

Evolutionary dataset optimisation: learning algorithm quality through evolution

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



GIG
CYMRU
NHS
WALES

Bwrdd Iechyd Prifysgol
Cwm Taf
University Health Board





Sign in



News

Sport

Weather

iPlayer

Sounds

More

Search



NEWS

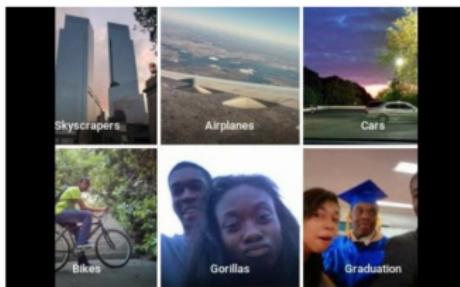
[Home](#) | [UK](#) | [World](#) | [Business](#) | [Politics](#) | [Tech](#) | [Science](#) | [Health](#) | [Family & Education](#) | [Entertainment & Arts](#) | [Stories](#) | [More](#) ▾

[Technology](#)

Google apologises for Photos app's racist blunder

⌚ 1 July 2015

f t e Share



Top Stories

EU considers potential Brexit delay

EU leaders remain locked in discussions amid reports that they may offer a delay until 7 May.

⌚ 15 minutes ago

Latest as EU leaders meet in Brussels

⌚ 18 March 2019

Trump: Time to recognise Golan as Israeli

⌚ 1 hour ago

Features



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

Reliability

R. Hyndman. *Prediction competitions*. 2014. URL:
<https://robjhyndman.com/hyndsight/prediction-competitions/>

Frailty

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



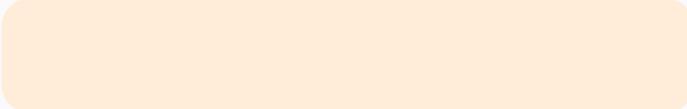
Data



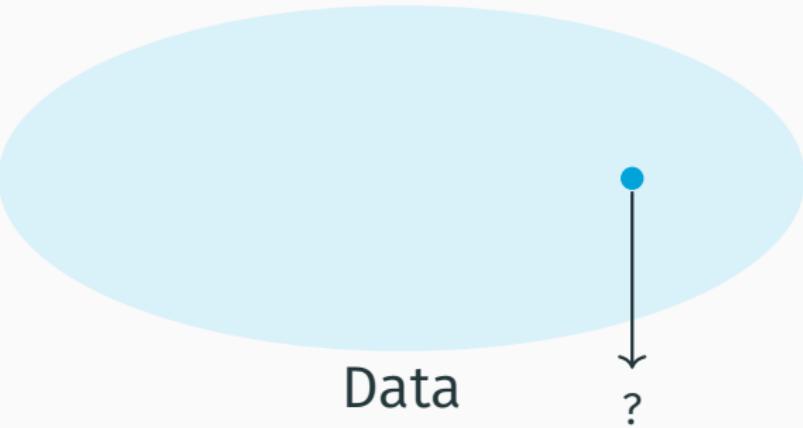
Algorithms



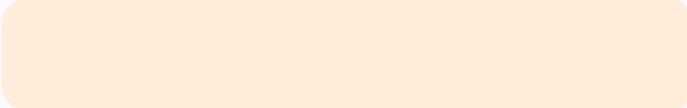
Data



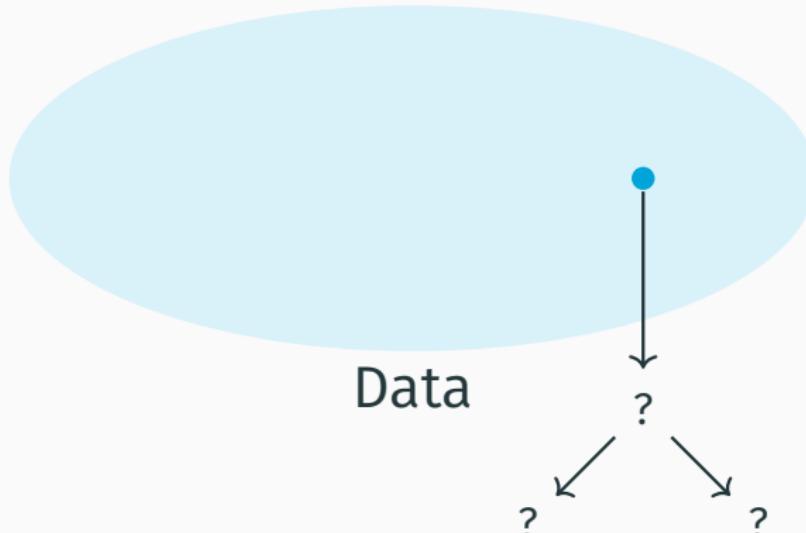
Algorithms



Data

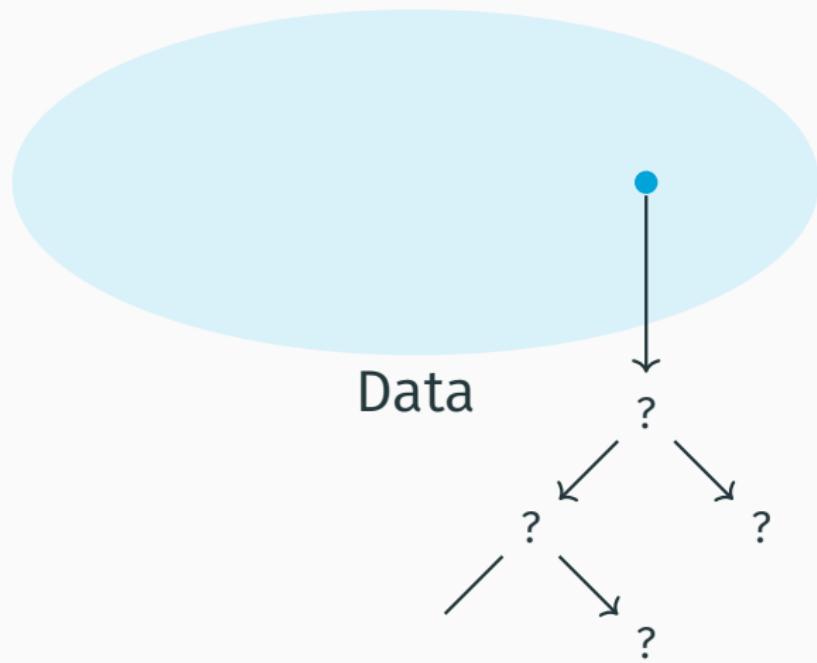


Algorithms

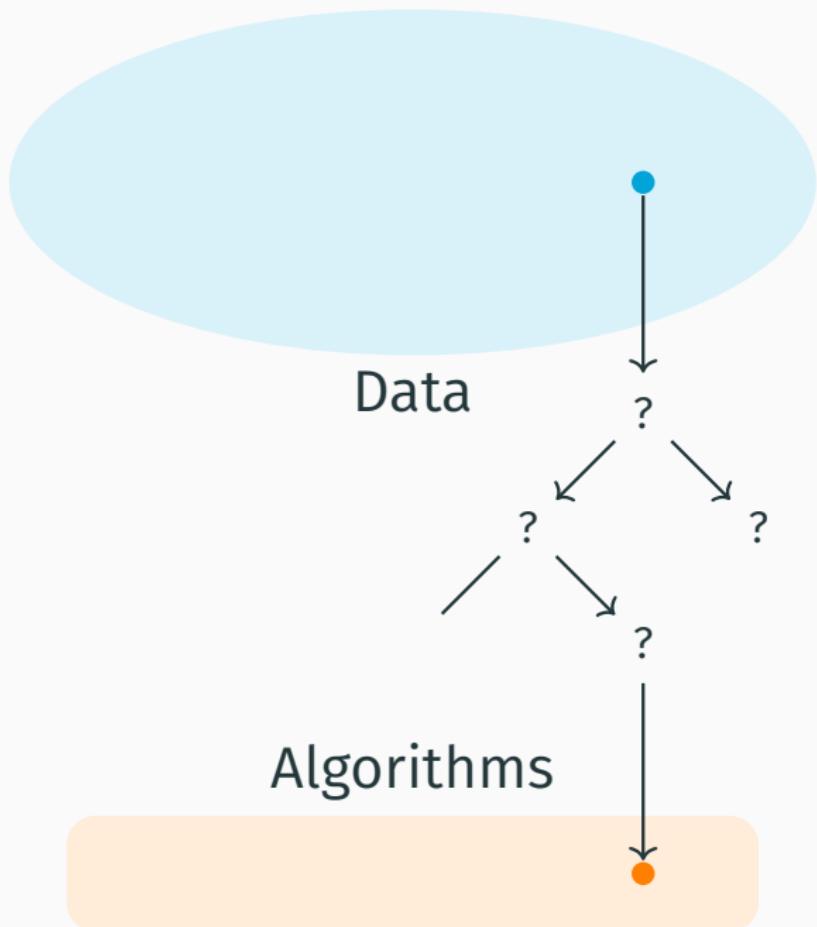


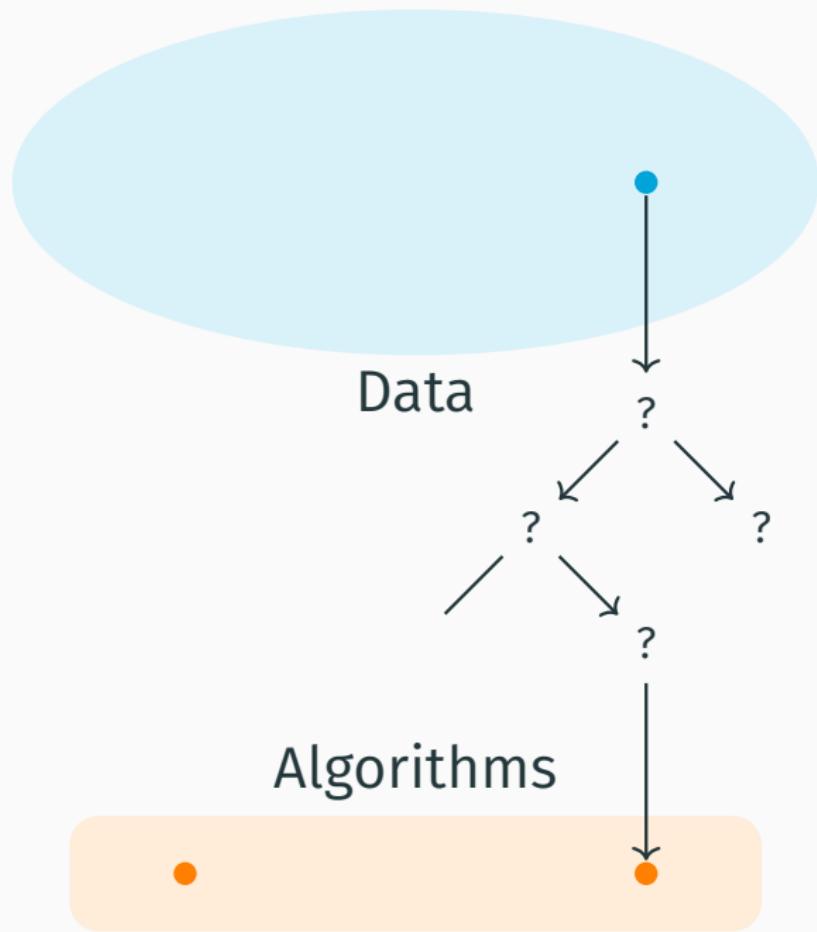
Data

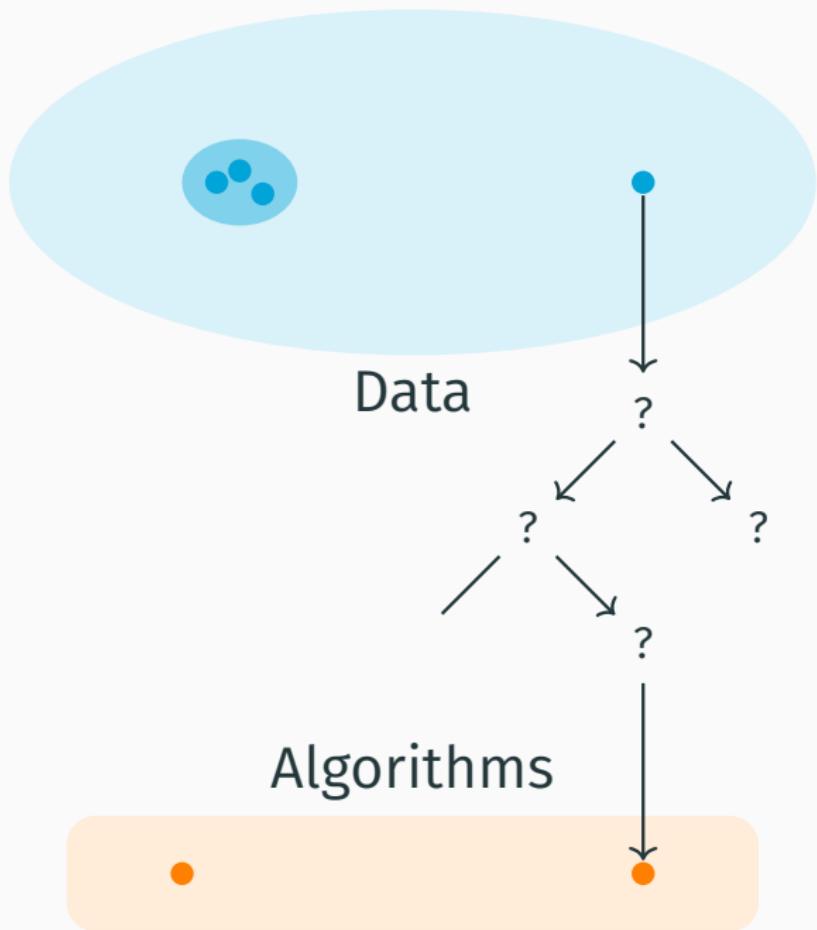
Algorithms

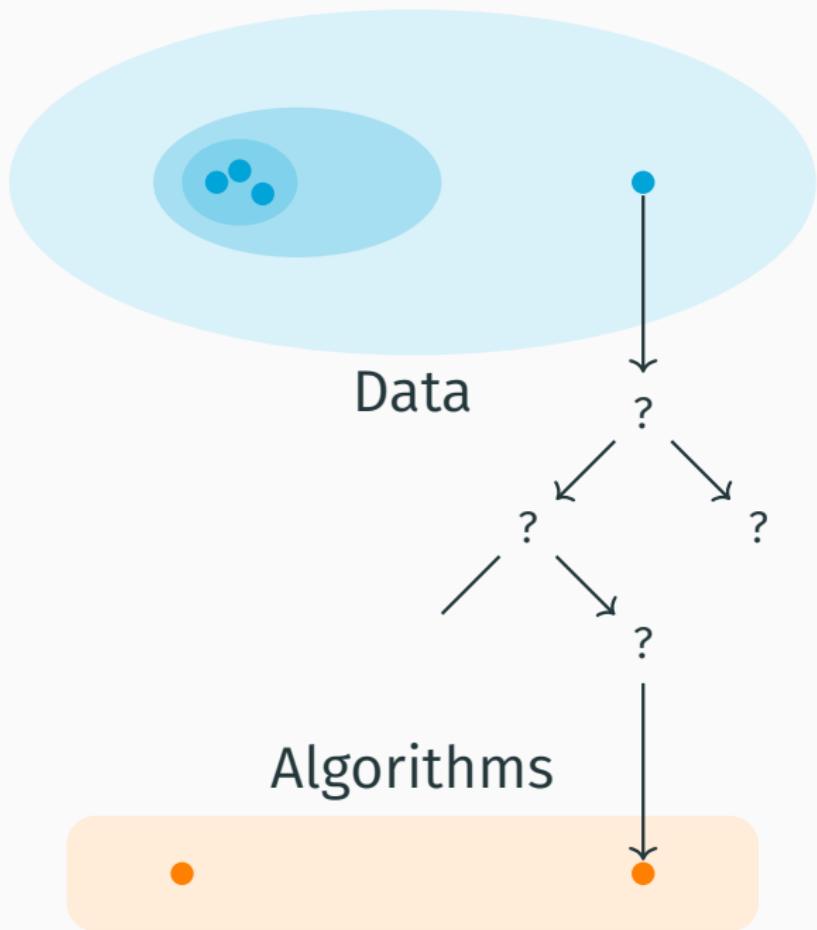


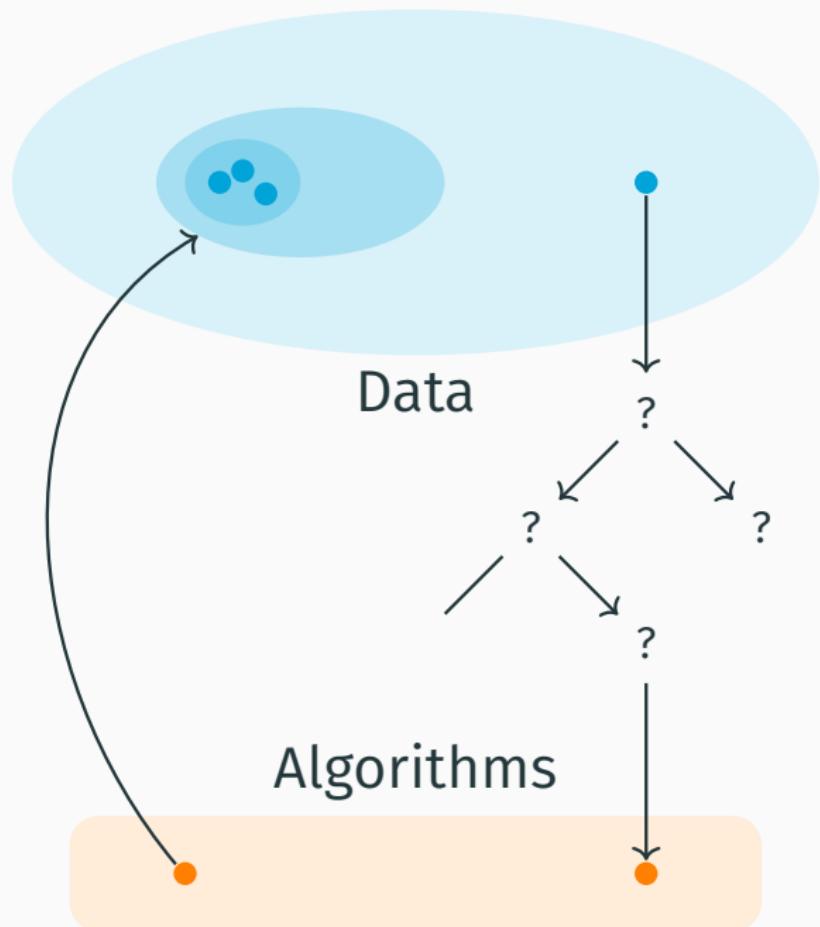
Algorithms









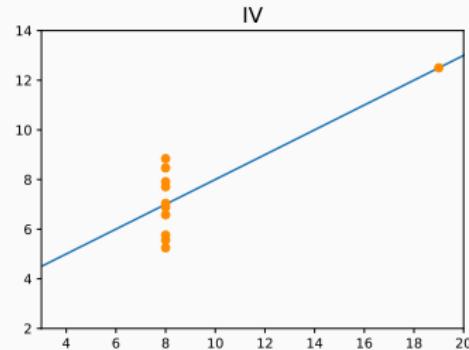
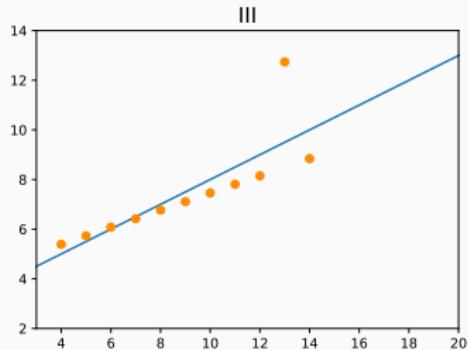
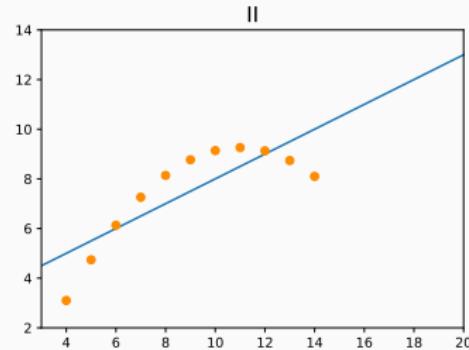
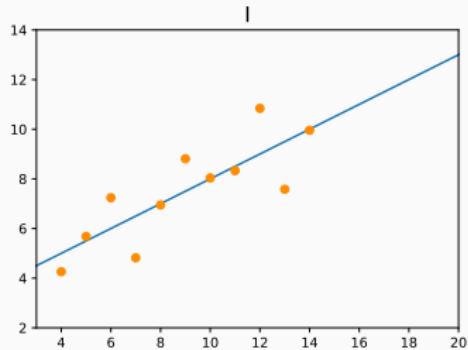


Generating artificial data

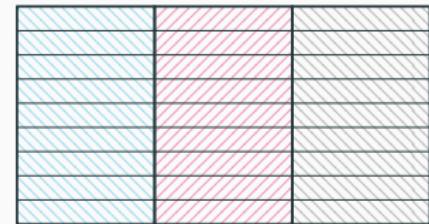


via: <https://thispersondoesnotexist.com>

Anscombe's quartet

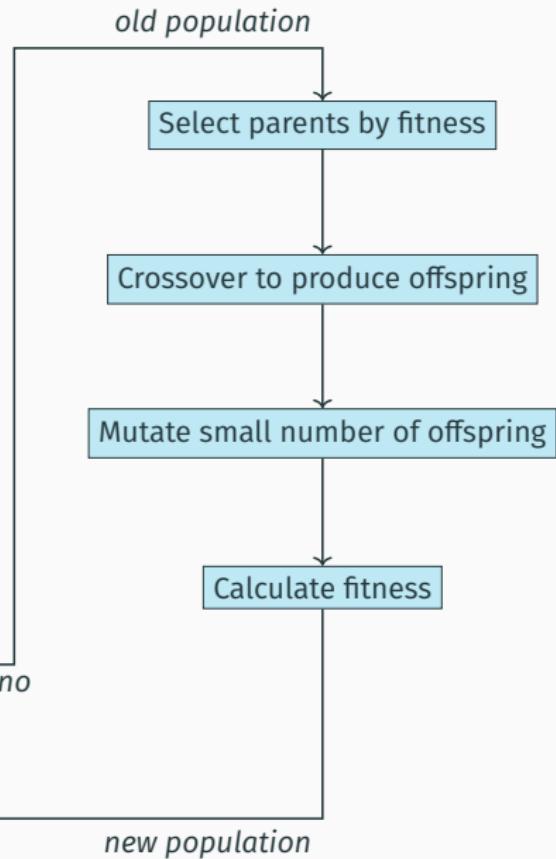
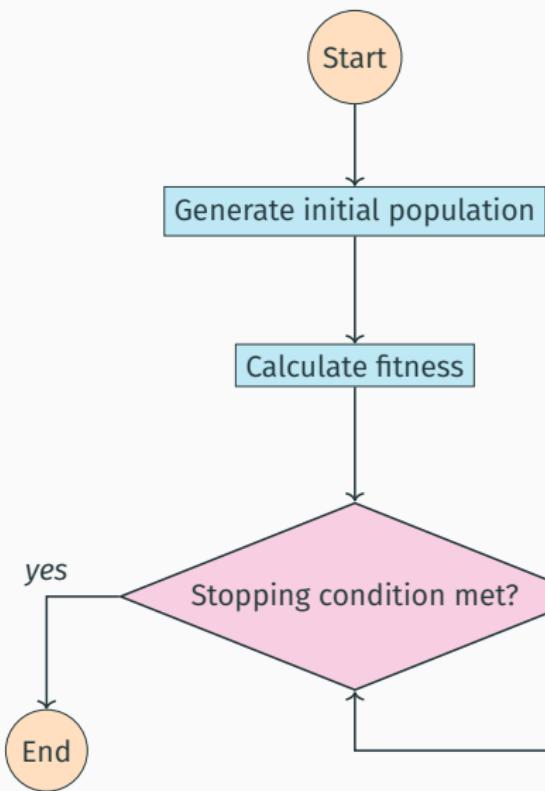


make ‘similar’



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

Evolutionary algorithms



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

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

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

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

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

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

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)

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

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)		

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

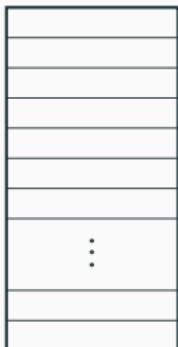
Population	(25, 30)	(12, 1)	(11, 0)	(20, 12)	(24, 25)
Get fitness	55	13	11	42	49
Select parents	(25, 30)			(20, 12)	(24, 25)
Create offspring		(24, 30)	(25, 12)		
Mutate offspring		(24, 30)	(25, 13)		

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

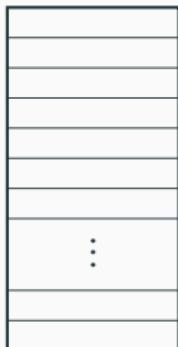
Population	(25, 30)	(12, 1)	(11, 0)	(20, 12)	(24, 25)
Get fitness	55	13	11	42	49
Select parents	(25, 30)			(20, 12)	(24, 25)
Create offspring		(24, 30)	(25, 12)		
Mutate offspring		(24, 30)	(25, 13)		
New generation	(25, 30)	(24, 30)	(25, 13)	(20, 12)	(24, 25)

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

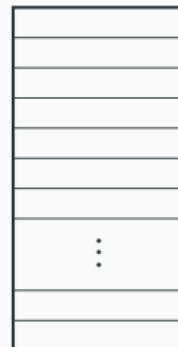
Population	(25, 30)	(12, 1)	(11, 0)	(20, 12)	(24, 25)
Get fitness	55	13	11	42	49
Select parents	(25, 30)			(20, 12)	(24, 25)
Create offspring		(24, 30)	(25, 12)		
Mutate offspring		(24, 30)	(25, 13)		
New generation	(25, 30)	(24, 30)	(25, 13)	(20, 12)	(24, 25)

$N(\mu, \sigma^2)$ $U(\alpha, \beta)$ $Po(\lambda)$ $N(0.25, 1)$ $U(1.2, 3.2)$ $N(-3.7, 0)$ 

+



+

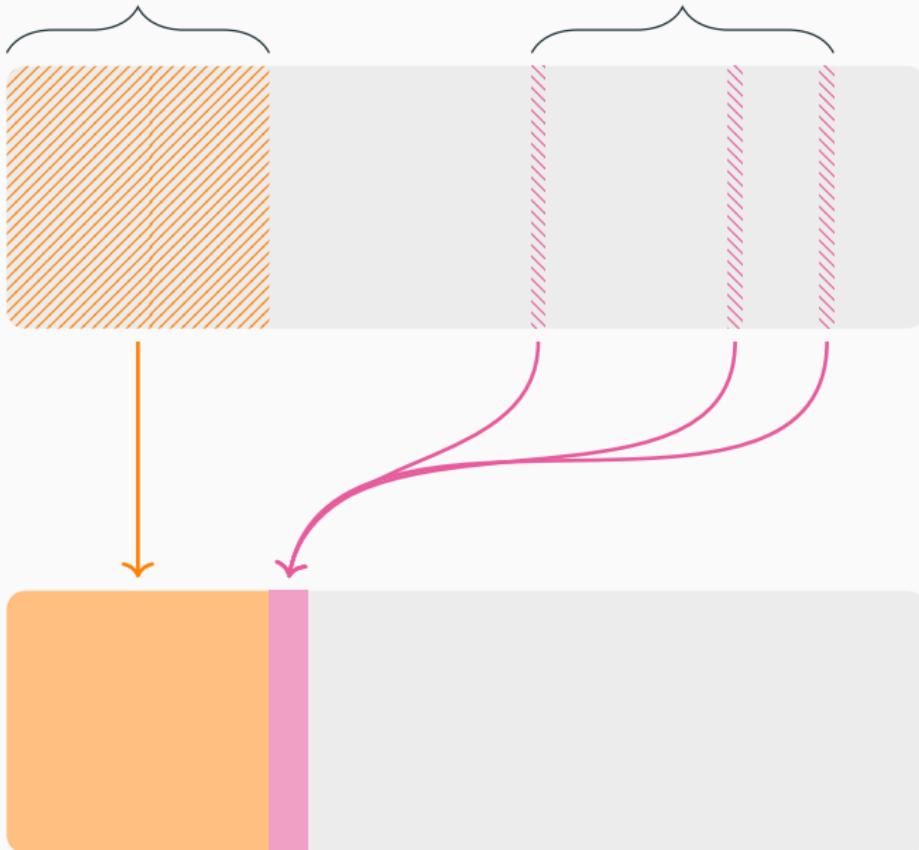


$$\max \quad f : \mathbb{N}^2 \rightarrow \mathbb{N}; \quad f(x_1, x_2) = x_1 + x_2$$

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		(24, 30)	(25, 13)		
New generation	(25, 30)	(24, 30)	(25, 13)	(20, 12)	(24, 25)

Best individuals

Lucky individuals



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

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		(24, 30)	(25, 13)		
New generation	(25, 30)	(24, 30)	(25, 13)	(20, 12)	(24, 25)

$$N(0, 1)$$

Po(3.6)

U(3, 5)

$$N(2, 2)$$

Po(2.5)

Dimensions

Columns

(1)

(2)

$$N(0, 1)$$

Po(2.5)

U(3,5)

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

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		(24, 30)	(25, 13)		
New generation	(25, 30)	(24, 30)	(25, 13)	(20, 12)	(24, 25)

$U(1.1, 3.2)$ $Po(1.2)$ $N(0.5, 1.2)$

$U(1.1, 3.2)$ $Po(1.2)$ $N(0.5, 1.2)$

+

$U(1.1, 3.2)$ $Po(1.2)$ $N(0.5, 1.2)$

Chosen at random

$U(1.1, 3.2)$ $Po(1.2)$ $N(0.5, 1.2)$

Chosen at random

$U(1.1, 3.2)$ $Po(1.2)$ $N(0.5, 1.2)$ + $Po(9.3)$

+

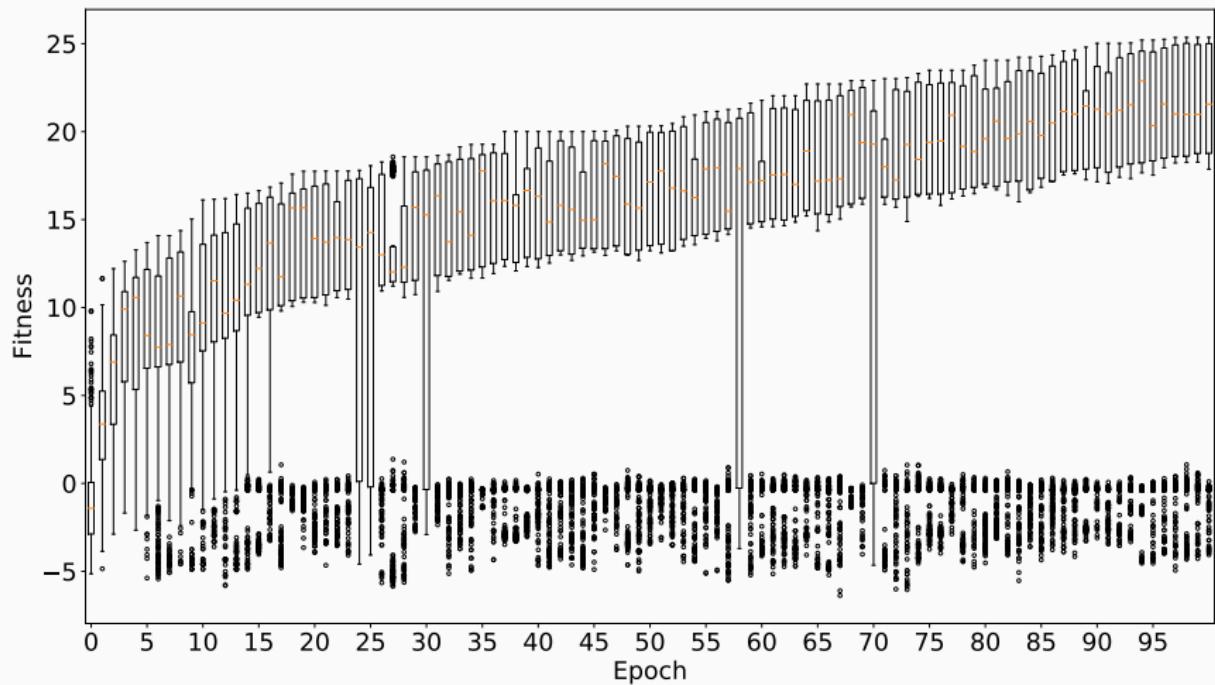
$U(1.1, 2.6)$ $Po(1.2)$ $N(0.2, 2.3)$

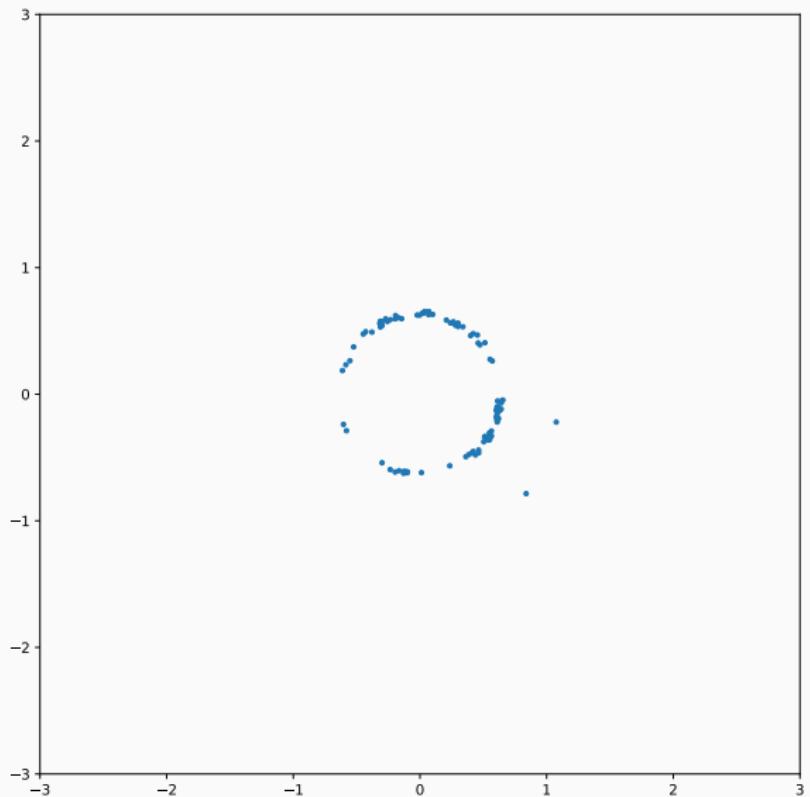
$U(1.1, 3.2)$ $Po(1.2)$ $N(0.5, 1.2)$

Some example use cases

Maximise

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

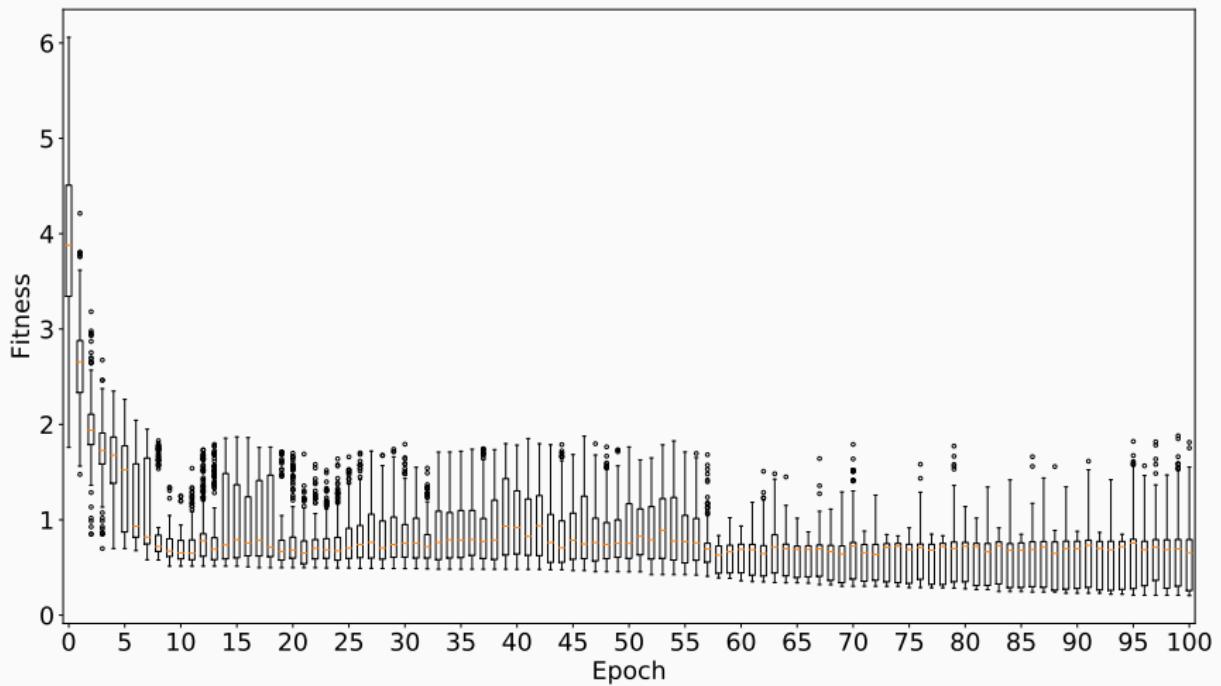




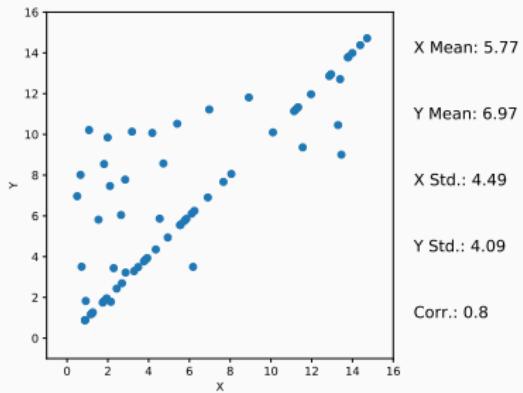
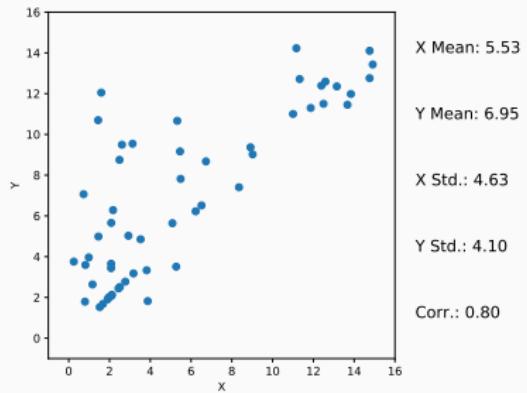
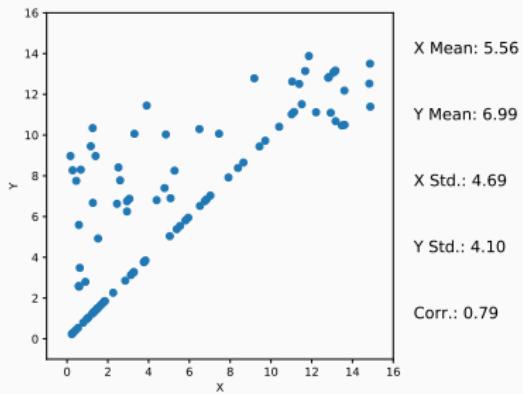
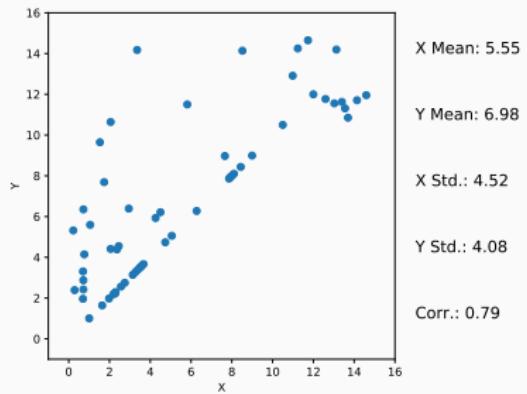
Given a set of k dissimilarity measures:

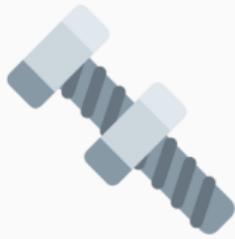
$$f_1, \dots, f_k : \mathbb{R}^n \times \mathbb{R}^n \rightarrow \mathbb{R}$$

Minimise their sum



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





Henry Wilde

Twitter: @daffidwilde

Email: wildehd@cardiff.ac.uk

Repository: github.com/daffidwilde/edo

Documentation: edo.readthedocs.io

Paper in preparation:

“Evolutionary Dataset Optimisation: understanding algorithm quality through evolution”

- 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:

$$C := \left(c_1, \dots, c_{|\mathcal{P}|} \right) \text{ where } c_j \in \left\{ (c_{\min}, c_{\max}) \in (\mathbb{N} \cup \{\infty\})^2 \mid c_{\min} \leq c_{\max} \right\}$$

for each $j = 1, \dots, |\mathcal{P}|$

- 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} , $w = (w_1, \dots, w_{|\mathcal{P}|})$
- 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