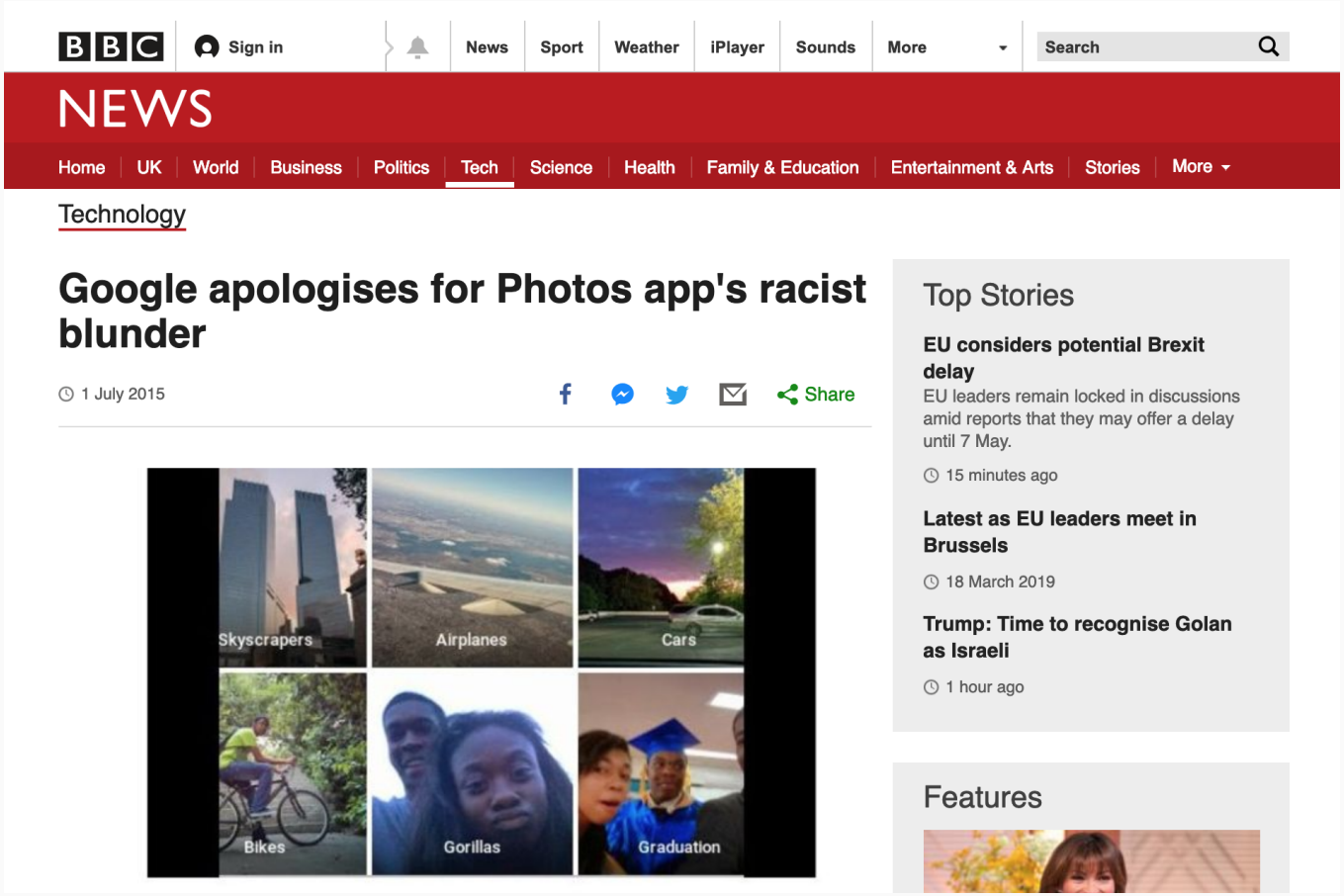
Evolutionary dataset optimisation: learning algorithm quality through evolution

Henry Wilde, Dr. Jonathan Gillard, Dr. Vincent Knight

Motivation



via: BBC News (`https://www.bbc.co.uk/news/technology-33347866`)

Reliability and frailty

- R. Hyndman. *Prediction competitions*. 2014. URL: https://robjhyndman.com/hyndsight/prediction-competitions/
- A. Torralba and A. A. Efros. “Unbiased Look at Dataset Bias”. In: *Proceedings of the 2011 IEEE Conference on Computer Vision and Pattern Recognition*. 2011, pp. 1521–1528. DOI: 10.1109/CVPR.2011.5995347

Generating artificial data



via: https://thispersondoesnotexist.com

Barney Sparks

@ barneysparks@gmail.com Allentown, Pennsylvania

EXPERIENCE

Operations Analyst

Youth **2014 - Ongoing** Allentown, Pennsylvania

Youth is a leading platform that is developing a product in cloud and in-house platforms.

- Provided support of over 50 international startups and change
- Managed a team of 10 people in a staff of 10 people
- Managed 10 projects with 4 projects per day management of the company and included an average of 200 companies and 2 employees in the first role.
- Increased the company by 100% in 2014 and 2011 and 2015.

Head Of Marketing And Controller

X-Main **2010 - 2014** Allentown, Pennsylvania

X-main is a software company that provides young people with leadership development and enterprise software used in Junico and the construction industry.

- Created 3 consultants to provide internal and staff & maintenance strategies and incorporated the company with timely companies resulting in $2MM in conduct and increased the company to 100 people in less than 3 months

SUMMARY

I am a highly motivated and proven pursuits where my work diverse individual with others into the field of interest and be like interependemy to go to their practice cliniz.

TECHNOLOGIES

PHP **Ansi C** **Perl** **Oracle BRM Pipeline** **Oracle BRM CMT** **Java** **Shell Script** **Linux** **Oracle BRM**

EDUCATION

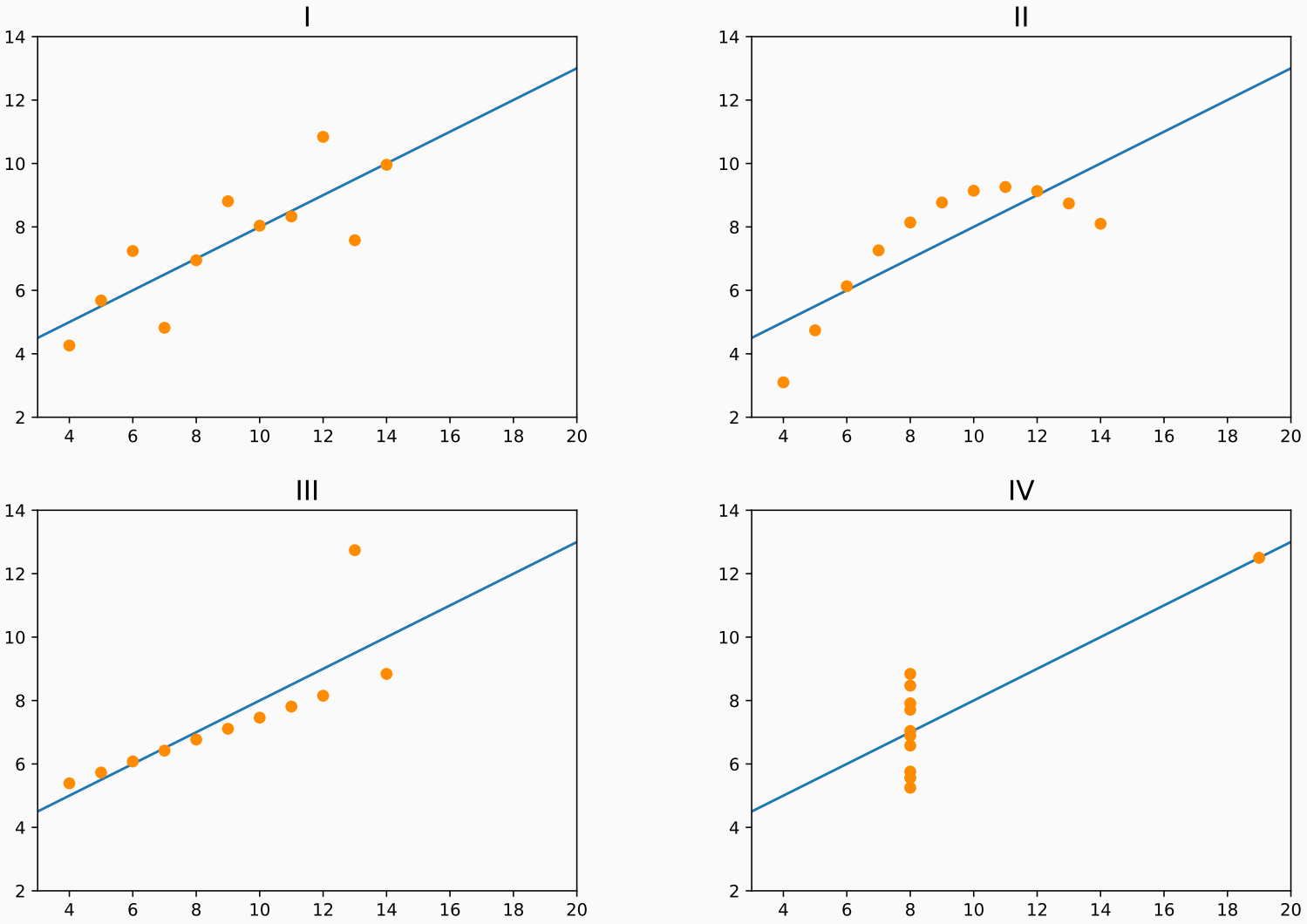
Unige, Faculty Of Medicine

University Of Geneva

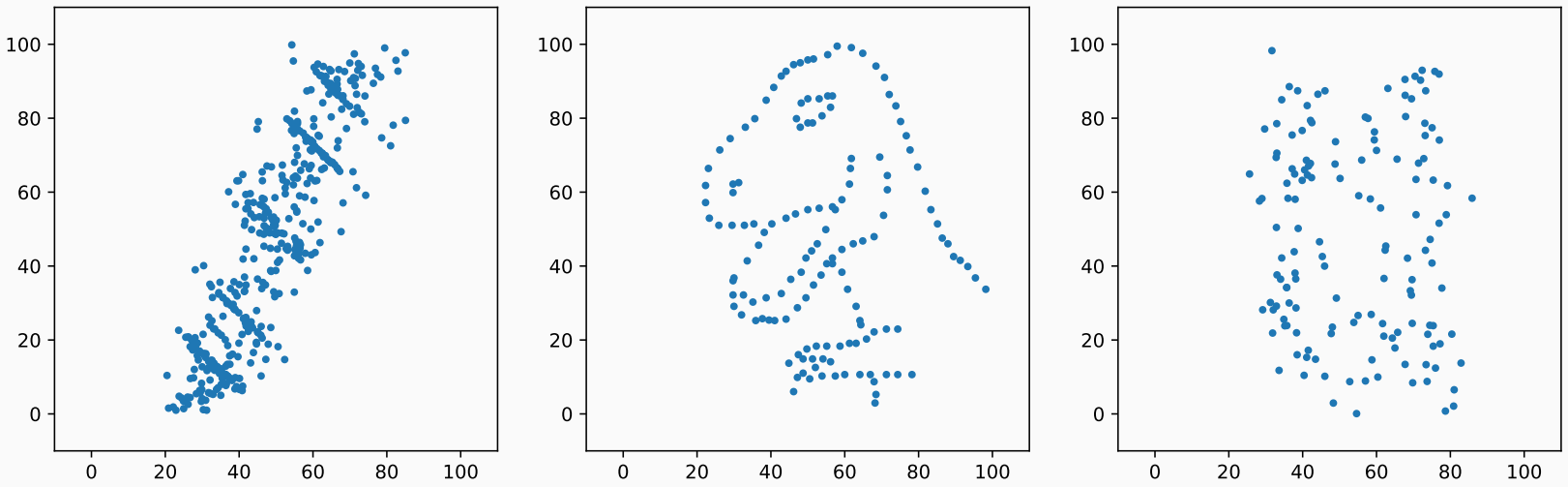
via: https://thisresumedoesnotexist.com

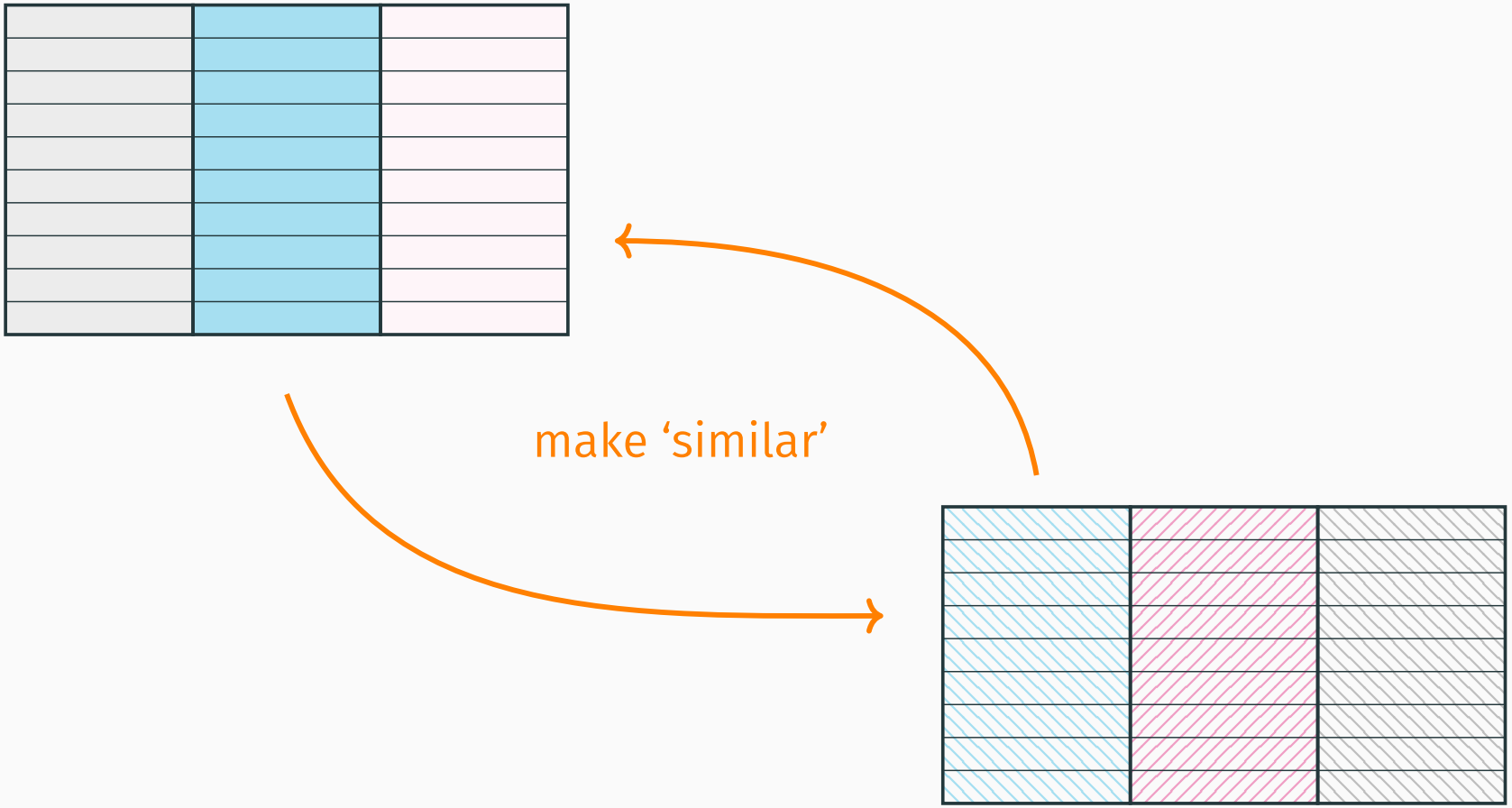
via: https://thiscatdoesnotexist.com

Anscombe’s quartet



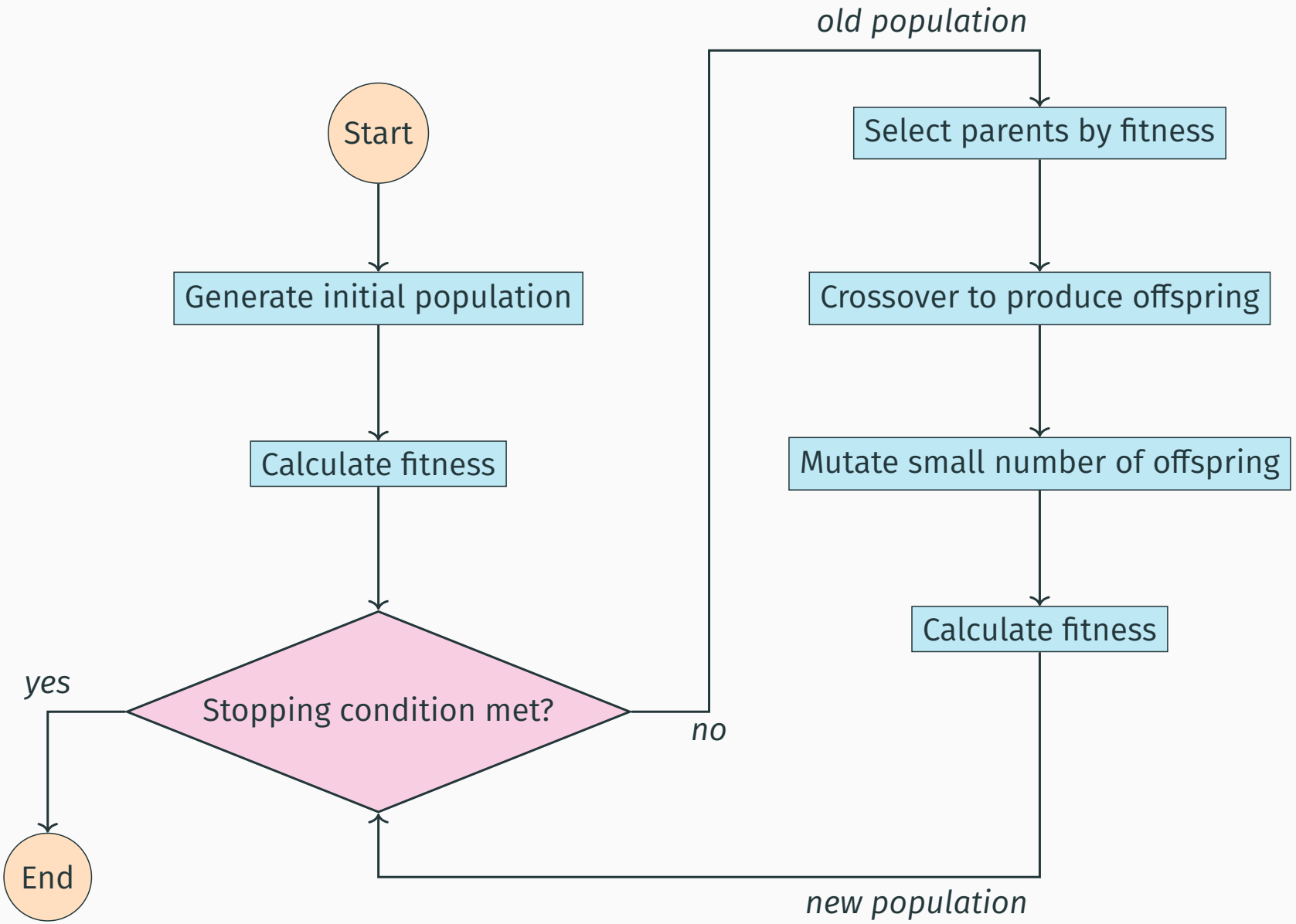
The Datasaurus dozen




make ‘similar’

Given an algorithm, how can one find data for which it performs well?

Evolutionary algorithms


Start
Generate initial population
Calculate fitness
Stopping condition met?
yes
End
no
old population
Select parents by fitness
Crossover to produce offspring
Mutate small number of offspring
Calculate fitness
new population

$$\max \quad f : \mathbb{N}^2 \to \mathbb{N}; \qquad f(x_1, x_2) = x_1 + x_2$$

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Population (25, 30) (12, 1) (11, 0) (20, 12) (24, 25)

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Population	(25, 30)	(12, 1)	(11, 0)	(20, 12)	(24, 25)
Get fitness	55	13	11	42	49

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Get fitness	55	13	11	42	49
Select parents	(25, 30)			(20, 12)	(24, 25)
Create offspring		(24, 30)	(25, 12)		
Mutate offspring		(15, 30)	(25, 26)		

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Population	(25, 30)	(12, 1)	(11, 0)	(20, 12)	(24, 25)
Get fitness	55	13	11	42	49
Select parents	(25, 30)			(20, 12)	(24, 25)
Create offspring		(24, 30)	(25, 12)		
Mutate offspring		(15, 30)	(25, 26)		
New generation	(25, 30)	(15, 30)	(25, 26)	(20, 12)	(24, 25)

- A fitness function, f, which acts on a single dataset
- A population size, $N \in \mathbb{N}$
- A maximum number of iterations, $M \in \mathbb{N}$
- A selection parameter to detail the proportion of the fittest individuals to carry forward, $b \in [0, 1]$
- A mutation probability, $p_m \in [0, 1]$

- Limits on the number of rows a dataset can have:

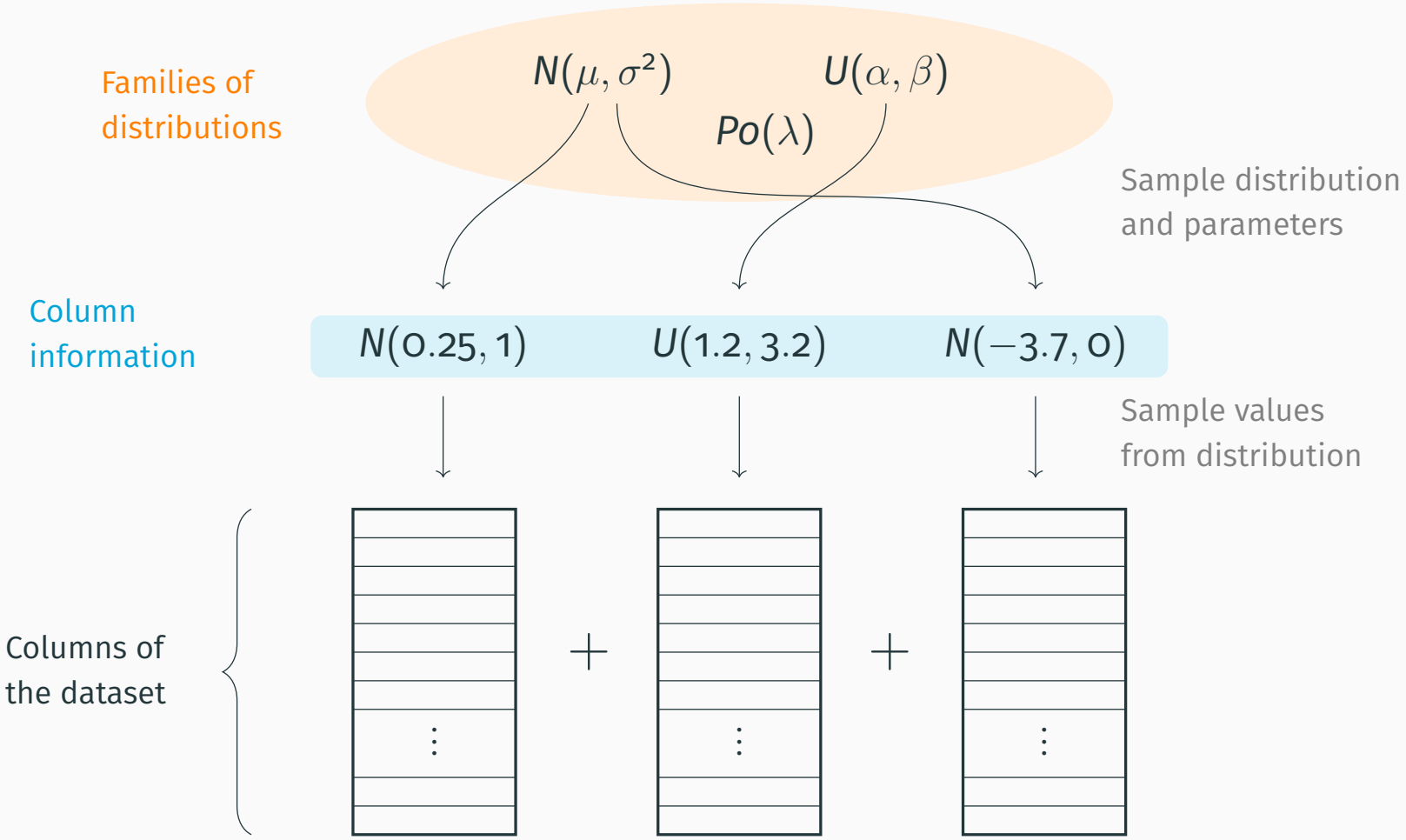
$$R \in \left\{ (r_{\min}, r_{\max}) \in \mathbb{N}^2 \mid r_{\min} \leq r_{\max} \right\}$$

- Limits on the number of columns a dataset can have:

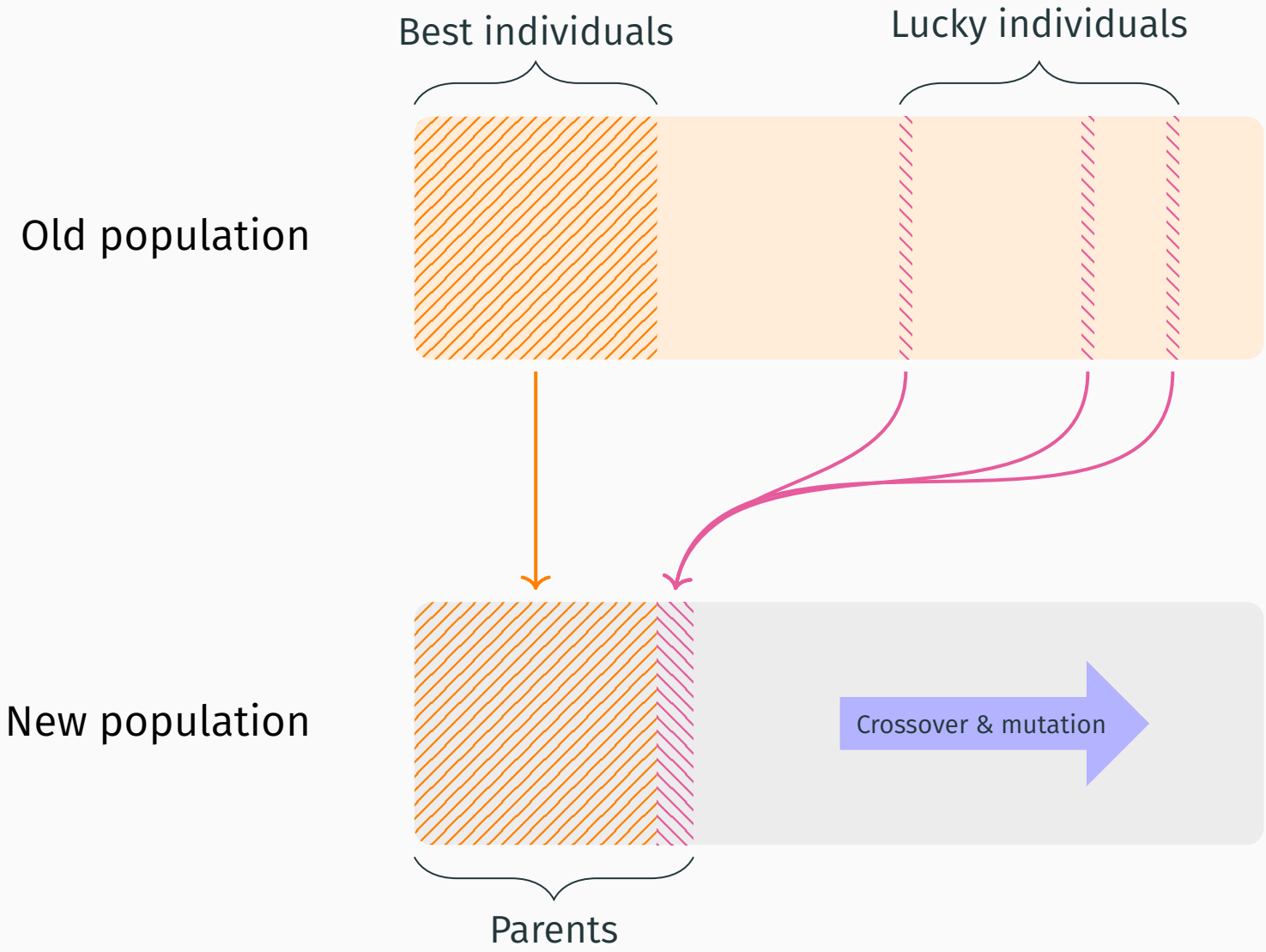
$$C := \left(C_1, \ldots, C_{|\mathcal{P}|} \right) \text{ where } C_j \in \left\{ (c_{\min}, c_{\max}) \in (\mathbb{N} \cup \{\infty\})^2 \mid c_{\min} \leq c_{\max} \right\}$$

  for each $j = 1, \ldots, |\mathcal{P}|$
- A set of probability distribution families, $\mathcal{P}$. Each family in this set has some parameter limits which form a part of the overall search space
- A probability vector to sample distributions from $\mathcal{P}$, $w = \left(w_1, \ldots, w_{|\mathcal{P}|} \right)$
- A second selection parameter, $l \in [0, 1]$, to allow for a small proportion of "lucky" individuals to be carried forward
- A shrink factor, $s \in [0, 1]$. The relative size of a component of the search space to be retained after adjustment

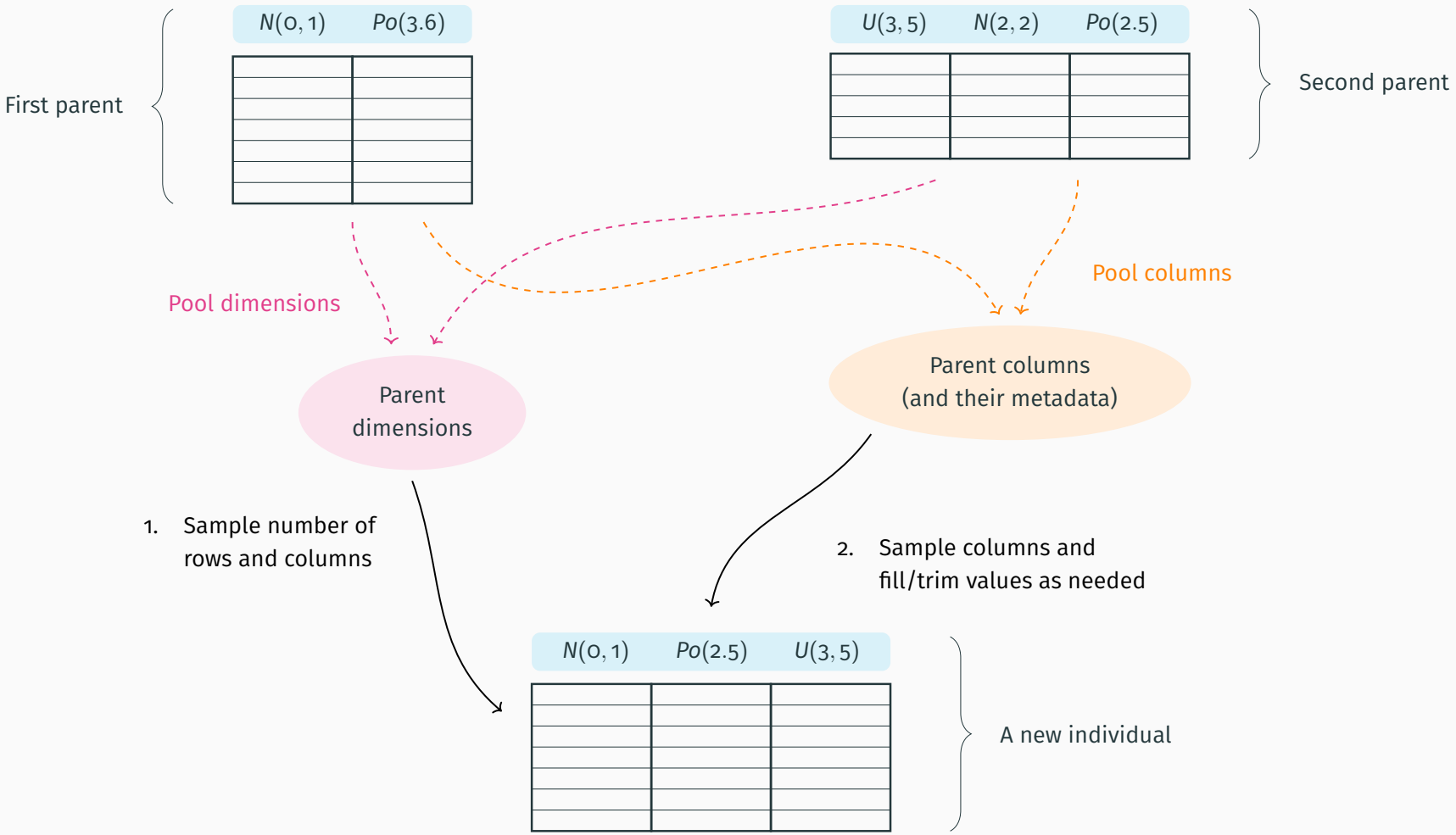
Individuals



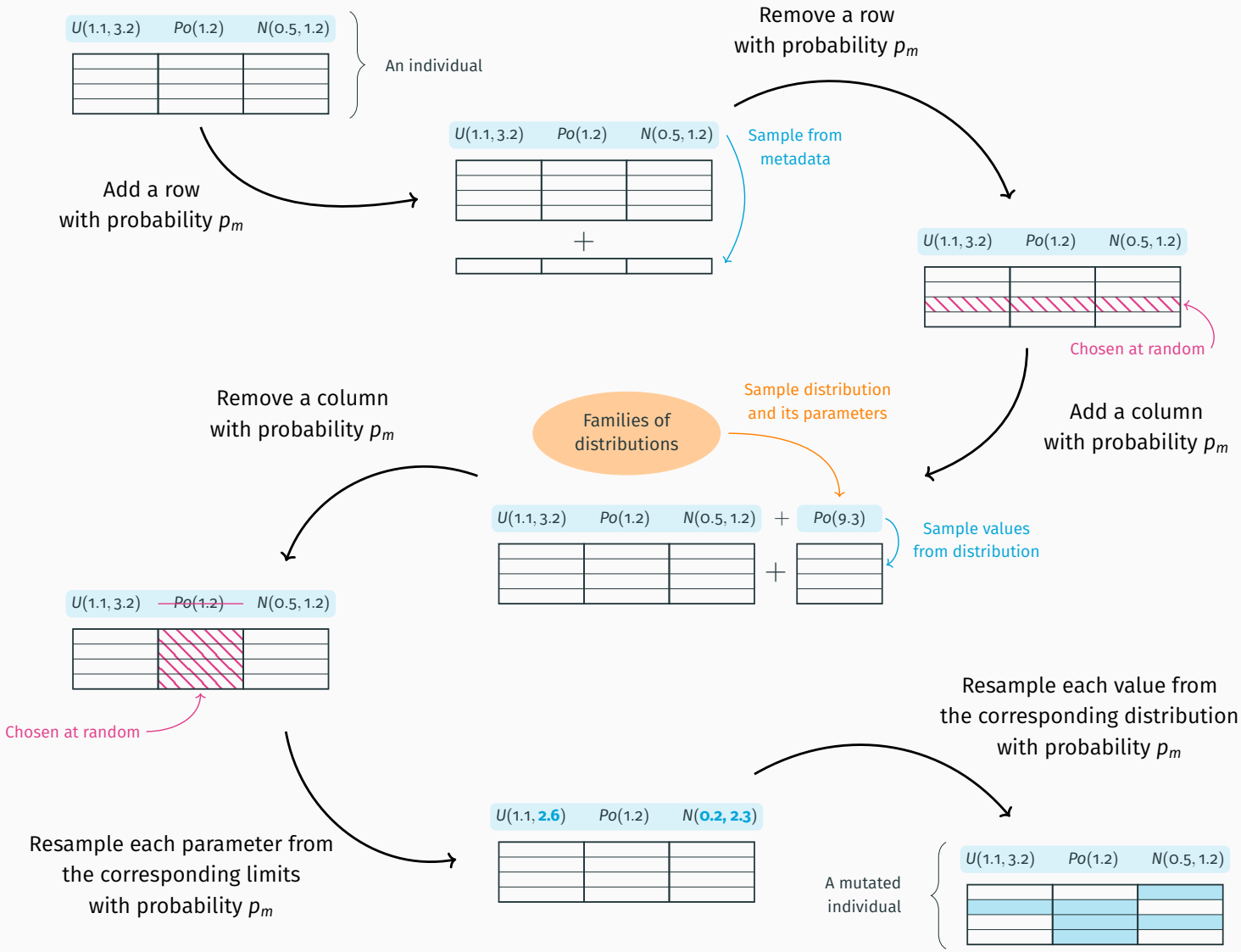
Selection


Best individuals
Lucky individuals
Old population
New population
Crossover & mutation
Parents

Crossover


First parent
N(0, 1)
Po(3.6)
U(3, 5)
N(2, 2)
Po(2.5)
Second parent
Pool dimensions
Pool columns
Parent dimensions
Parent columns
(and their metadata)
1. Sample number of rows and columns
2. Sample columns and fill/trim values as needed
N(0, 1)
Po(2.5)
U(3, 5)
A new individual

Mutation


U(1.1, 3.2) Po(1.2) N(0.5, 1.2)
An individual
Add a row with probability p_m
Remove a row with probability p_m
Sample from metadata
Chosen at random
Add a column with probability p_m
Sample distribution and its parameters
Families of distributions
Sample values from distribution
Remove a column with probability p_m
Chosen at random
Resample each parameter from the corresponding limits with probability p_m
U(1.1, 2.6) Po(1.2) N(0.2, 2.3)
Resample each value from the corresponding distribution with probability p_m
A mutated individual

Some example use cases

Input: A dataset, $X \in \mathbb{R}^n \times \mathbb{R}^n$;

$$f : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}, \quad f(A, B) = Var(A) - \max_i |B_i - 1|$$

Output: The maximal value for f

$values \leftarrow \emptyset$

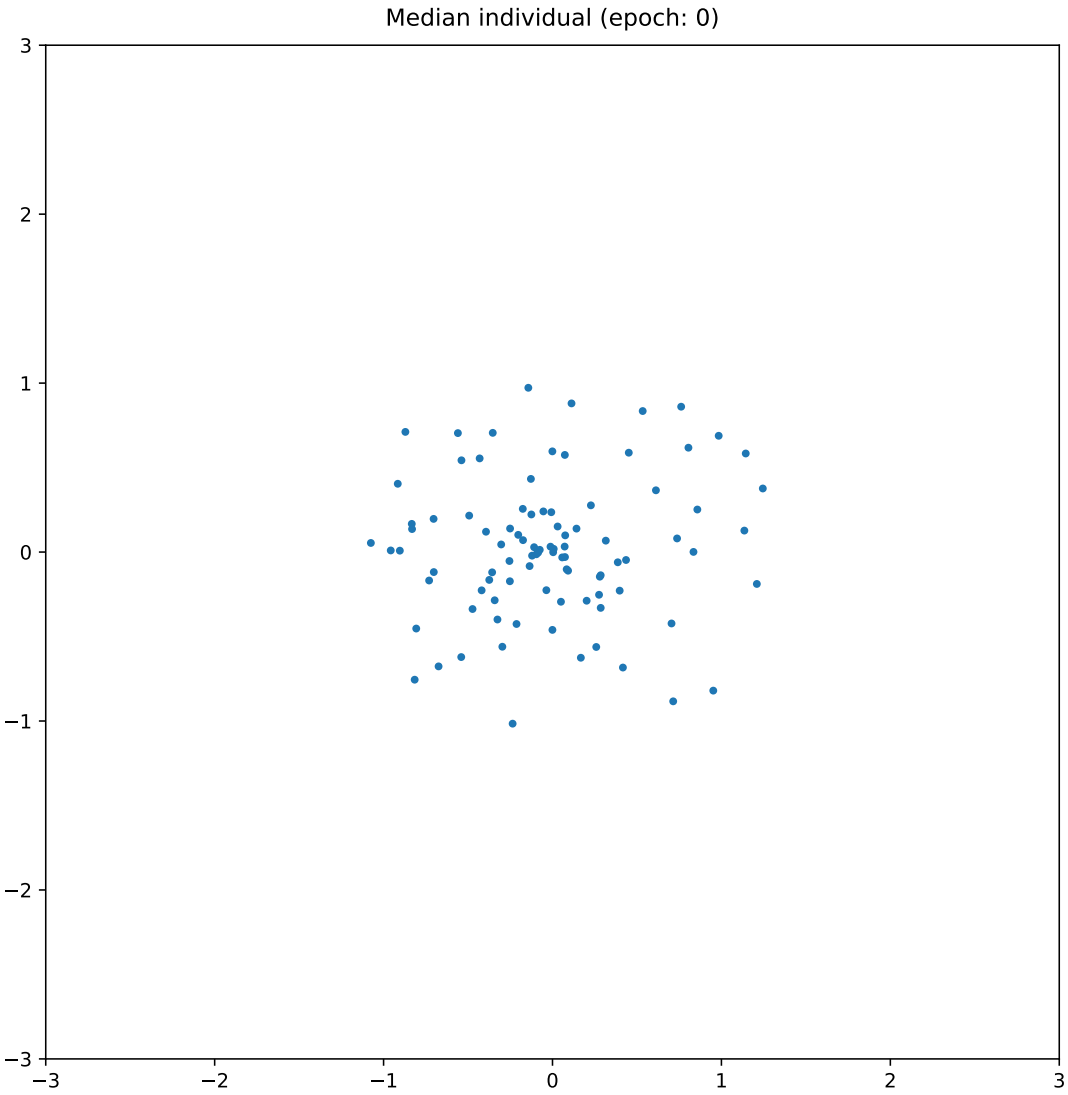
for *each ordering,* $a, b \in \{0, 1\}^2$, *of the columns* **do**

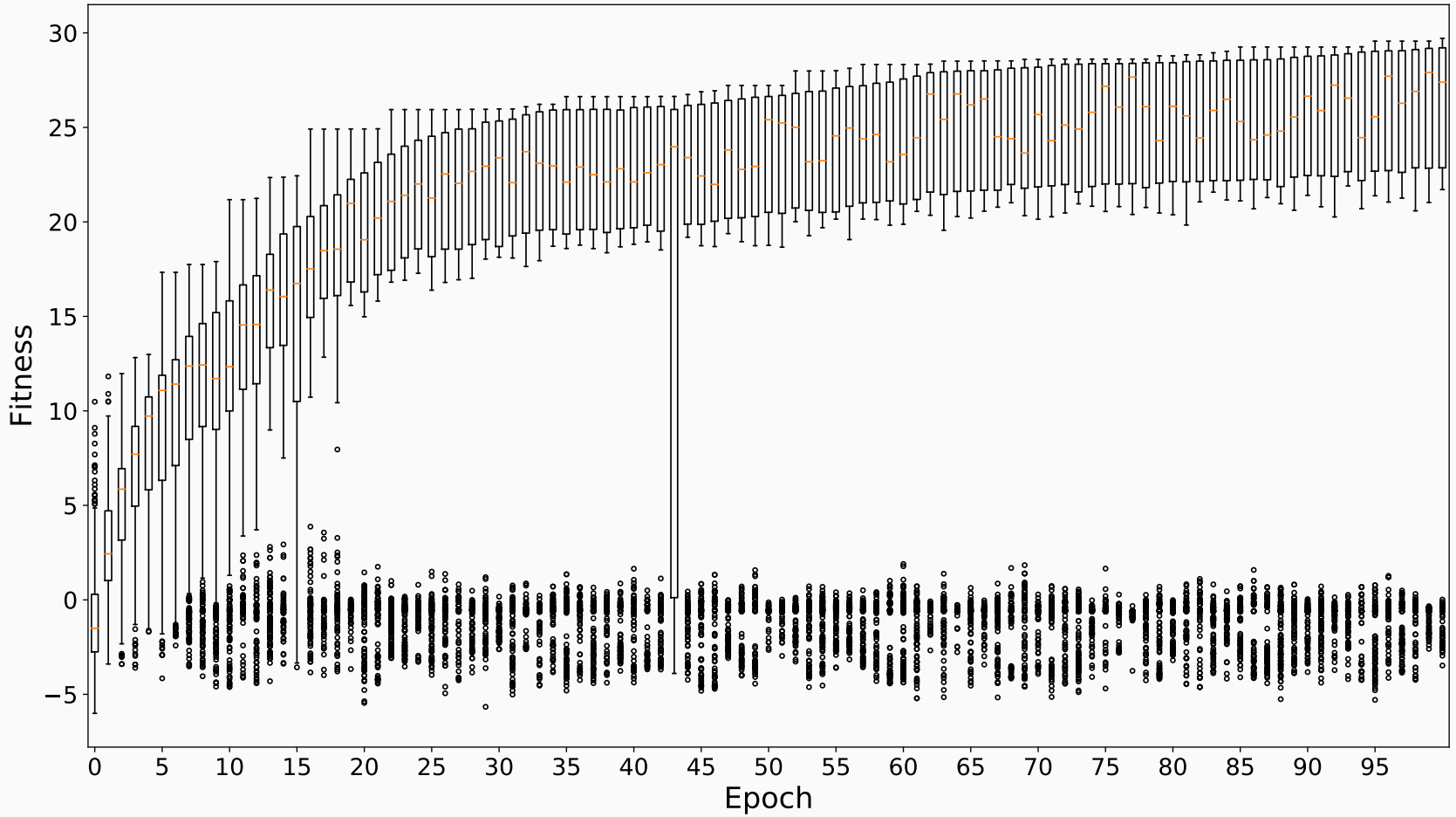
  calculate $f\left(X^{(a)}, X^{(b)}\right)$

  append this to *values*

end

return max *values*


Median individual (epoch: 0)
3
2
1
0
−1
−2
−3
−3
−2
−1
0
1
2
3


Fitness
Epoch
30
25
20
15
10
5
0
−5
0
5
10
15
20
25
30
35
40
45
50
55
60
65
70
75
80
85
90
95

Input: A dataset, $X \in \mathbb{R}^n$; some sampling proportion, $p \in [0, 1]$;
a number of samples to take, k

Output: The maximum difference between each sampled mean of X and 0

$values \leftarrow \emptyset$

for $i = 1, \ldots, k$ **do**

$Y \leftarrow$ a random sample of $\lfloor np \rfloor$ entries from X

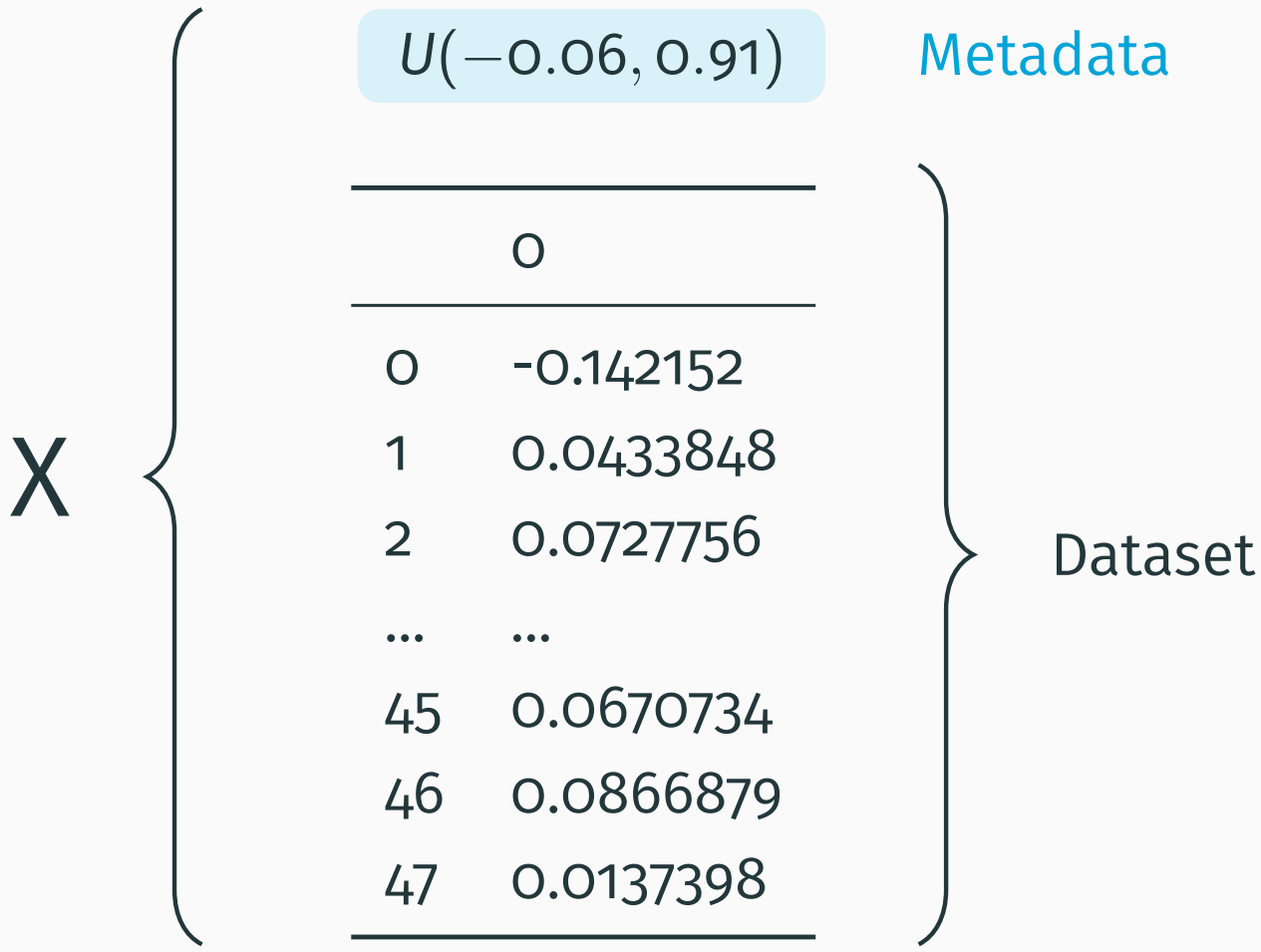
evaluate the mean of Y:

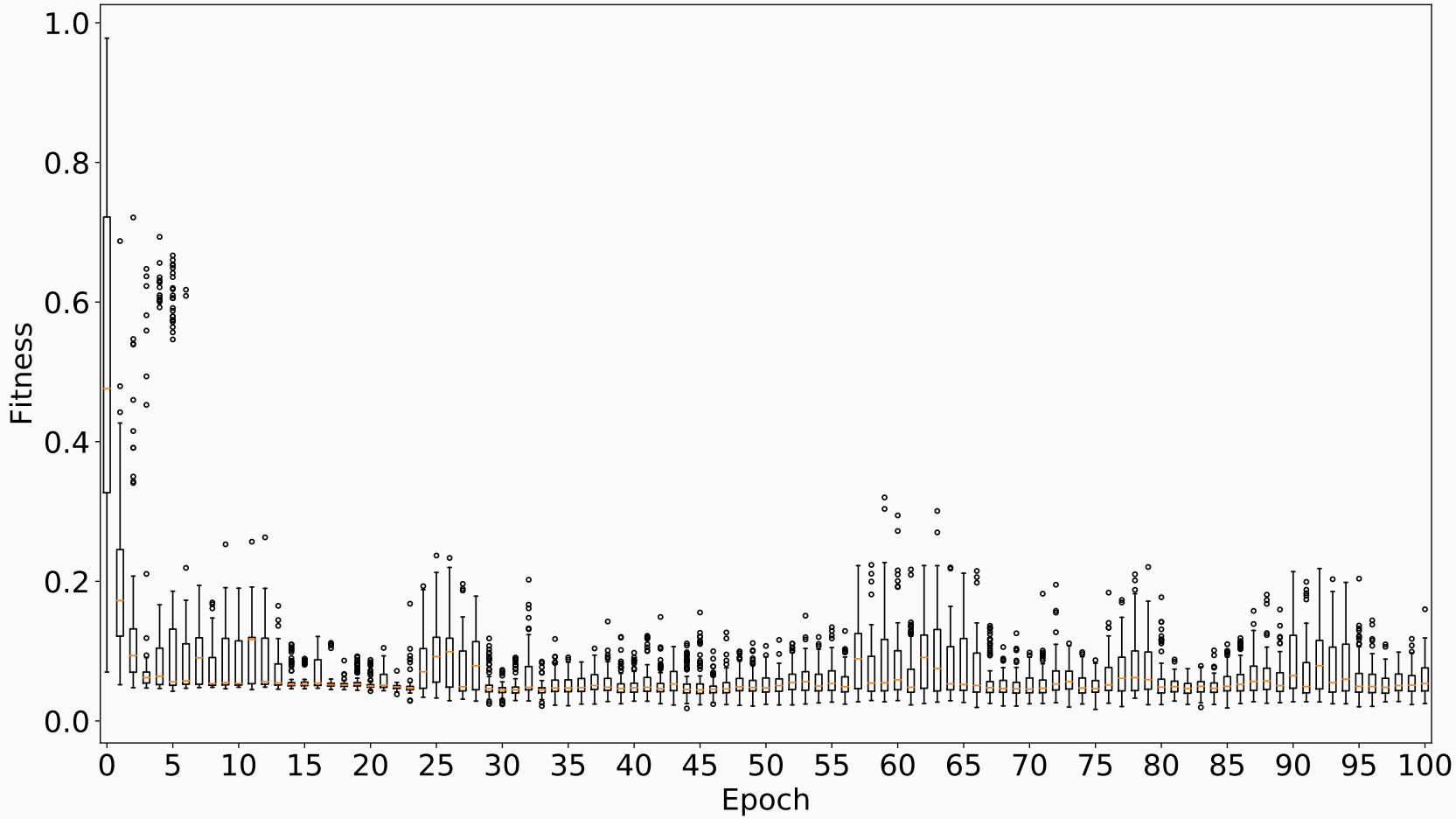
$$\bar{Y} = \frac{1}{|Y|} \sum_{i=1}^{|Y|} Y_i$$

append $\bar{Y}$ to $values$

end

return $\max values$


X
$U(-0.06, 0.91)$
Metadata
0
0 -0.142152
1 0.0433848
2 0.0727756
... ...
45 0.0670734
46 0.0866879
47 0.0137398
Dataset


Fitness
1.0
0.8
0.6
0.4
0.2
0.0
0
5
10
15
20
25
30
35
40
45
50
55
60
65
70
75
80
85
90
95
100
Epoch

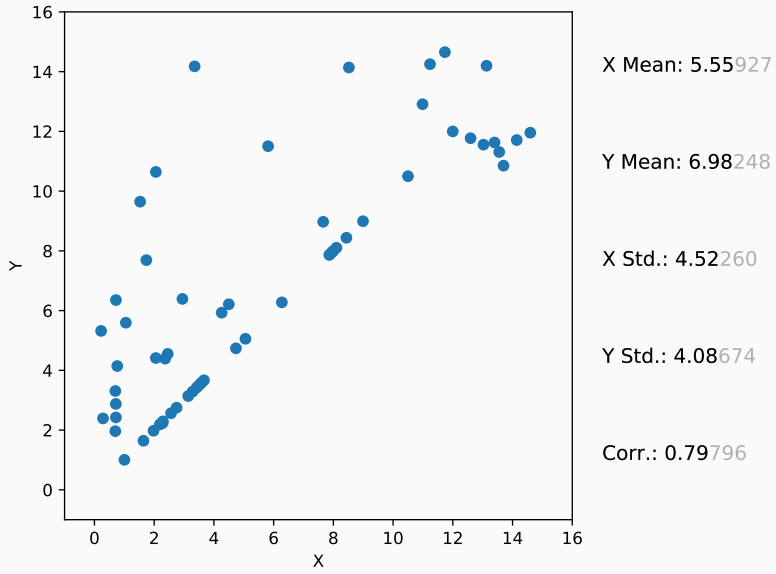
Input: A dataset, $X \in \mathbb{R}^n \times \mathbb{R}^n$; a set of dissimilarity measures,

$$f_1, \ldots, f_k : \mathbb{R}^n \times \mathbb{R}^n \to \mathbb{R}$$

Output: The total of the measures: $\sum_{i=1}^{k} f_i(X)$

$sum \leftarrow 0$
for $i = 1, \ldots, k$ **do**
    evaluate $f_i(X)$
    add this to *sum*
end
return *sum*

X Mean: 5 *Y* Mean: 7 *X* Std.: 4.7 *Y* Std.: 4.1 Corr.: 0.8



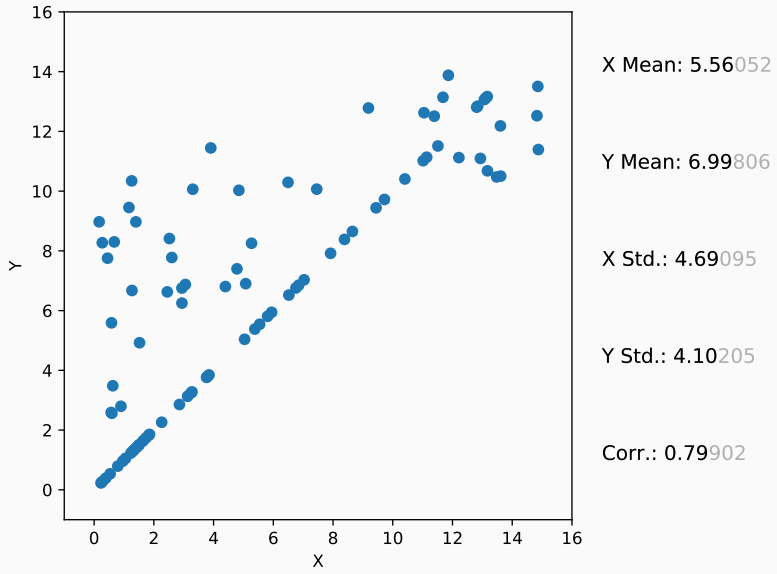
X Mean: 5.55927

Y Mean: 6.98248

X Std.: 4.52260

Y Std.: 4.08674

Corr.: 0.79796



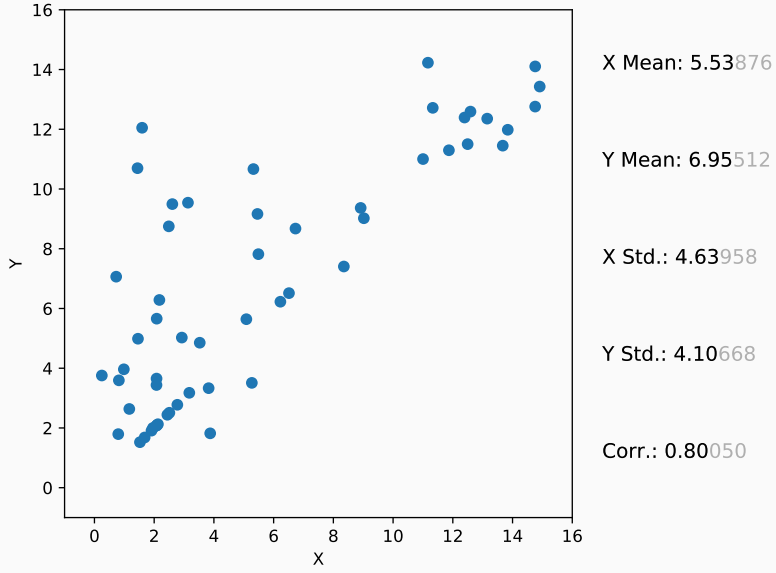
X Mean: 5.56052

Y Mean: 6.99806

X Std.: 4.69095

Y Std.: 4.10205

Corr.: 0.79902



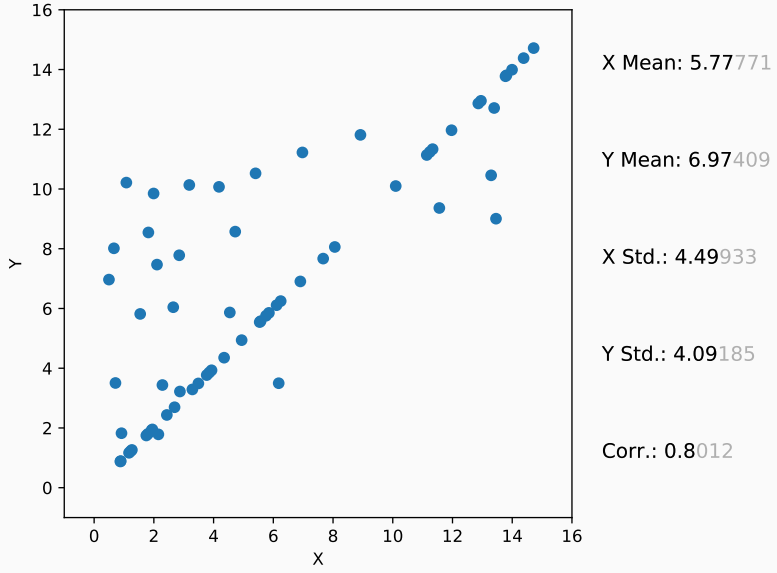
X Mean: 5.53876

Y Mean: 6.95512

X Std.: 4.63958

Y Std.: 4.10668

Corr.: 0.80050



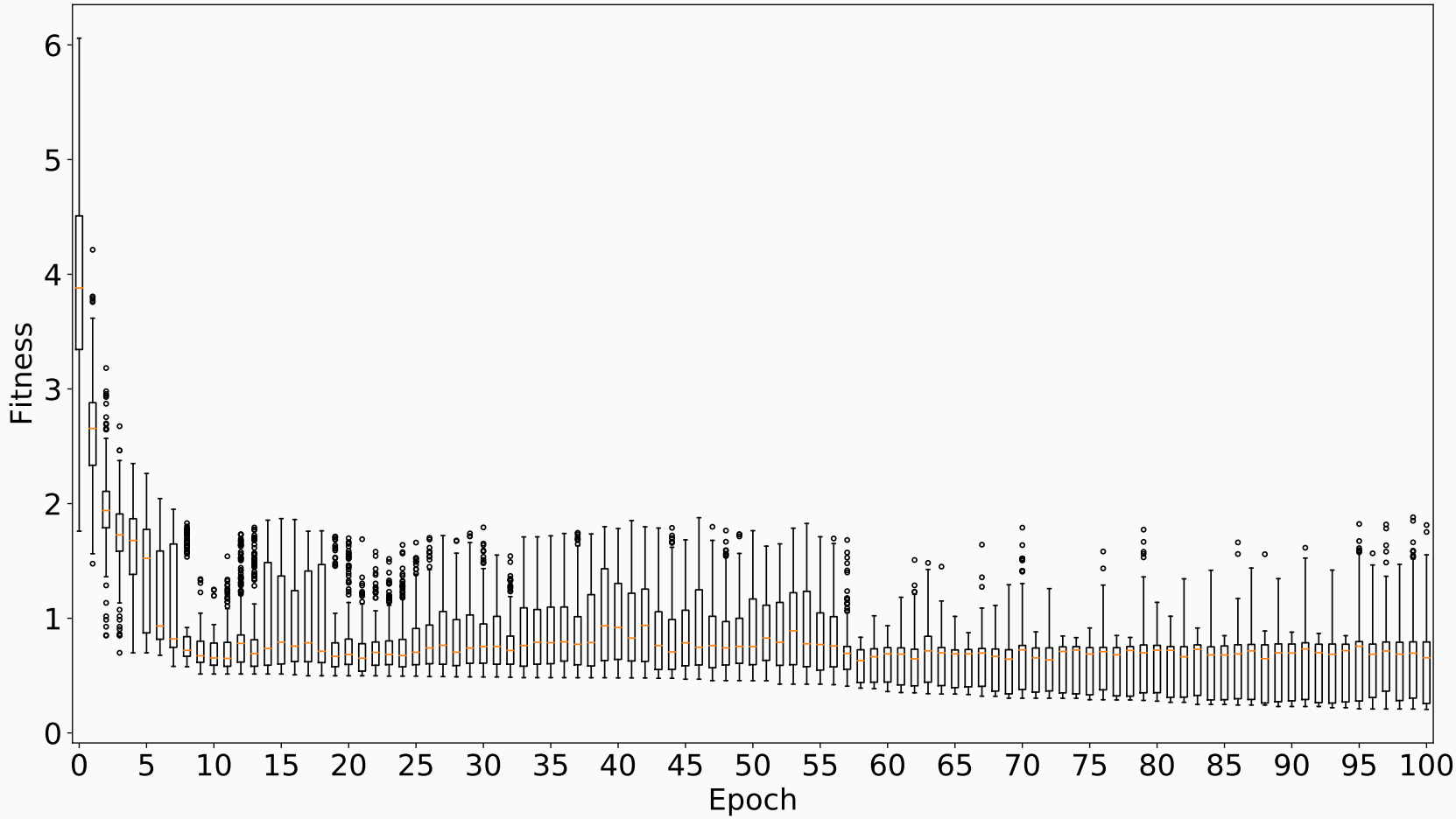
X Mean: 5.77771

Y Mean: 6.97409

X Std.: 4.49933

Y Std.: 4.09185

Corr.: 0.8012


Fitness
Epoch
0
1
2
3
4
5
6
0
5
10
15
20
25
30
35
40
45
50
55
60
65
70
75
80
85
90
95
100

```
$ pip install edo
```

Henry Wilde

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Repository: `https://github.com/daffidwilde/edo`

Documentation: `https://edo.readthedocs.io`

Paper in preparation:

"Evolutionary Dataset Optimisation: understanding algorithm quality through evolution"