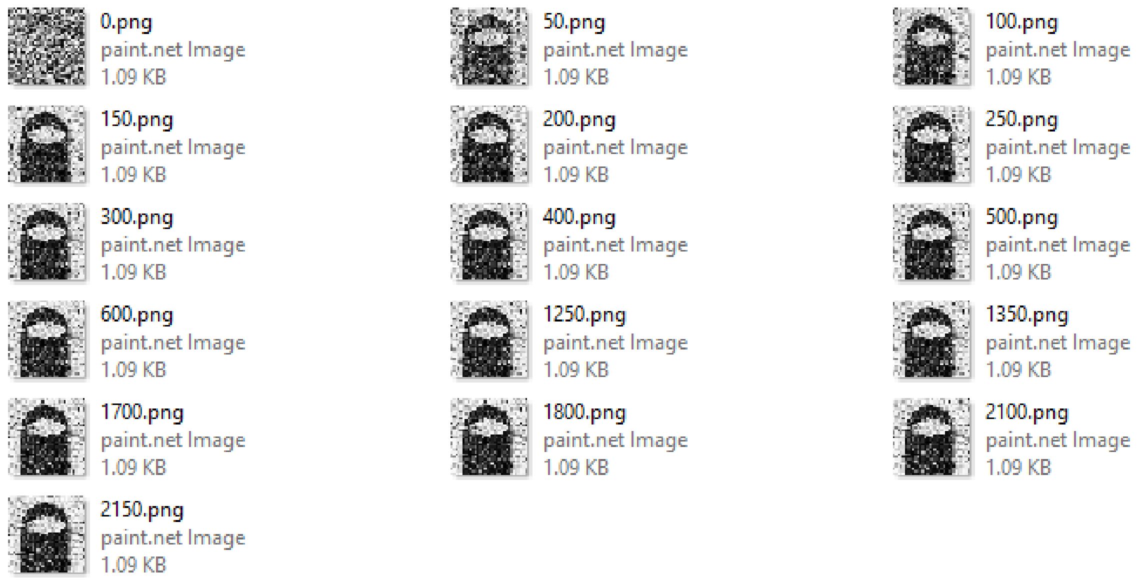
> Threshold value? -> Random Offspring

- Increasing population size / decreasing search space

Genetic algorithm – decreasing search space







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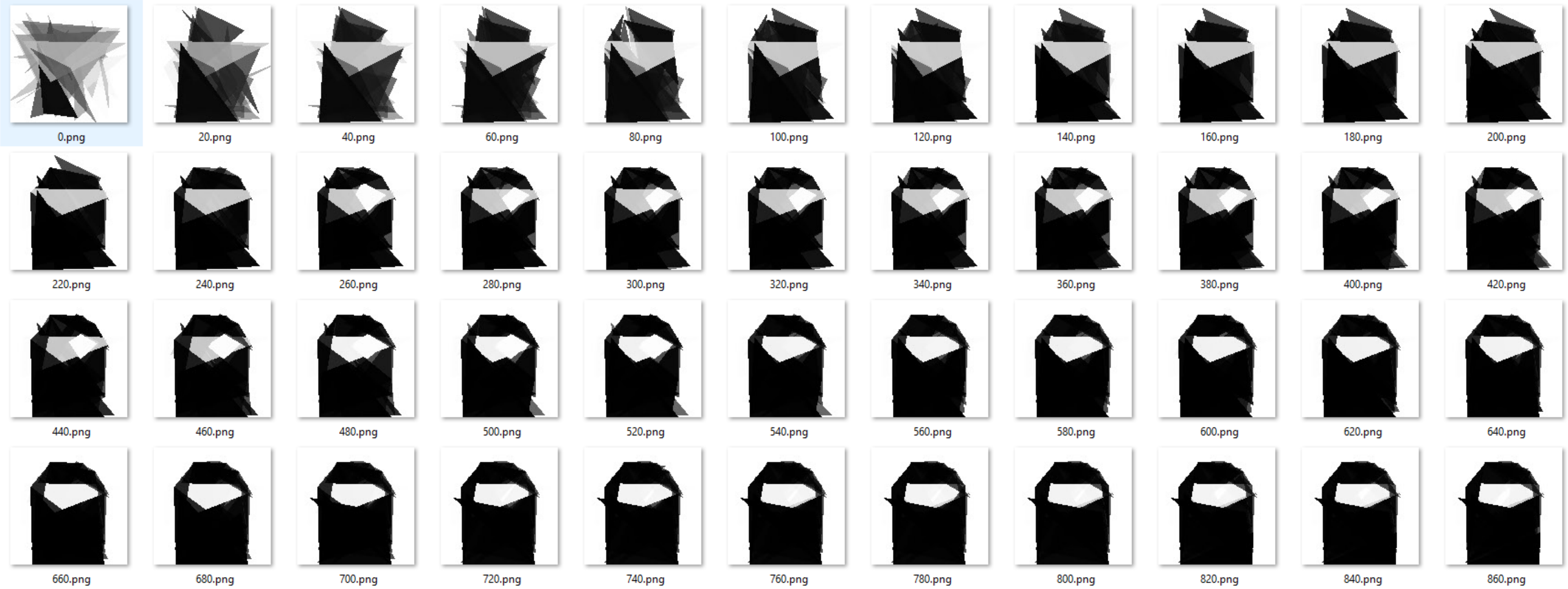
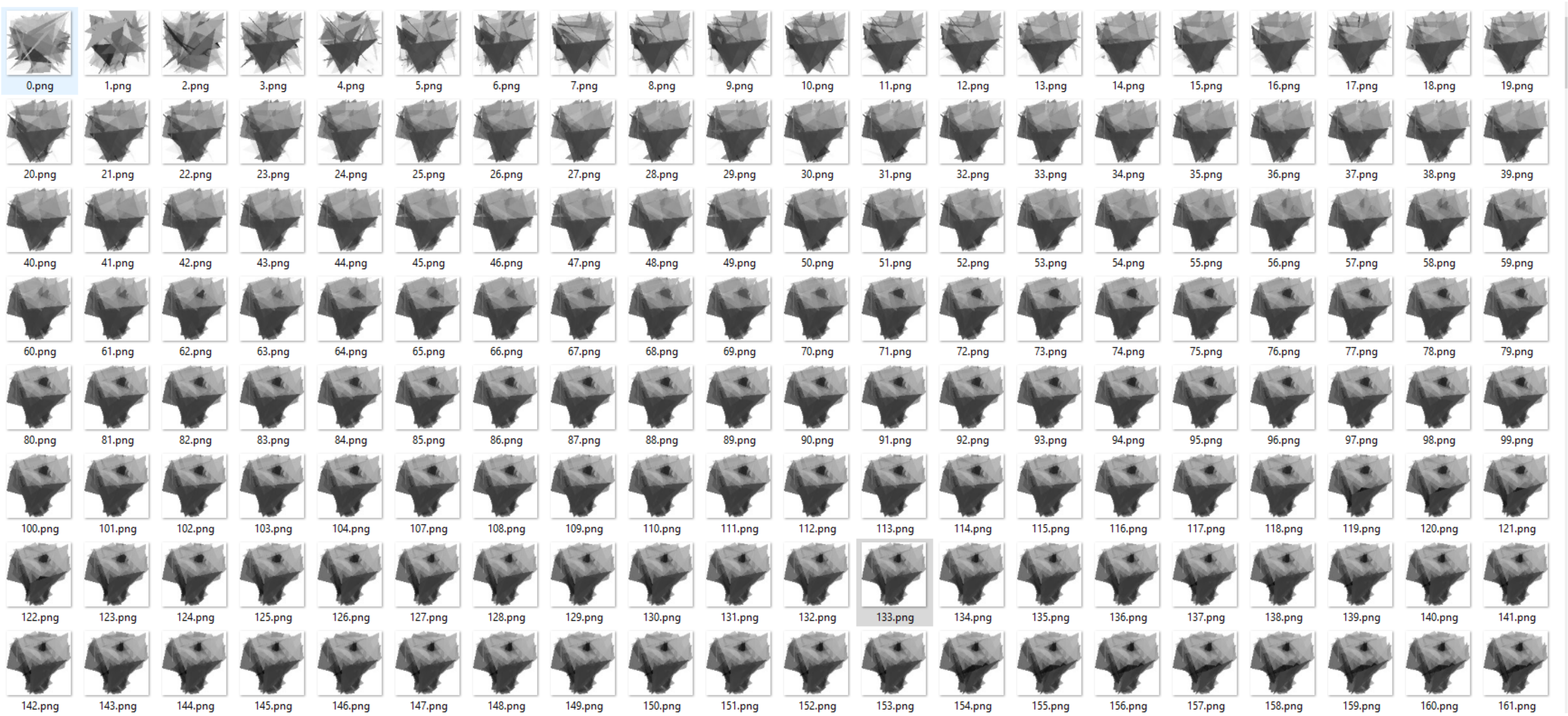
Genetic algorithm – decreasing search space

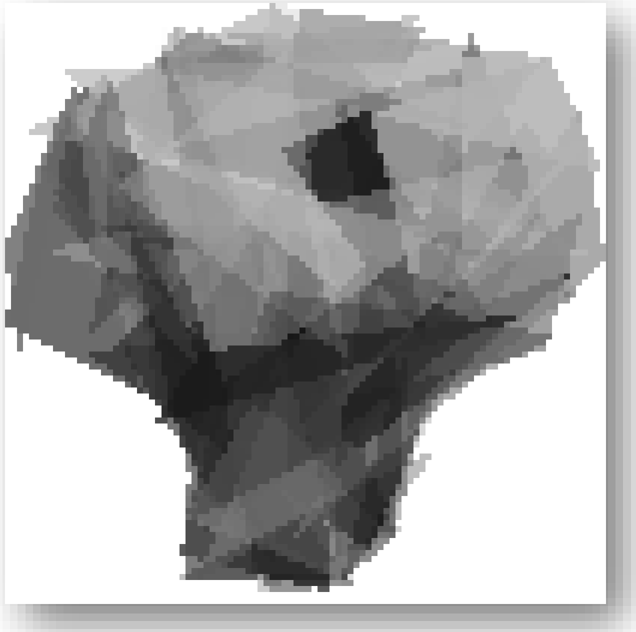
- **Triangles:**



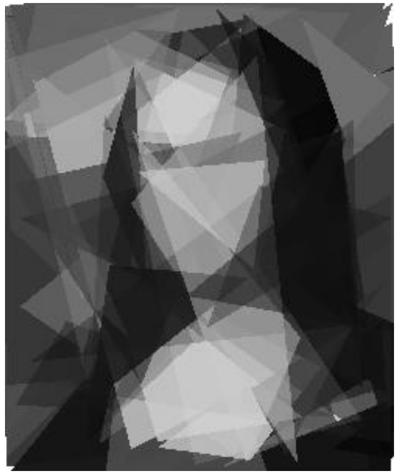
Genetic algorithm – decreasing search space

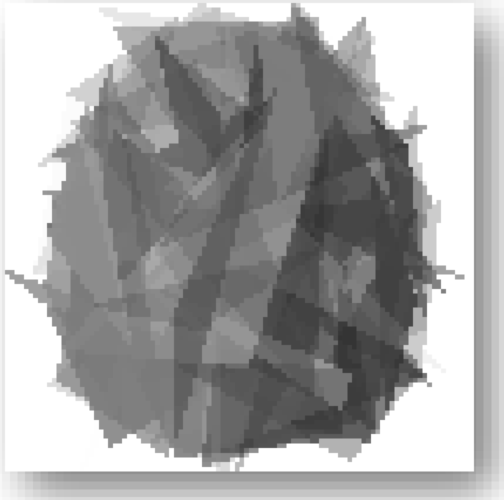


Genetic algorithm – decreasing search space



Genetic algorithm – decreasing search space





Project progress

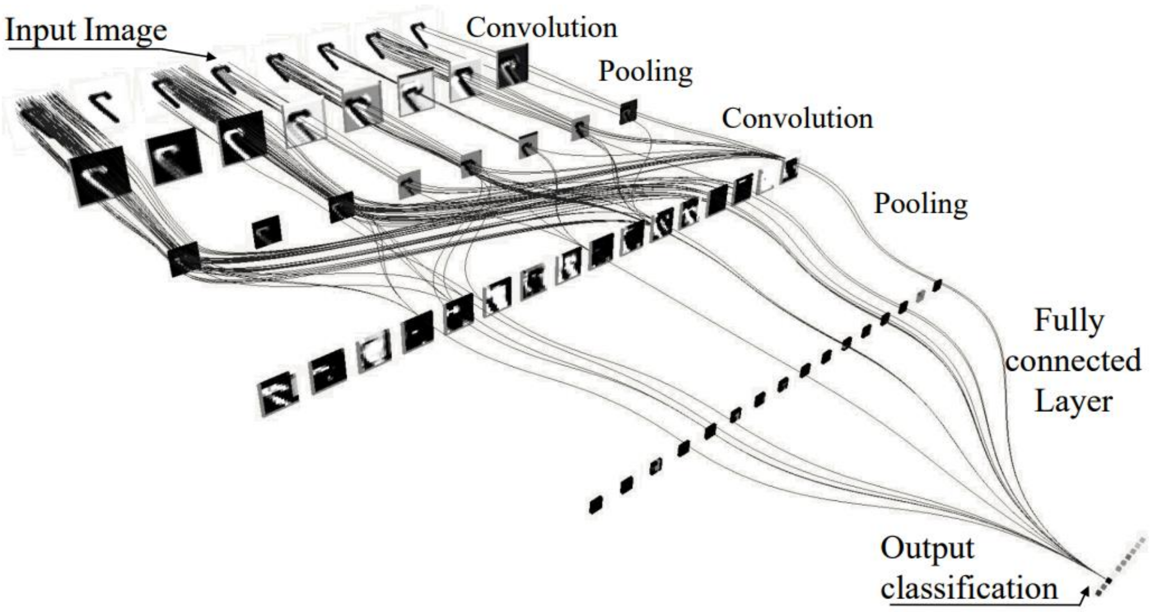
CNN Classifier

Classifier

- Arno & Mohammed
- No experience ⇒ research needed

Classifier - Research

- **Learn the basics of CNN's**
  - Mentors provided resources
- **Get acquainted with PyTorch**

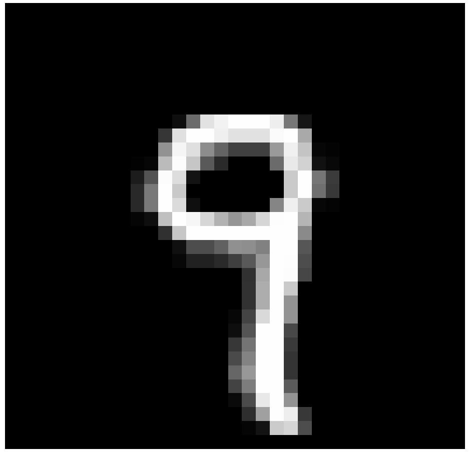


Classifier - Start

- **Experiment with existing models**
  - Trying EfficientNet – Is a more complex model feasible?
- **Come up with own model**
- **Deciding on the dataset**
  - CIFAR-10, CIFAR-100, MNIST & Fashion MNIST

Classifier – First implementation

- **Decided on MNIST digit dataset**
  - Easy training ⇒ faster development & testing
- **Good accuracy (± 99% TOP-1)**



INPUT

. . .

Predicted: 9
Confidence: xx%

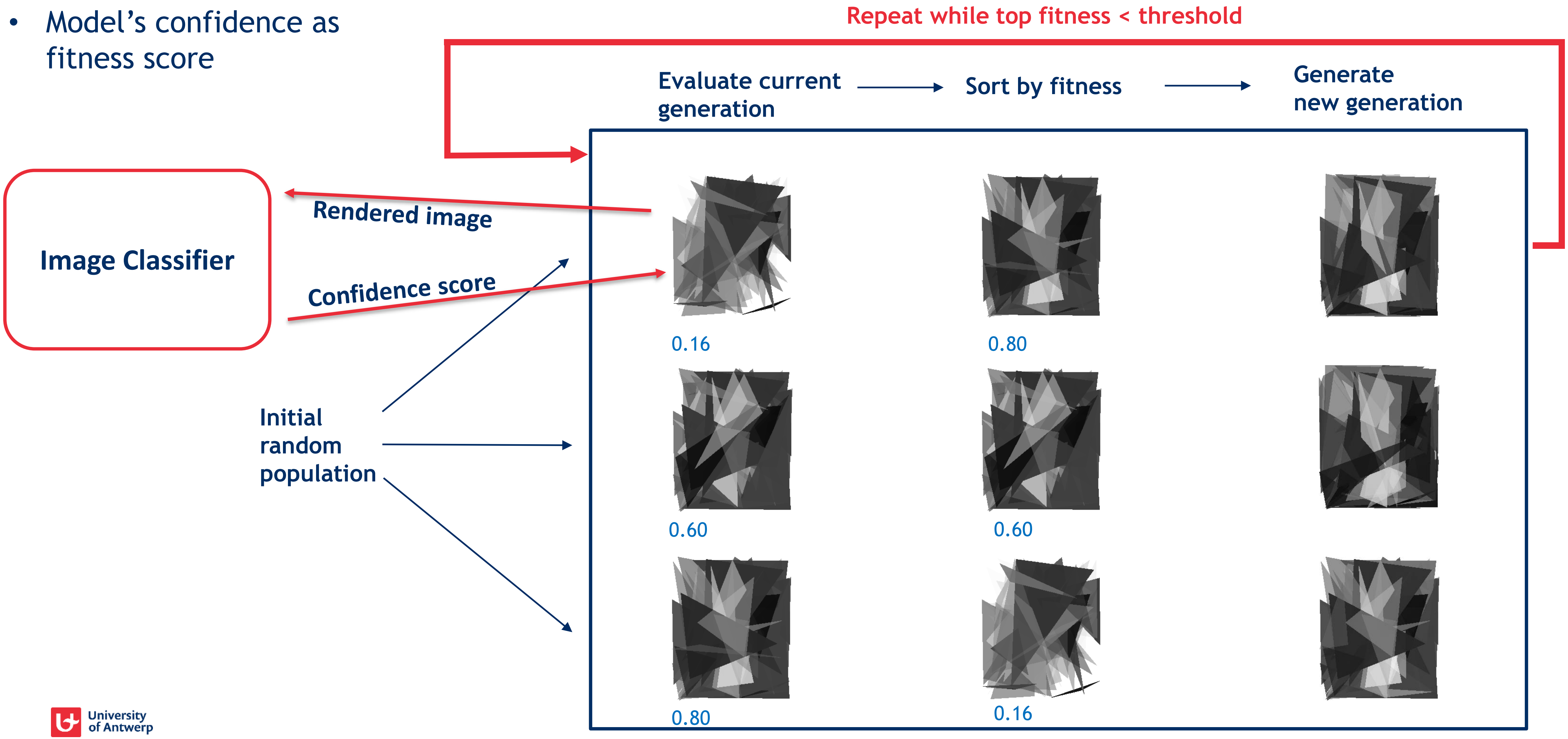
OUTPUT

Project progress

First Integration

First Integration – The straightforward way

- Model’s confidence as fitness score



Repeat while top fitness < threshold

Evaluate current generation → Sort by fitness → Generate new generation

Image Classifier

Rendered image

Confidence score

Initial random population

0.16

0.80

0.60

0.60

0.80

0.16

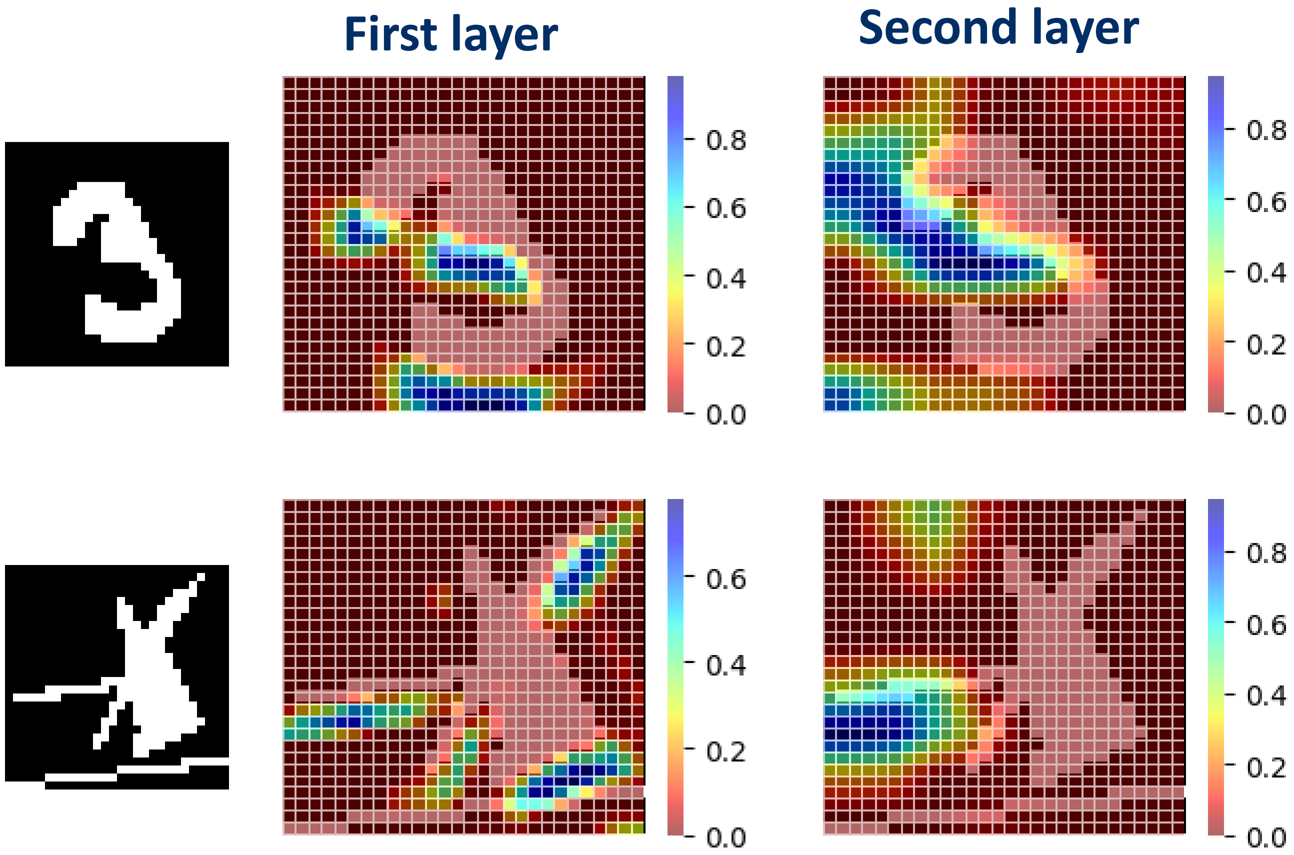
First Integration – Problems

- **Model learns difference between classes**
  - What makes a “3” a “3” instead of an “8”?
  - Obvious in hindsight, but an important intuition
- **Universe composed of the training data**
  - Everything is decided based on the data

First Integration – Mitigations

- **Add an extra class to the model**
  - Use representative data

  ⇒ Still overconfident
- **Try to find an explanation**
  - E.g., Using GradCAM

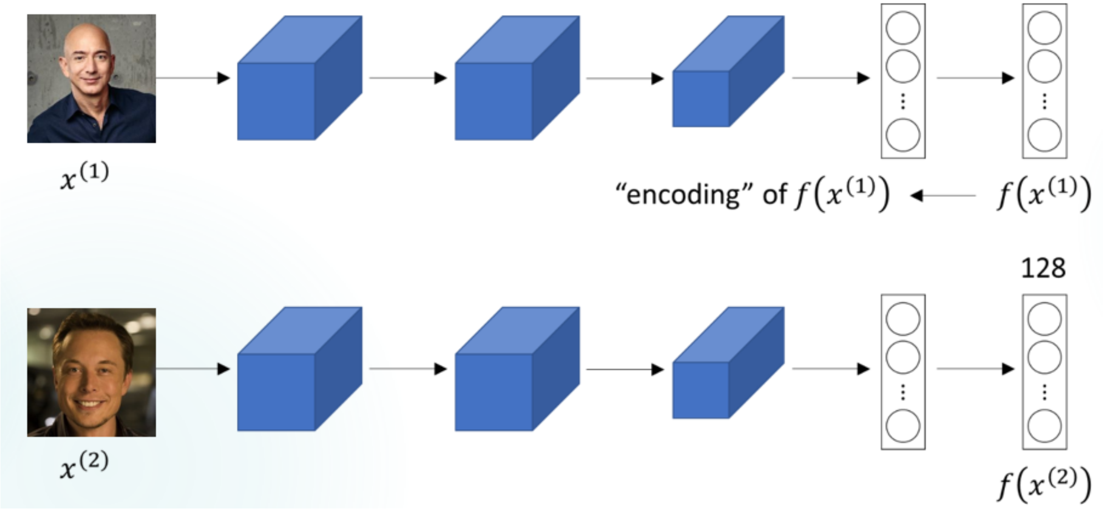


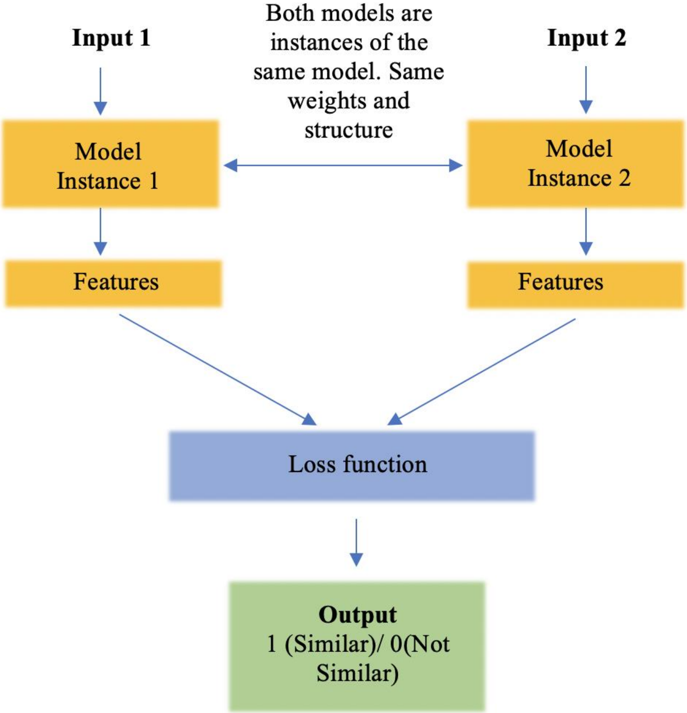
Project progress

Siamese Networks

Siamese Networks

- Predict similarity input – output
- Two inputs, painter & reference





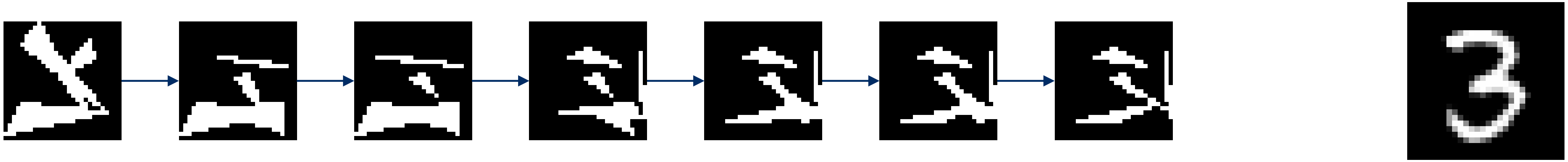
Input 1
Both models are instances of the same model. Same weights and structure
Input 2
Model Instance 1
Model Instance 2
Features
Features
Loss function
Output
1 (Similar)/ 0(Not Similar)

Project progress

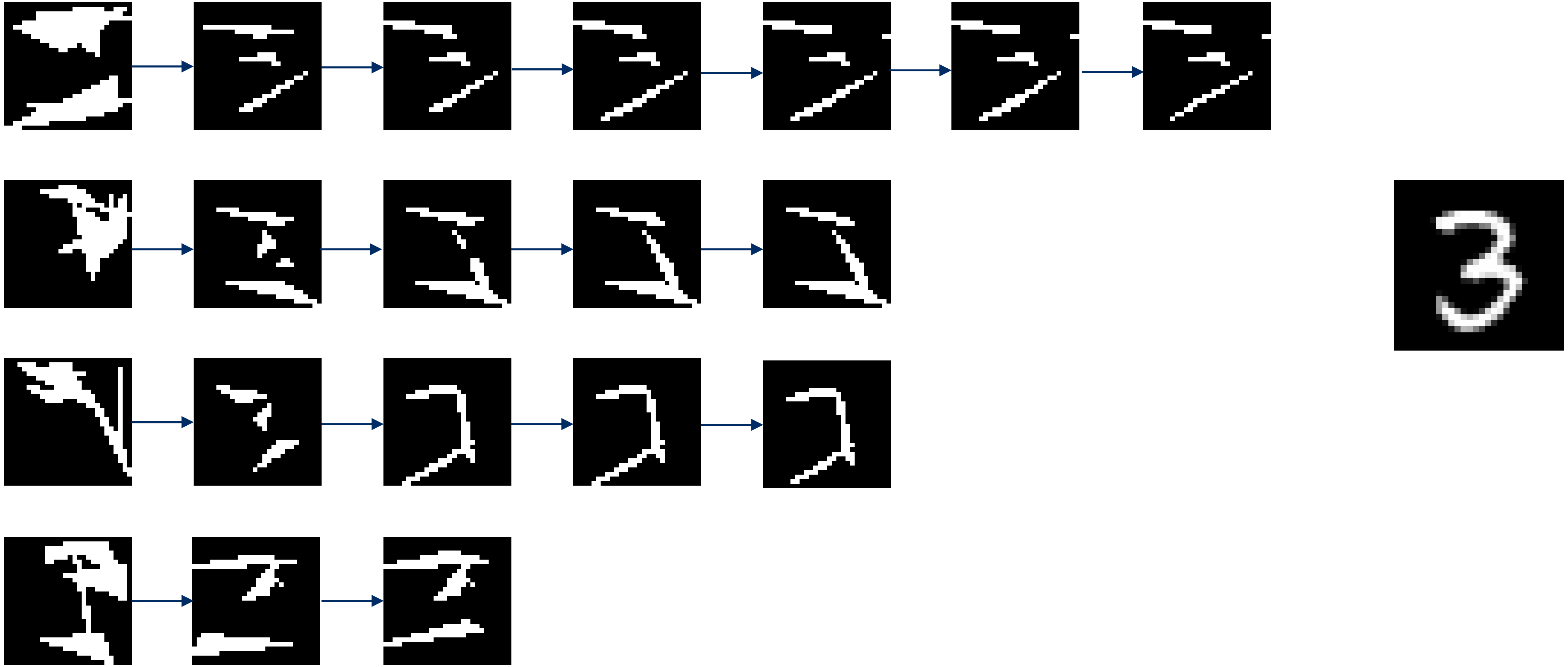
Second Integration

Second Integration – The Siamese network way

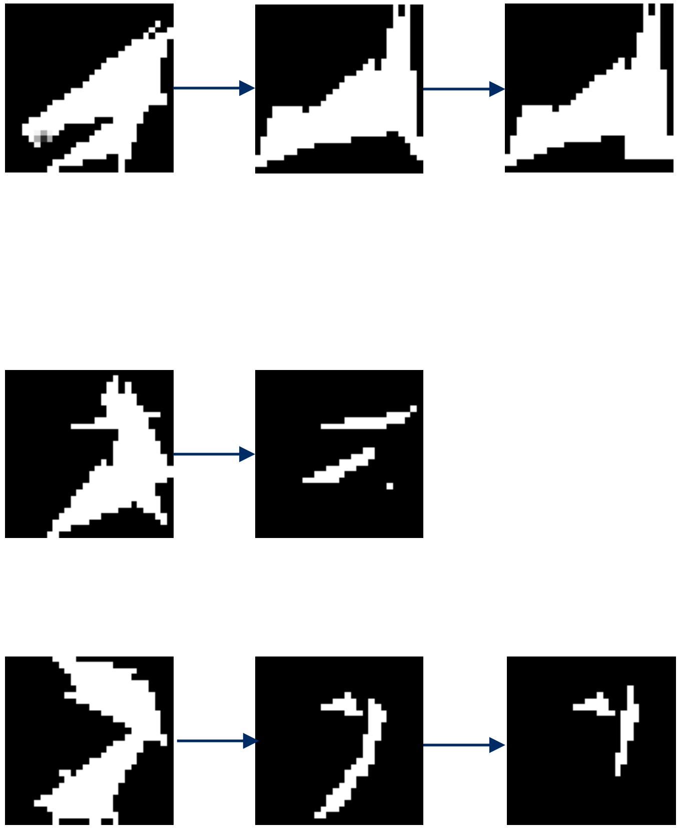
- **Use similarity as fitness score**
- **Intuition: Should act more like a comparator network**
  - Compares features not pixels



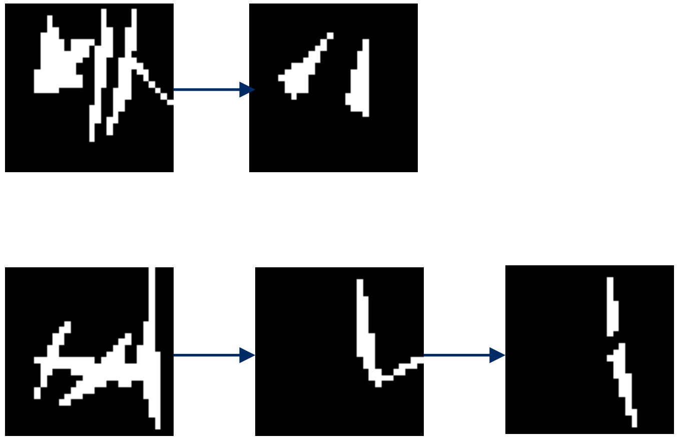
Second Integration – The Siamese network way

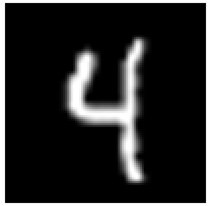


Second Integration – The Siamese network way



Second Integration – The Siamese network way





Second Integration – Limitations

- **Siamese networks add computation overhead**
- **Hard to find representative data**
- **Performance at scale unknown**
  - Could not test it

Second Integration – Further experiments

- **Siamese network with multiple reference images**
  - Average out the features and calculate loss
  - More computation overhead
- **MNIST Fashion dataset**
- **Binary Siamese network**
  - Hypothesis: Works better and easier to optimize
    - Easier training
    - Needs further research

Conclusion

Conclusion – What we learnt

- **We learnt a lot, especially**
  - Classifier: derivative image generation
  - Possible Siamese network visualization method?

Conclusion – Feedback

- Open for further research
- Good teamwork
- Great mentors
- Satisfying results

Thank you

The end