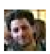
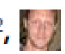
# Modern Robotics: Evolutionary Robotics

COSC 4560 / COSC 5560

Professor Cheney

3/23/18

# Evolutionary Developmental Soft Robotics As a Framework to Study Intelligence and Adaptive Behavior in Animals and Plants

 Francesco Corucci[1,2]*,  Nick Cheney[2,3],  Sam Kriegman[2],  Josh Bongard[2] and  Cecilia Laschi[1]

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[2]Morphology, Evolution & Cognition Laboratory, University of Vermont, Burlington, VT, United States

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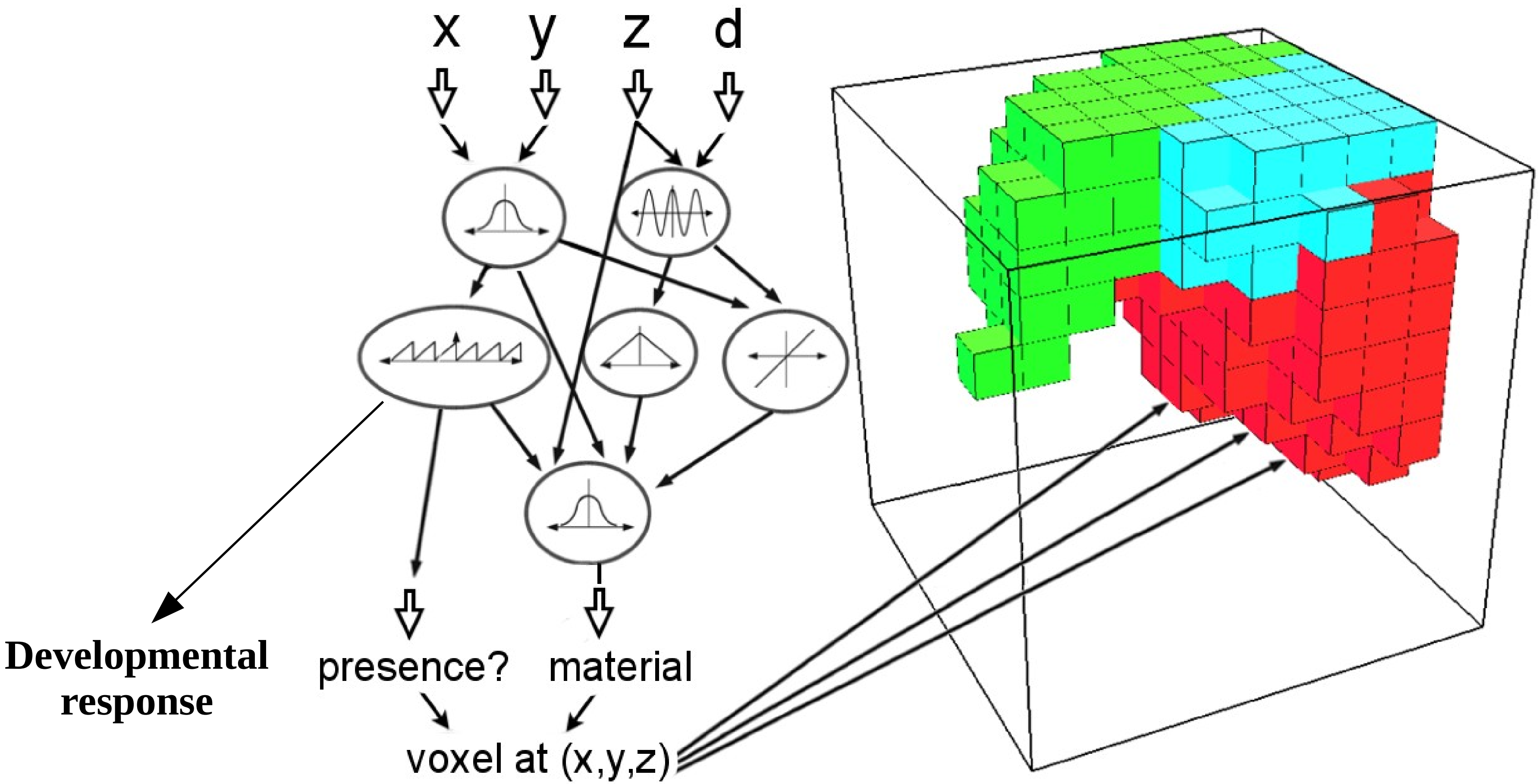
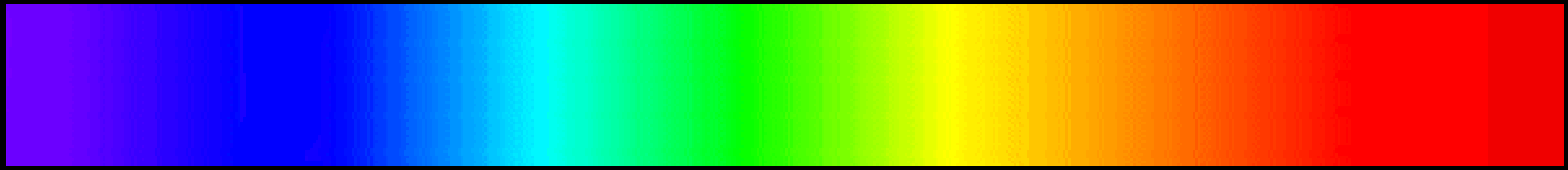


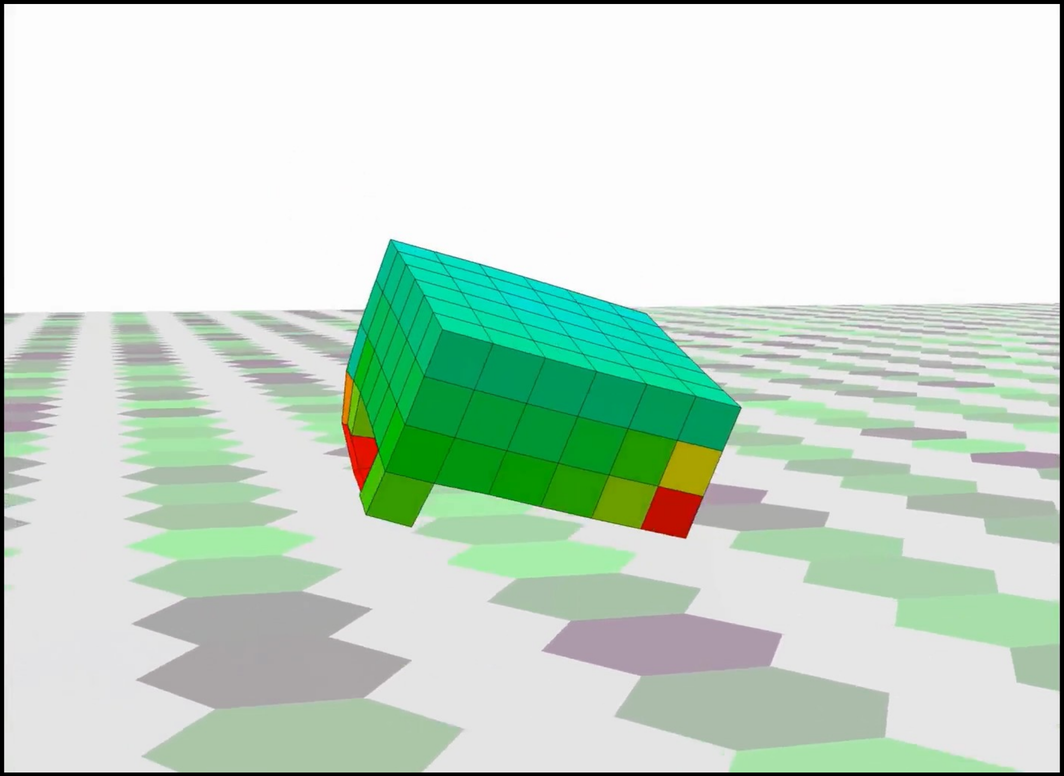
x
y
z
d
Developmental response
presence?
material
voxel at (x,y,z)

Sensory dependent ("closed-loop") material changes:

Evolution finds a voxel-stiffening reaction to mechanical stress



softer stiffer



# Interoceptive robustness through environment-mediated morphological development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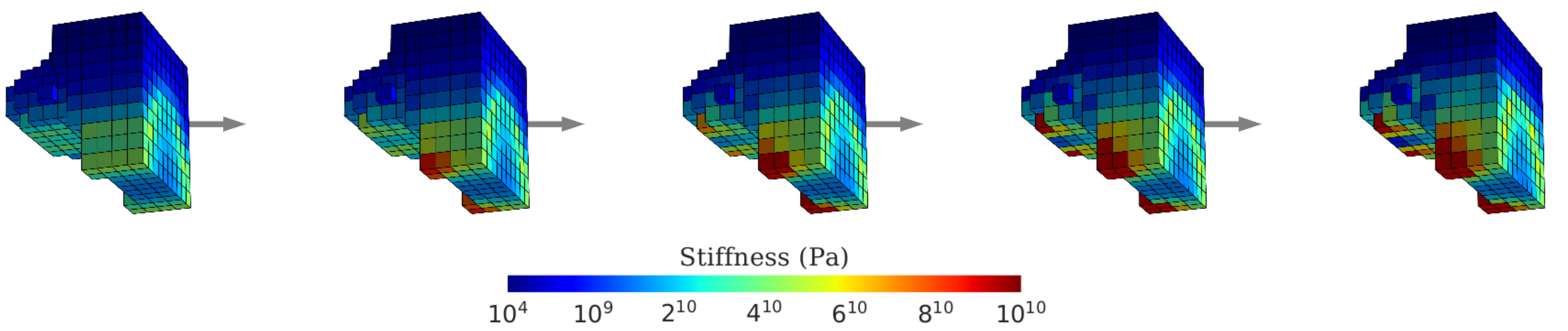
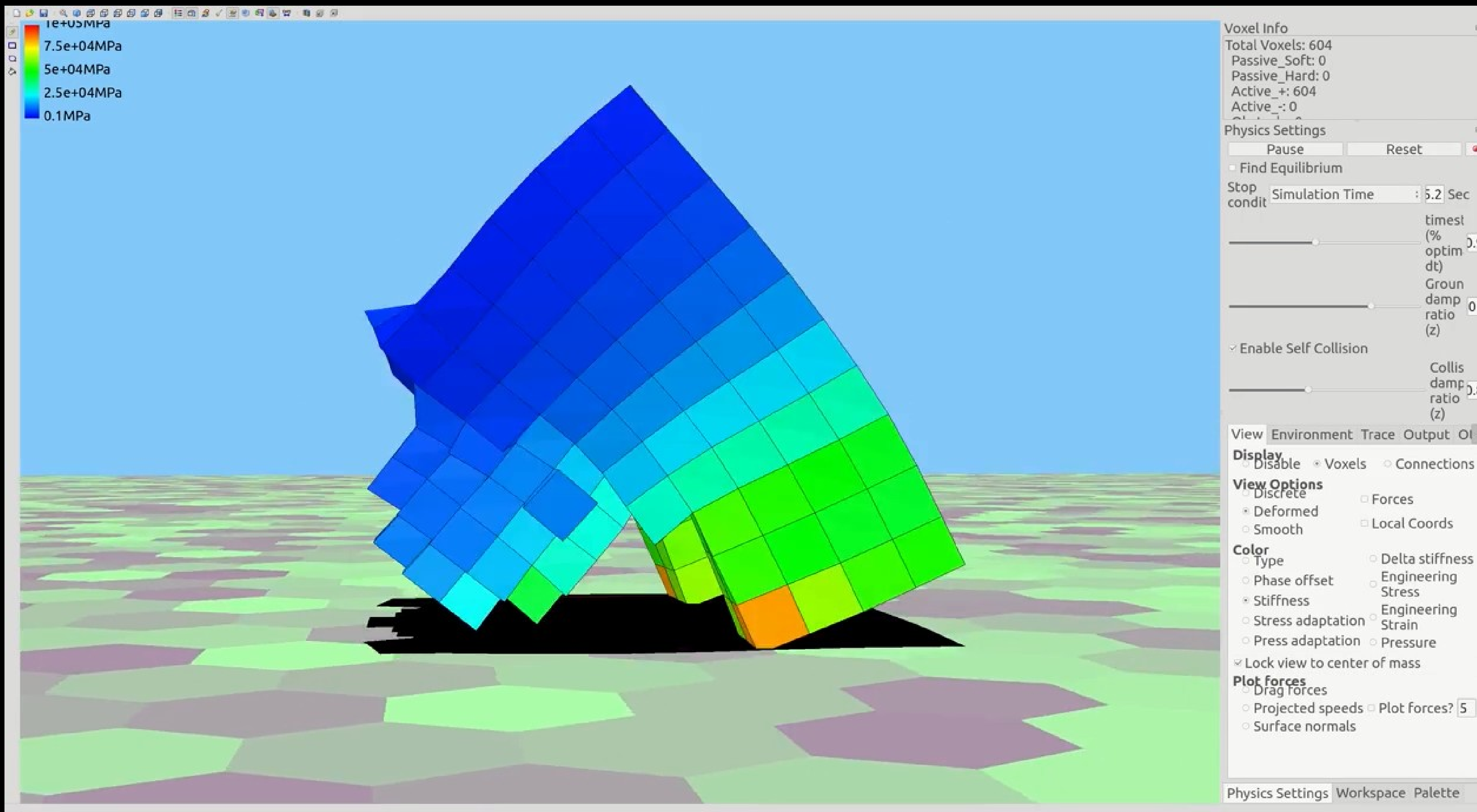
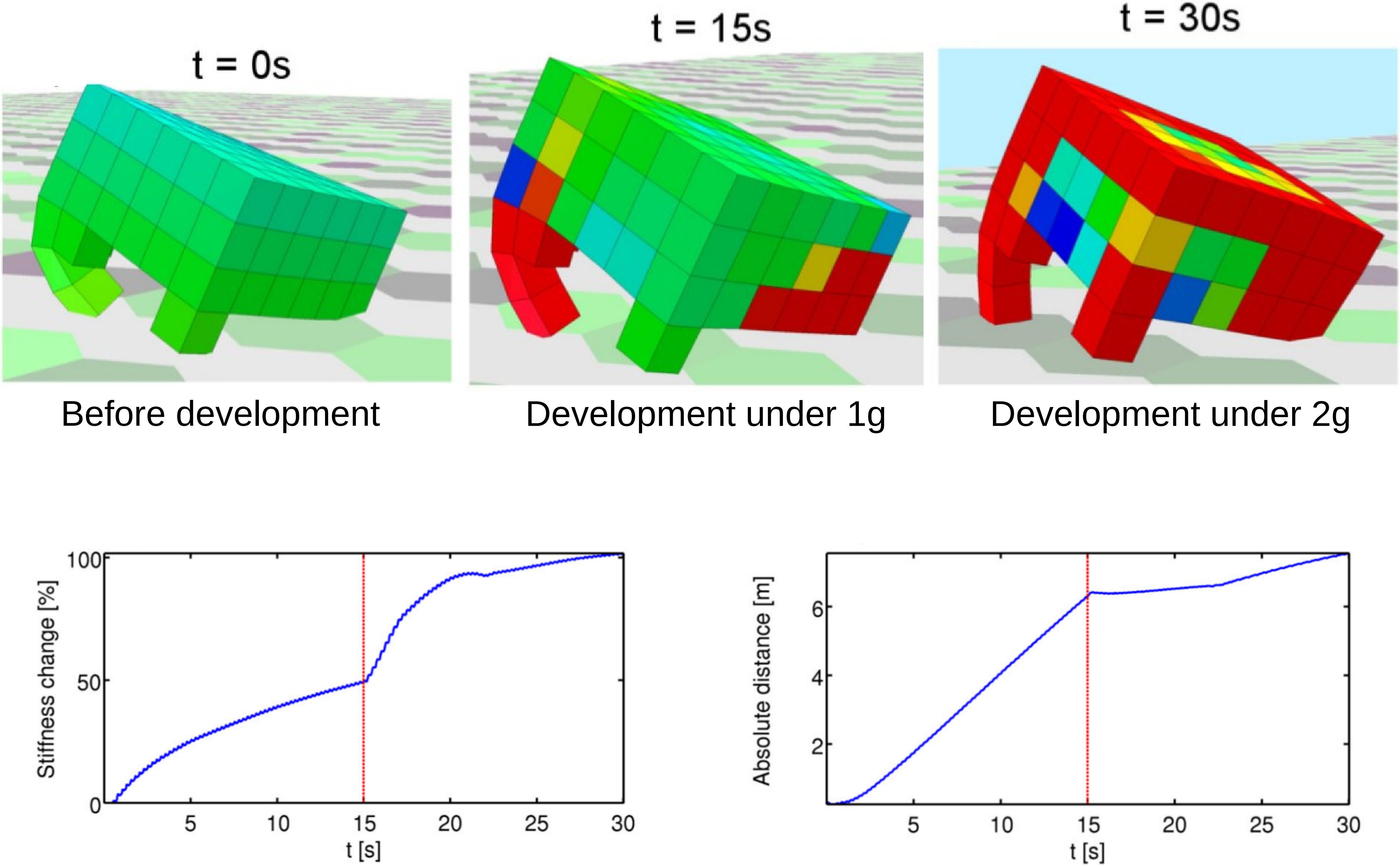



1e+05MPa
7.5e+04MPa
5e+04MPa
2.5e+04MPa
0.1MPa
Voxel Info
Total Voxels: 604
Passive_Soft: 0
Passive_Hard: 0
Active_+: 604
Active_-: 0
Physics Settings
Pause
Reset
Find Equilibrium
Stop condit
Simulation Time
Sec
Enable Self Collision
View
Environment
Trace
Output
Display
Disable
Voxels
Connections
View Options
Discrete
Deformed
Smooth
Forces
Local Coords
Color
Type
Phase offset
Stiffness
Stress adaptation
Press adaptation
Delta stiffness
Engineering Stress
Engineering Strain
Pressure
Lock view to center of mass
Plot forces
Drag forces
Projected speeds
Surface normals
Plot forces?
Physics Settings
Workspace
Palette



t = 0s
t = 15s
t = 30s
Before development
Development under 1g
Development under 2g
Stiffness change [%]
0
50
100
5
10
15
20
25
30
t [s]
Absolute distance [m]
2
4
6
5
10
15
20
25
30
t [s]

# How Learning Can Guide Evolution

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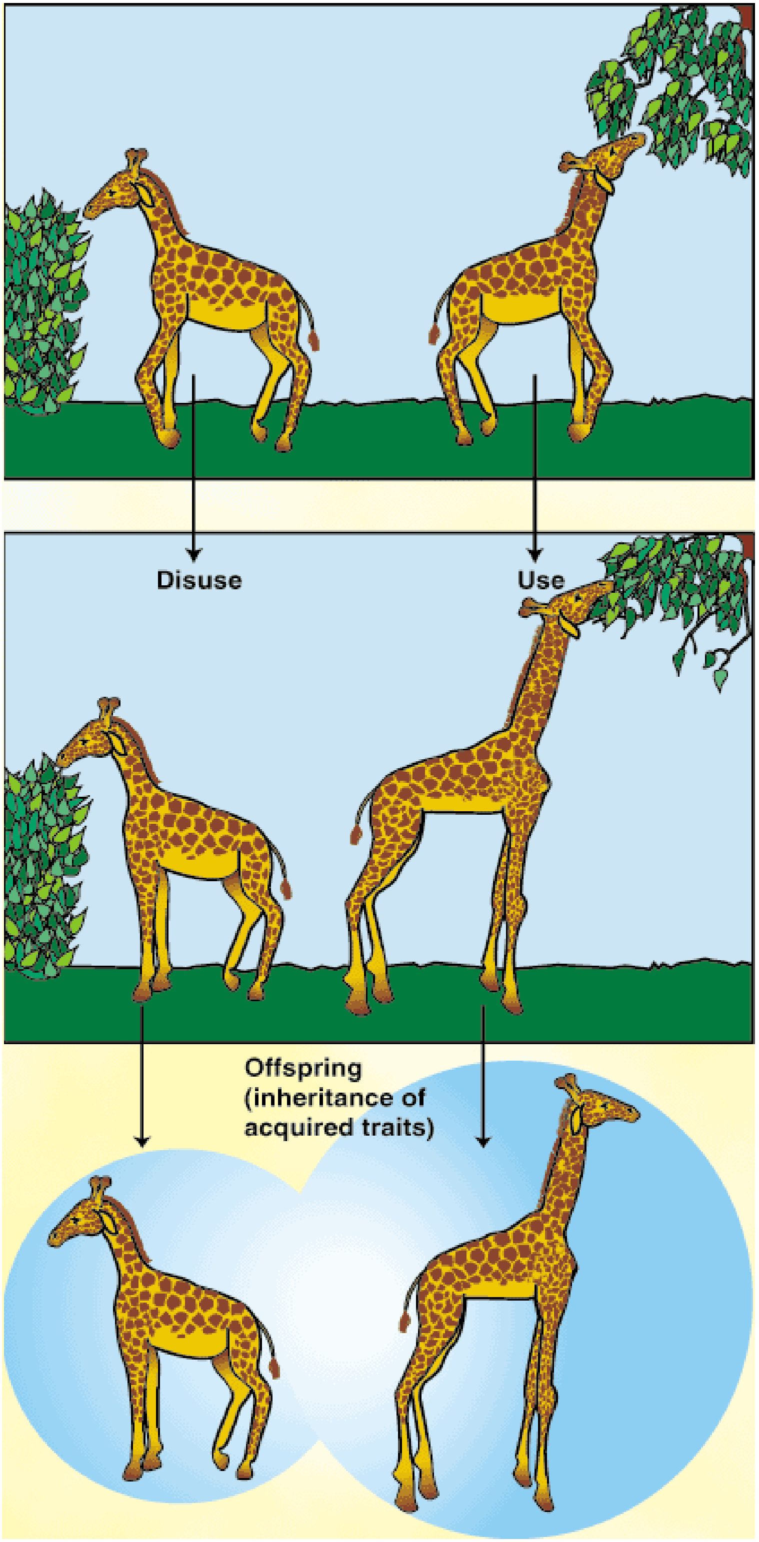
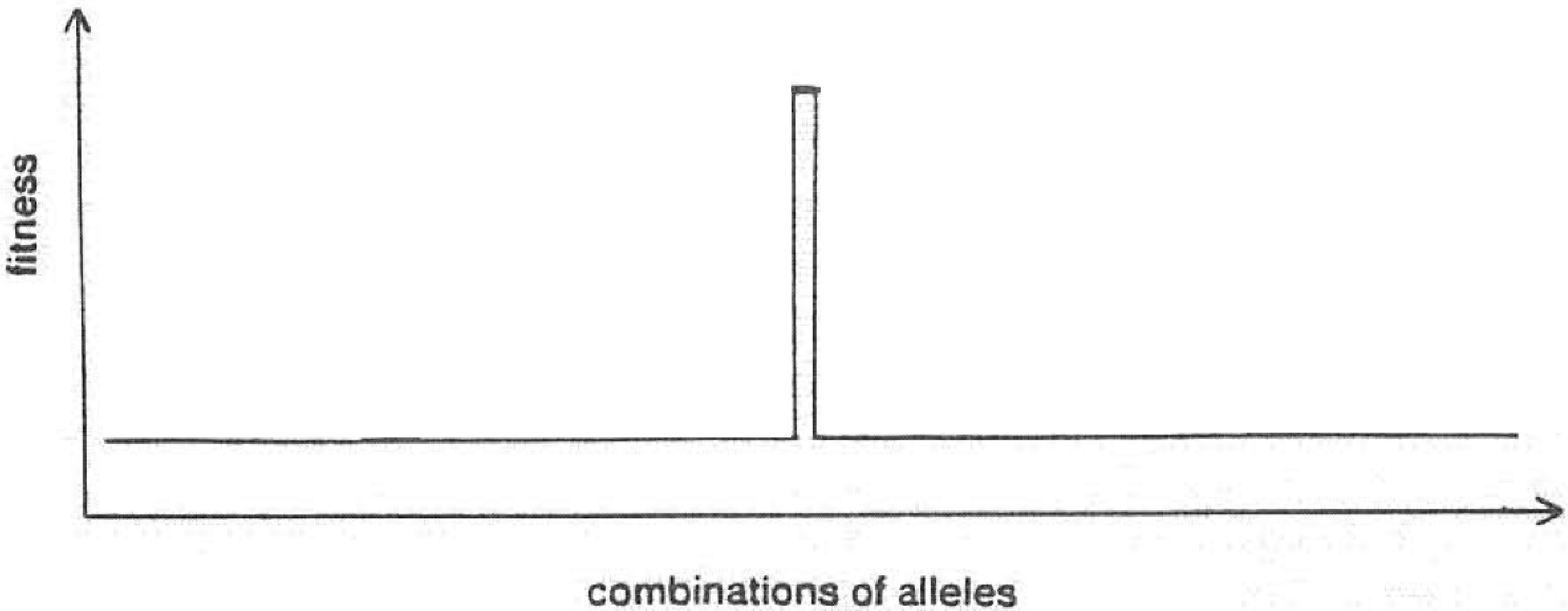
# Lamarckian inheritance



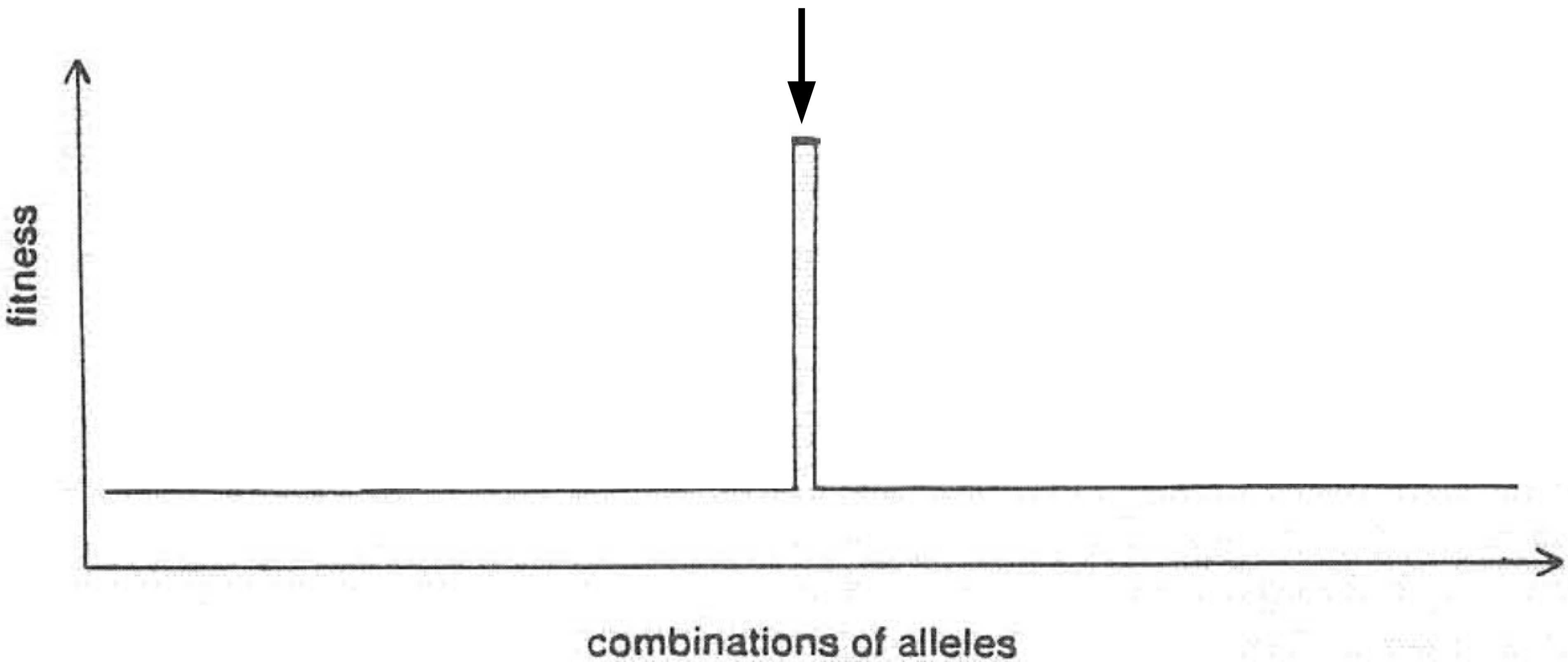
## 3. A simulation

We have simulated a simple example of this kind of interaction between learning and evolution. The neural net has 20 potential connections, and the genotype has 20 genes[1], each of which has three alternative forms (alleles) called 1, 0, and ?. The 1 allele specifies that a connection should be present, 0 specifies that it should be absent, and ? specifies a connection containing a switch which can be open or closed. It is left to learning to decide how the switches should be set. We assume, for simplicity, a learning mechanism that simply tries a random combination of switch settings on every trial. If the combination of the switch settings and the genetically specified decisions ever produce the one good net we assume that the switch settings are frozen. Otherwise they keep changing.[2]

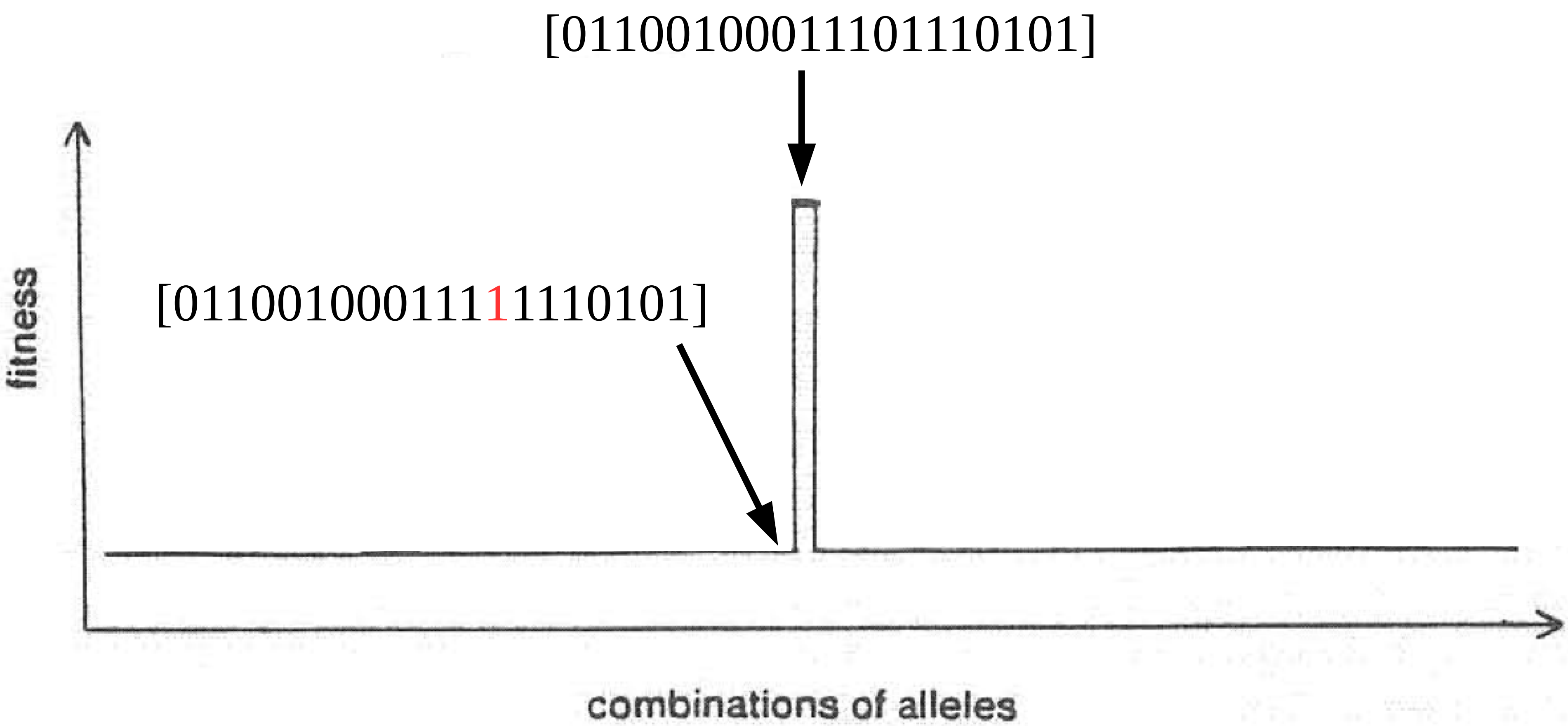

fitness
combinations of alleles

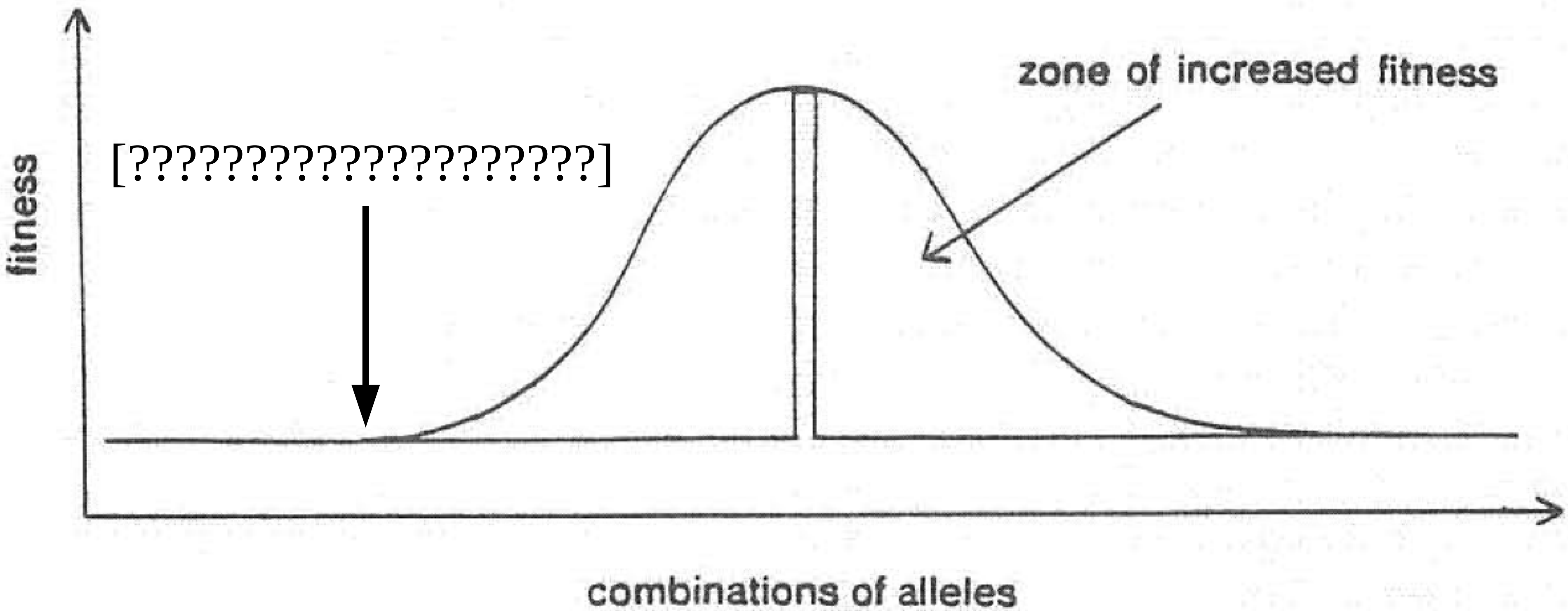
Chance of being found through mutation: $(1/2)^{20} = 0.000000954$

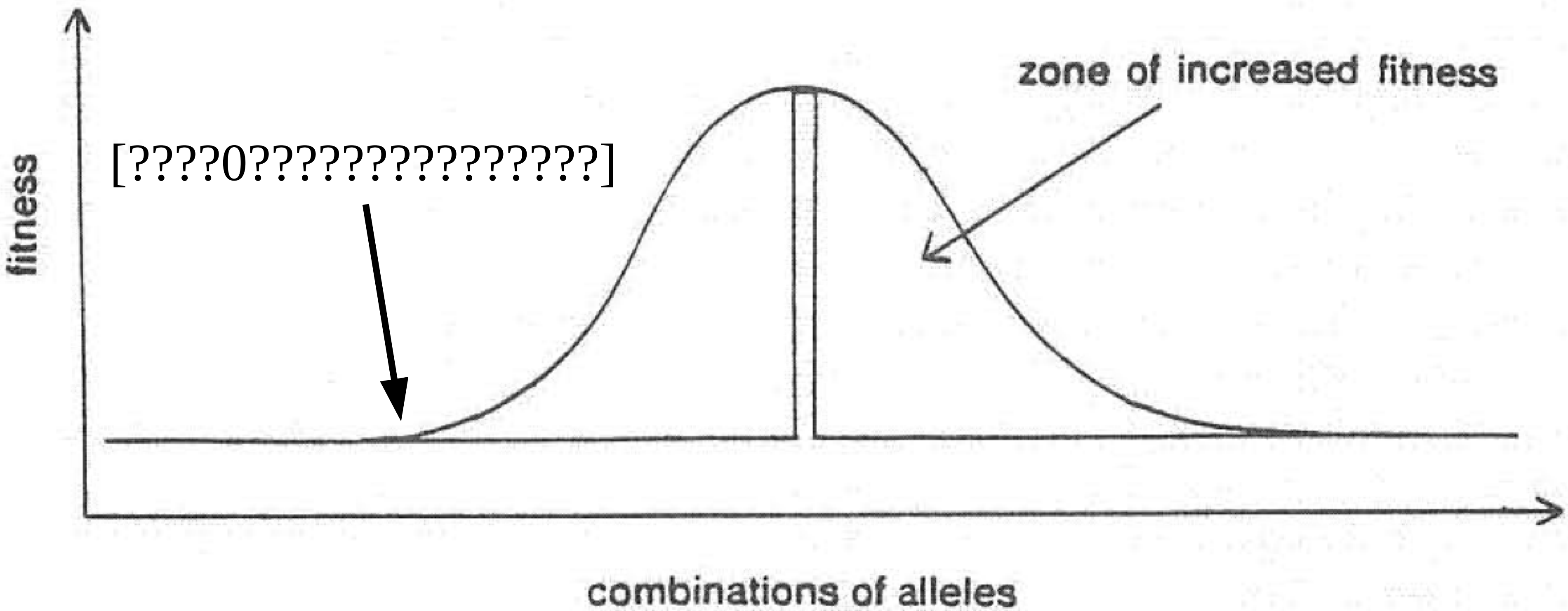
[01100100011101110101]

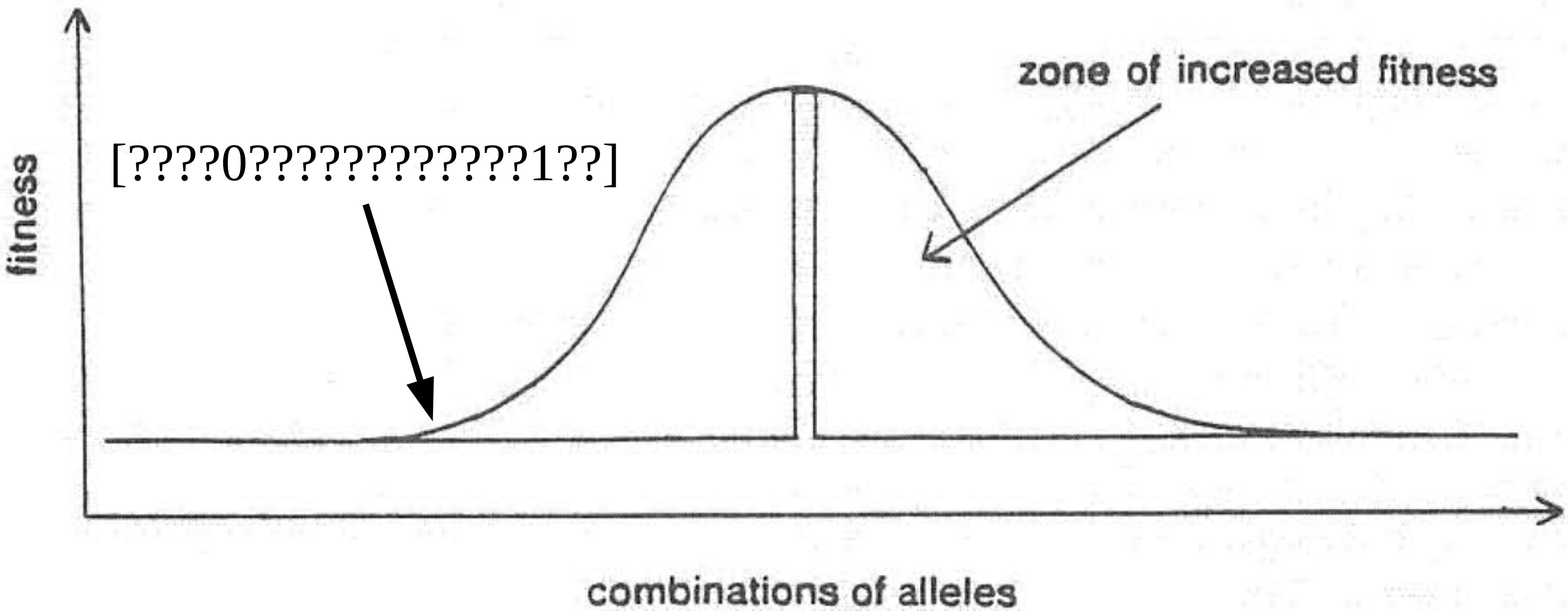


Chance of being found through mutation: $(1/2)^{20} = 0.000000954$

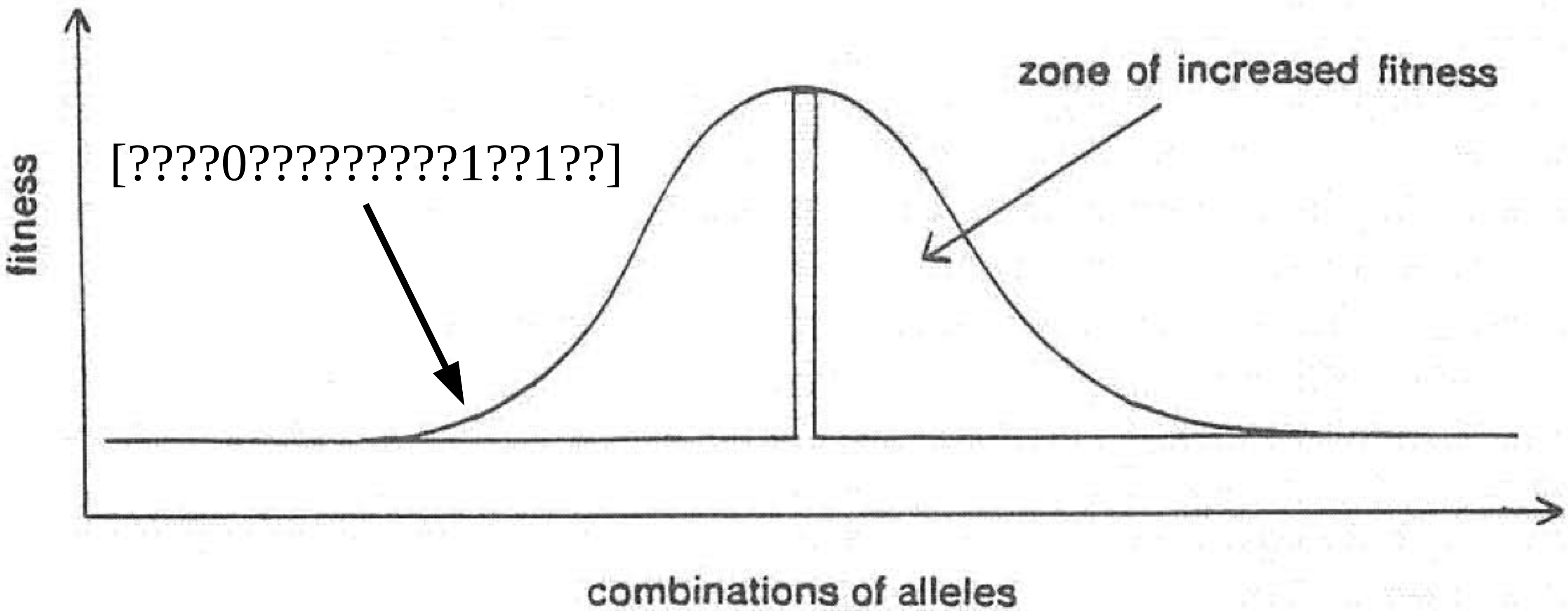


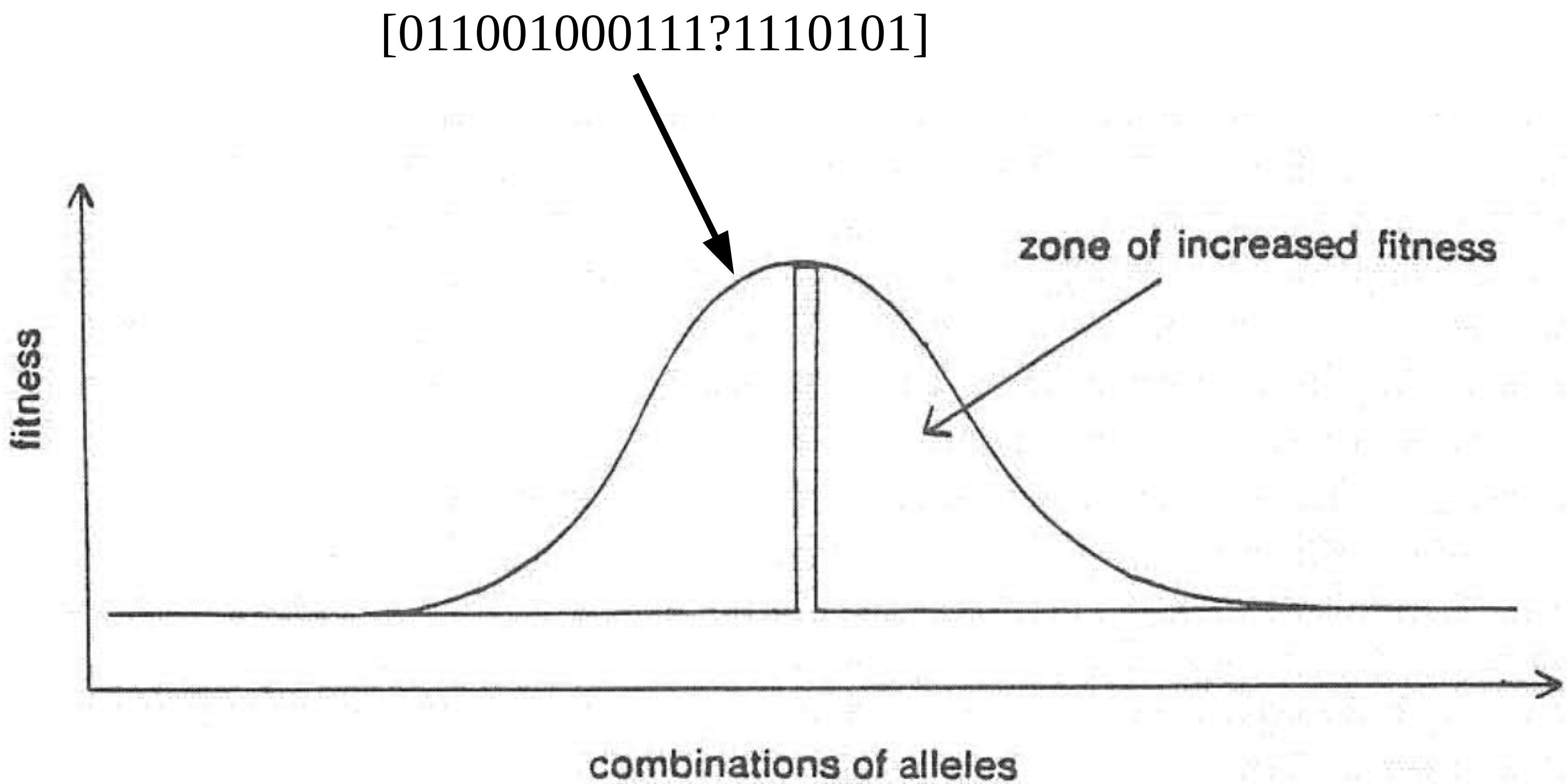

zone of increased fitness
[????????????????????]
fitness
combinations of alleles


zone of increased fitness
fitness
combinations of alleles

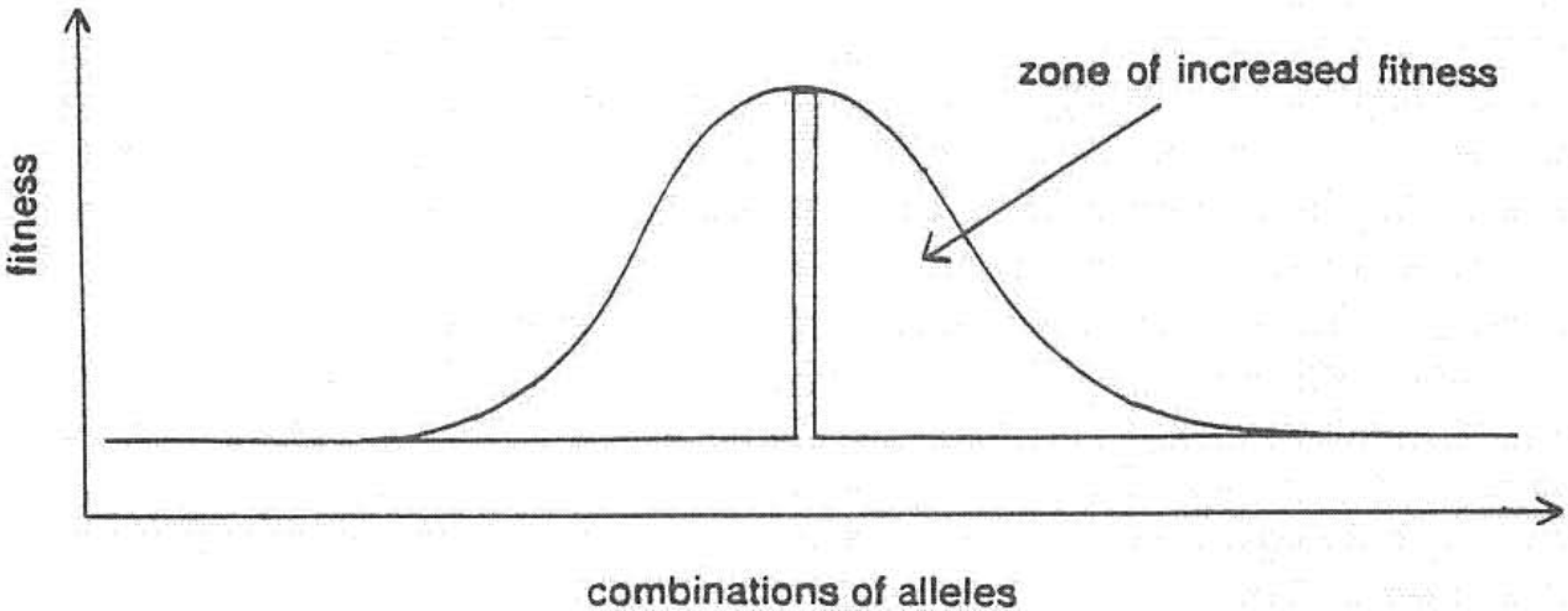


zone of increased fitness
[????0????????????1??]
fitness
combinations of alleles


zone of increased fitness
[????0?????????1??1??]
fitness
combinations of alleles


[01100100011?1110101]
zone of increased fitness
fitness
combinations of alleles

(the potential for) behaviors during a lifetime
(even outside the germline, and/or after reproduction)
can affect evolutionary fitness and be inherited!



# How morphological development can guide evolution

**Sam Kriegman[1,*], Nick Cheney[2], and Josh Bongard[1]**

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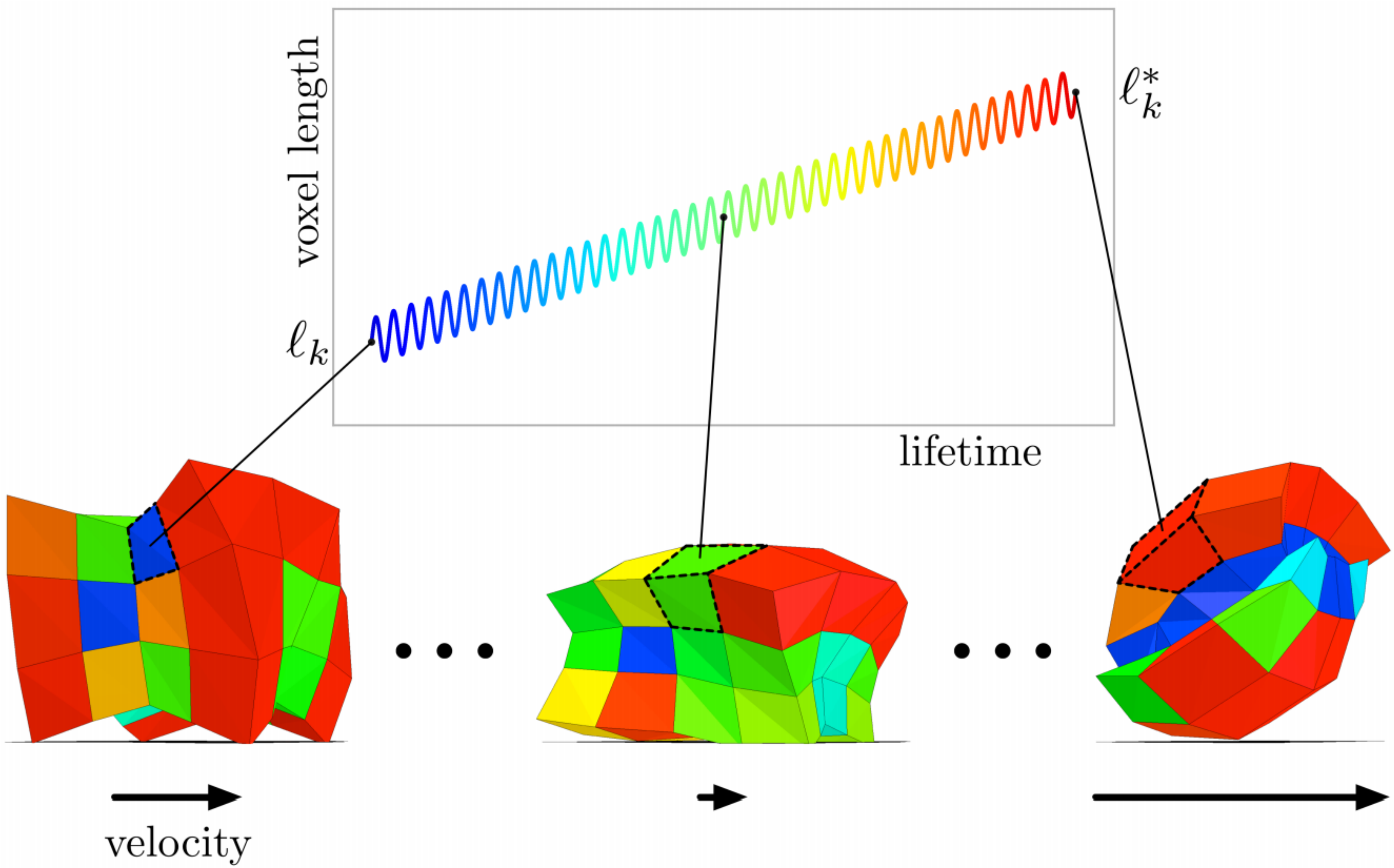
[*]sam.kriegman@uvm.edu




[Kriegman et al. 2017]

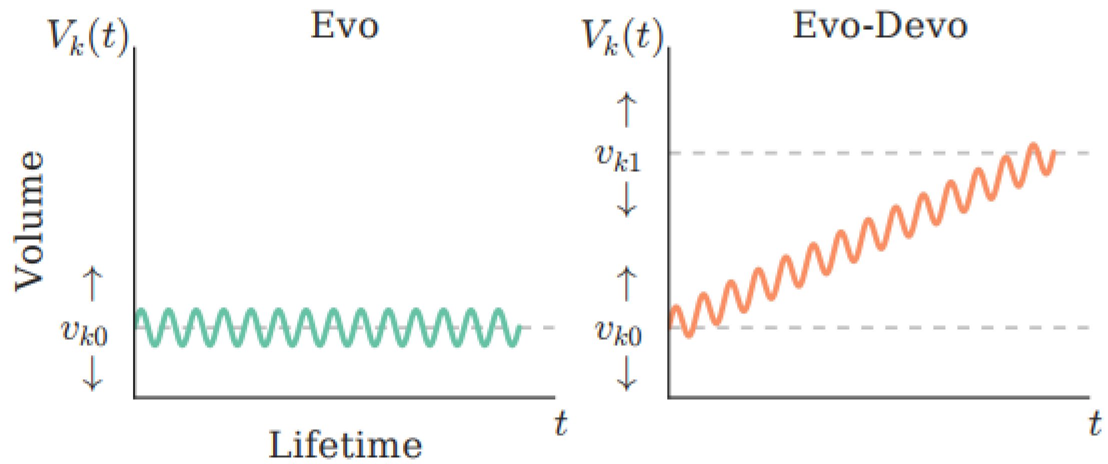



**Figure 2: The voxel picture. The $k^{\text{th}}$ voxel in an Evo robot maintains a fixed resting volume, $v_{k0}$, throughout the robot's lifetime. Sinusoidal actuation is applied on top of the resting volume. In contrast, the $k^{\text{th}}$ voxel in an Evo-Devo robot changes linearly from a starting volume, $v_{k0}$, to a final volume, $v_{k1}$, over the robot's entire lifetime. Growth, the case when $v_{k1} > v_{k0}$, is pictured here, but shrinkage is also possible and occurs when $v_{k1} < v_{k0}$. When $v_{k1} = v_{k0}$, Evo-Devo voxels are behaviorally equivalent to Evo voxels. Voxels actuate at 4 Hz in our experiments (for 8 sec or 32 cycles) however actuation is drawn here at a lower frequency to better convey the sinusoidal volumetric structure in time.**

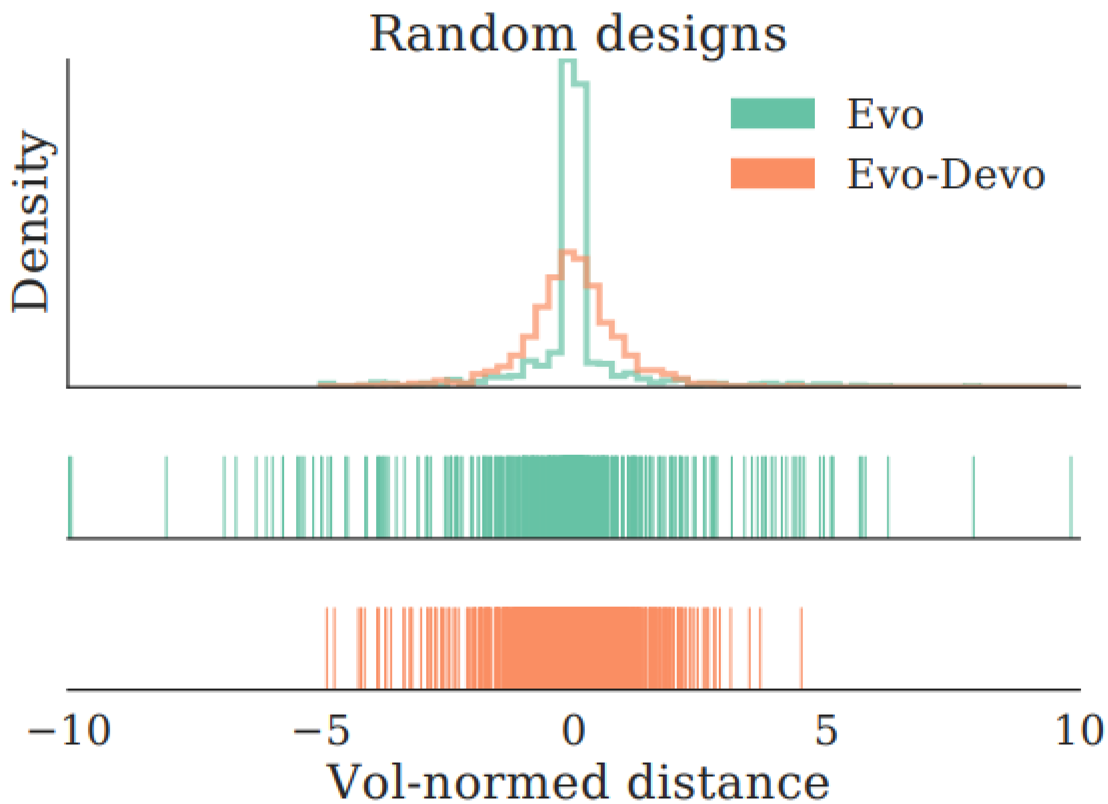
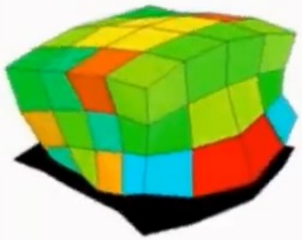
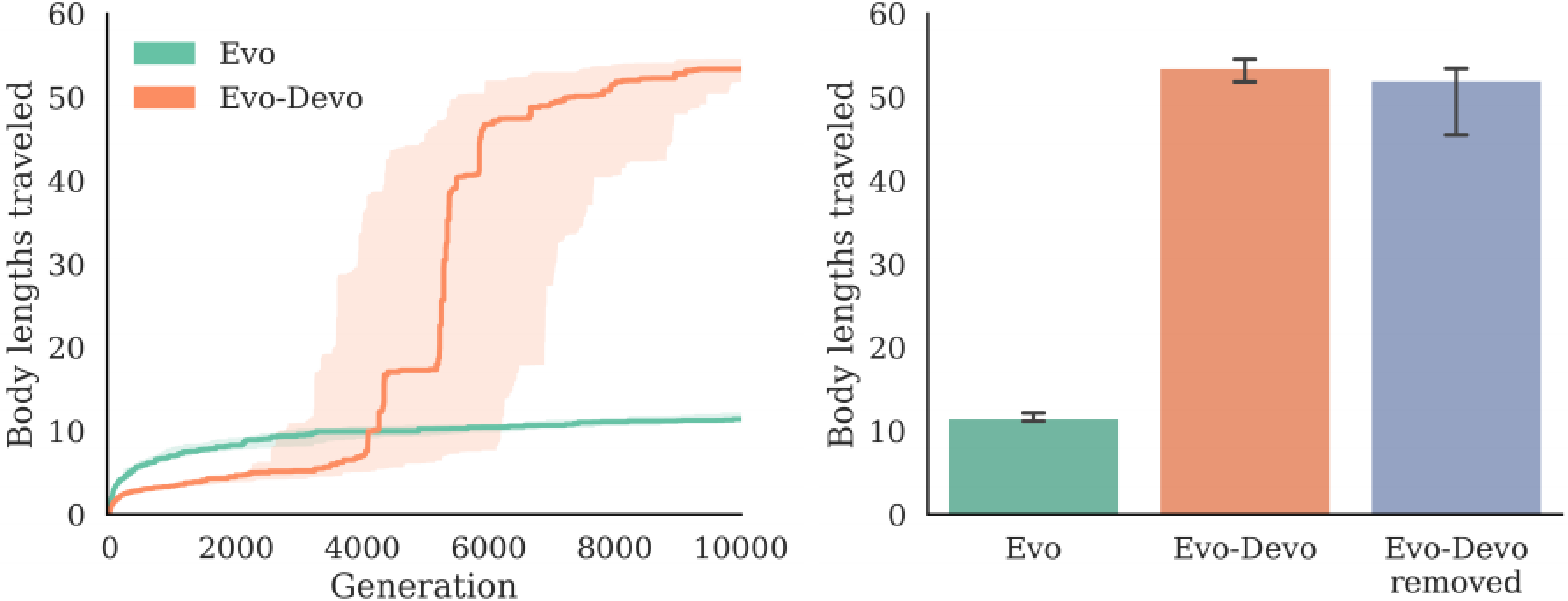



**Figure 3: One thousand randomly generated robots for each group. The horizontal axes measure fitness: volume normalized distance in the positive $y$ direction. The best overall designs are the best Evo robots since they maintain their good form as they behave. However, most designs are immobile (mode at zero) and Evo-Devo robots are more likely to move (less mass around zero) since they explore a continuum of body plans rather than a single static guess.**





Evo
Evo-Devo
Body lengths traveled
Generation
0
10
20
30
40
50
60
0
2000
4000
6000
8000
10000
Body lengths traveled
Evo
Evo-Devo
Evo-Devo removed

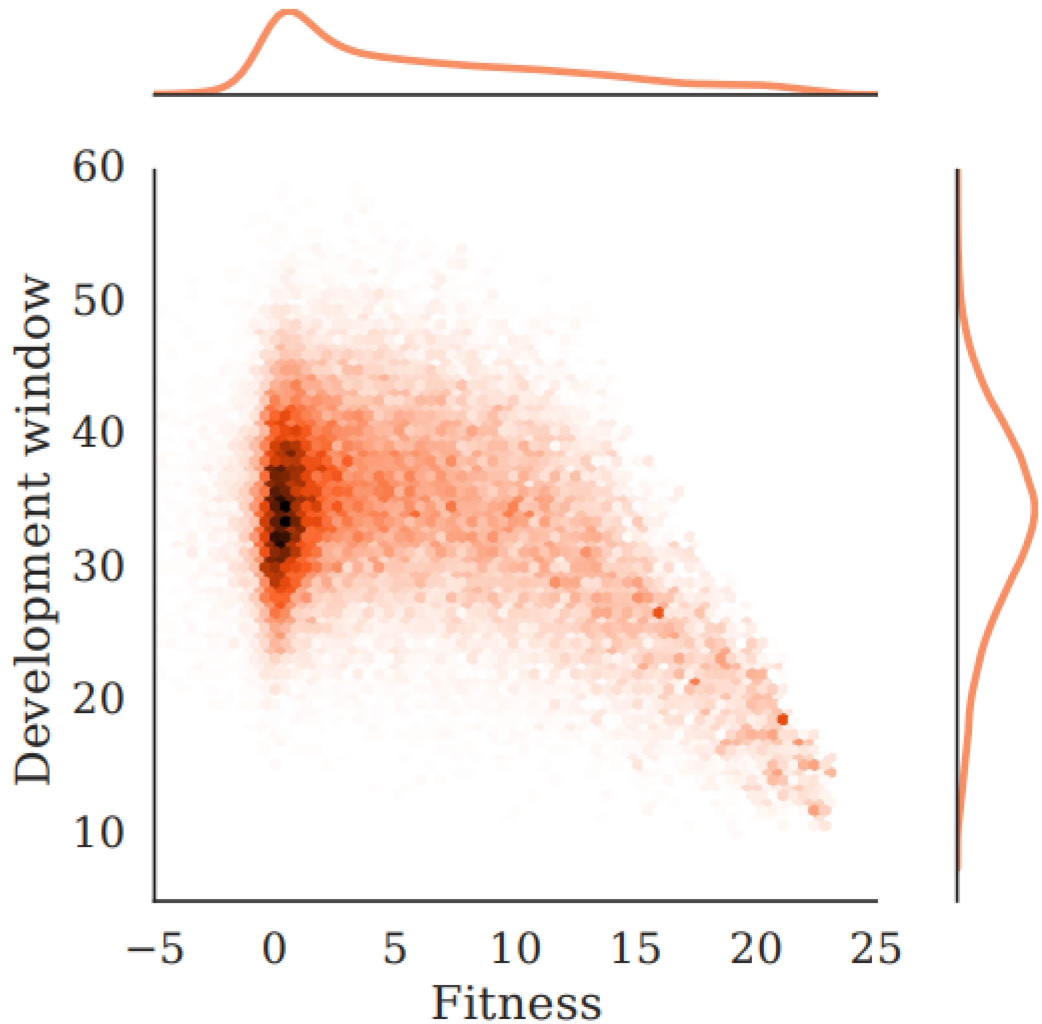
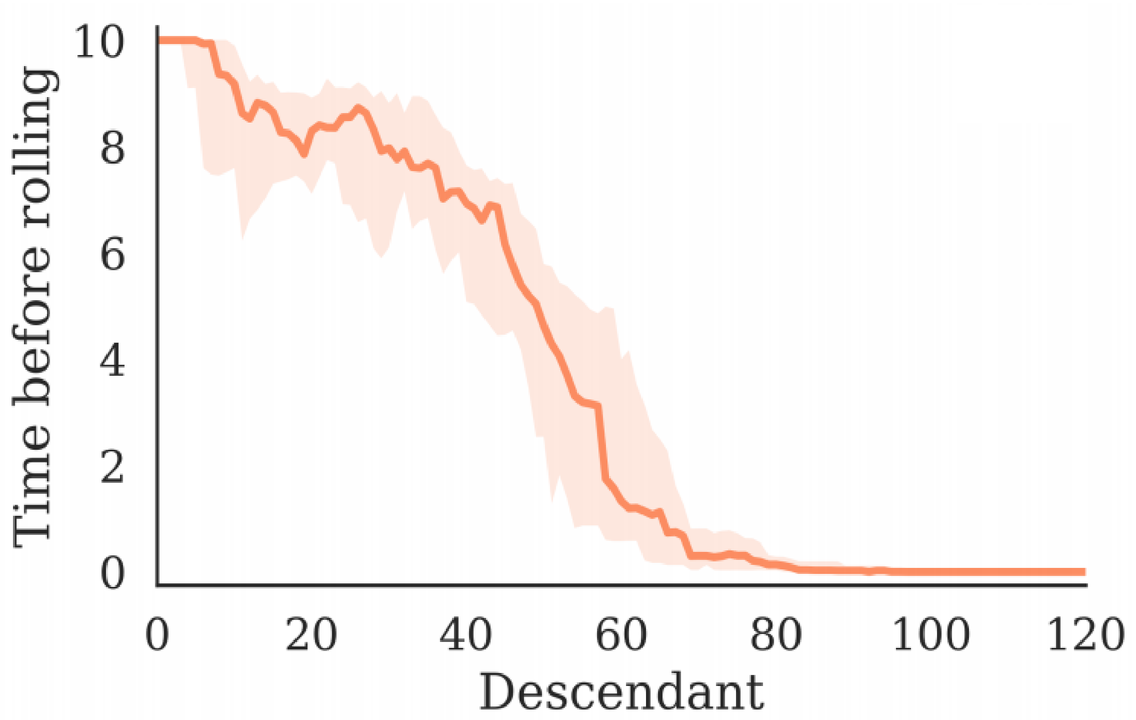
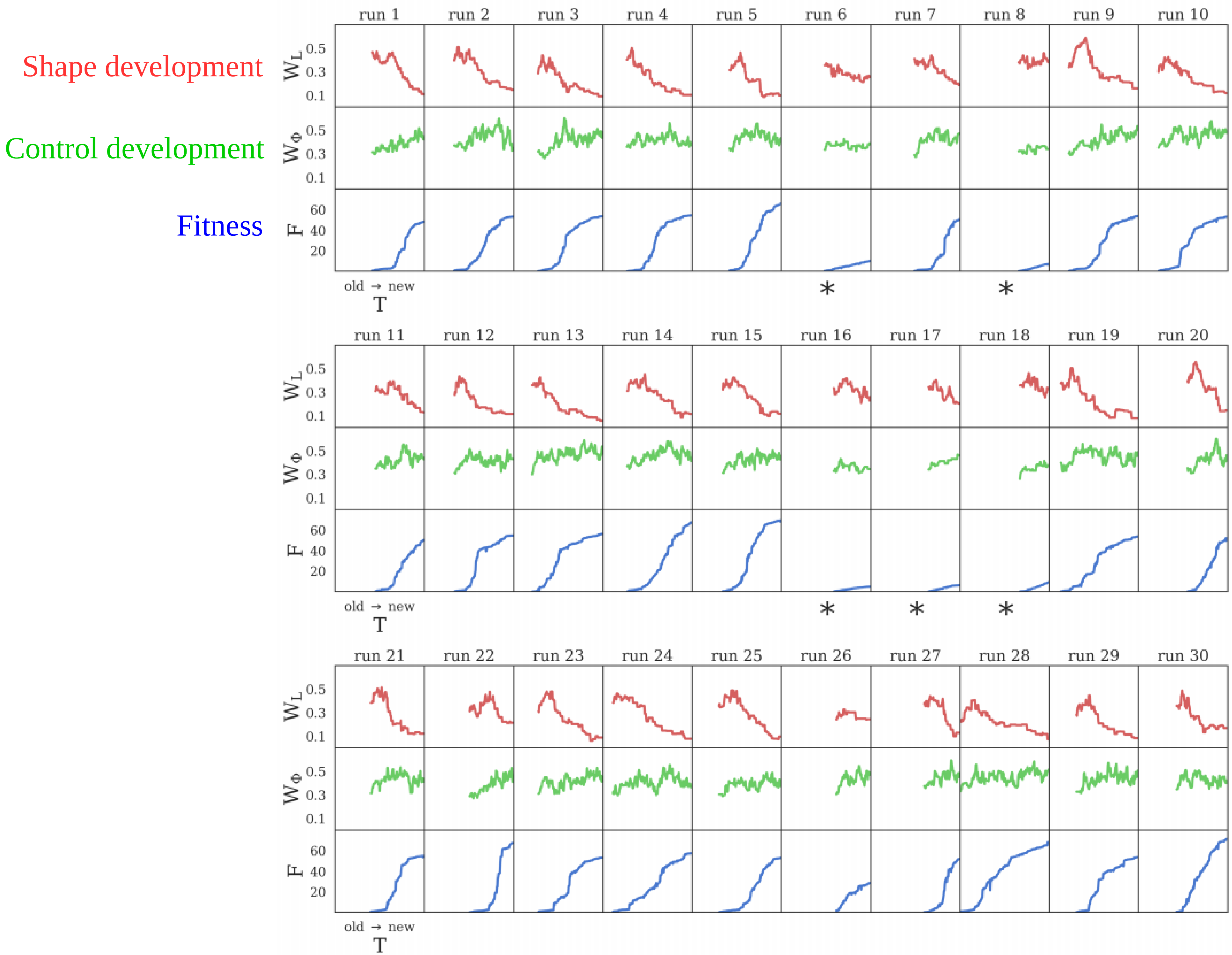


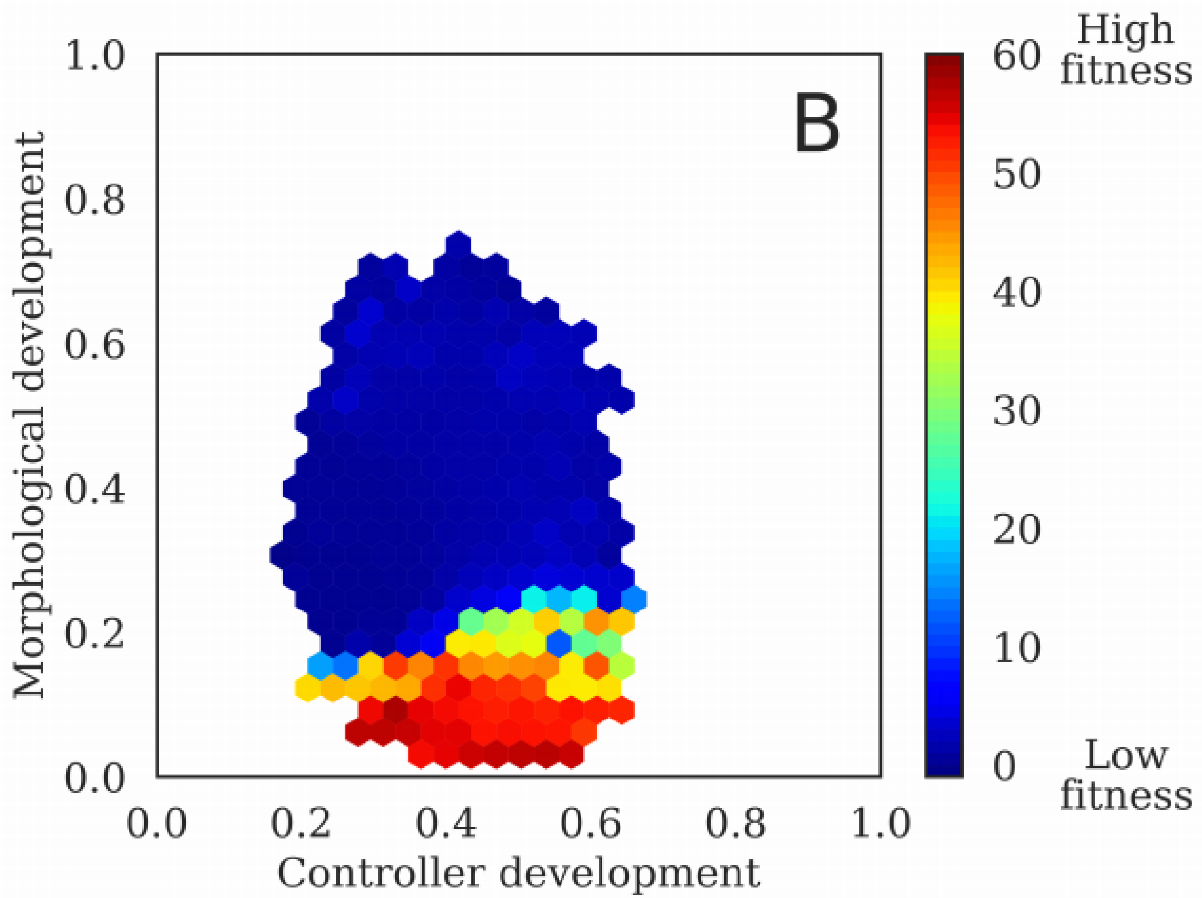

**Figure 5: The relationship between the amount of development at the individual level ($W$) and fitness ($F$). The fastest individuals have small developmental windows surrounding a fast body plan.**



Time before rolling
10
8
6
4
2
0
0
20
40
60
80
100
120
Descendant



Shape development
Control development
Fitness
run 1
run 2
run 3
run 4
run 5
run 6
run 7
run 8
run 9
run 10
run 11
run 12
run 13
run 14
run 15
run 16
run 17
run 18
run 19
run 20
run 21
run 22
run 23
run 24
run 25
run 26
run 27
run 28
run 29
run 30
$W_L$
$W_\Phi$
F
0.5
0.3
0.1
60
40
20
old → new
T
*


B
Morphological development
Controller development
0.0
0.2
0.4
0.6
0.8
1.0
0
10
20
30
40
50
60
High fitness
Low fitness