Computational Fabrication

Wojciech Matusik, Adriana Schulz

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Course Schedule

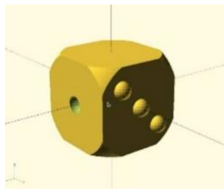
9:00 am – 9:10 am	Introduction
9:10 am – 9:25 am	Hardware Review
9:25 am – 9:50 am	From Design to Machine Code
9:50 am – 10:15 am	Design Space Representations
10:15 am – 10:25 am	Performance-Driven Design
10:25 am - 10:40 am	Break
10:40 am – 10:55 am	Performance Space Representation
10:55 am - 11:15 am	Inverse Methods
11:15 am - 11:35 am	Multi-objective Inverse Methods
11:35 am - 12:00 pm	Advanced Performance-Driven Design
12:00 pm - 12:15 pm	Course Review

Performance Space Representations

Hardware

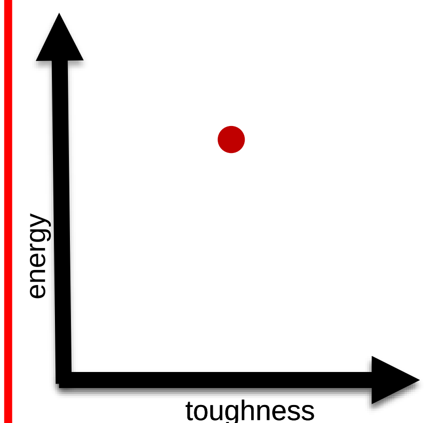
```
;Layer count: 336
;LAYER:0
M107
G0 F9000 X91.800 Y93.520 Z0.300
;TYPE:SKIRT
G1 F1200 X92.617 Y92.870 E0.01964
G1 X93.518 Y92.412 E0.03865
G1 X94.458 Y92.141 E0.05705
G1 X95.218 Y92.072 E0.07141
G1 X95.998 Y92.064 E0.08608
G1 X96.894 Y92.071 E0.10294
```

Machine Code



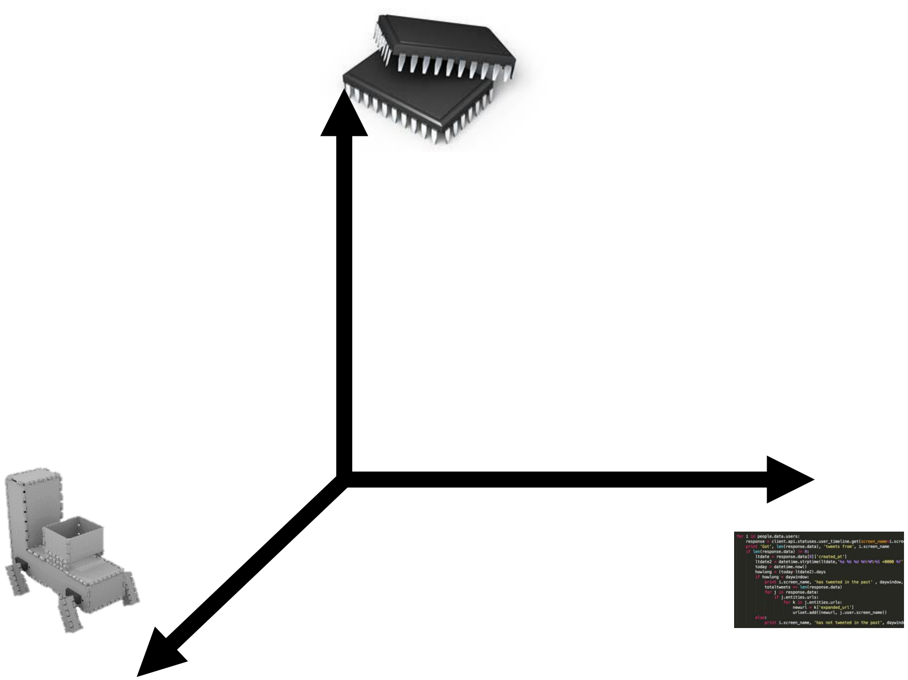
```
difference(){
//cuerpo del dado
intersection(){
cube(20,center=true);
sphere(15,$fn=100);}
//cara del 1
translate([10,0,0])
sphere(2,$fn=20);
}
translate([0,10,0])
sphere(2,$fn=20);
translate([5,10,5])
sphere(2,$fn=20);
translate([-5,10,-5])
sphere(2,$fn=20);
```

Design

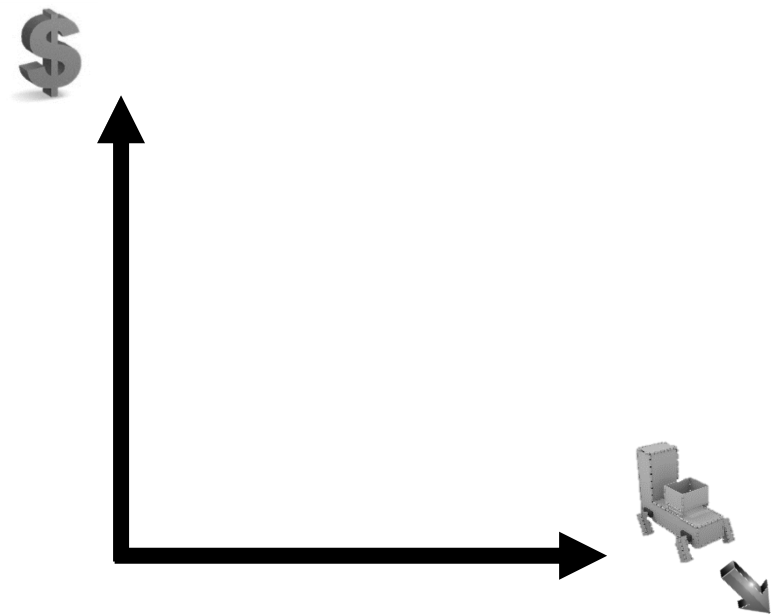


Performance

Recap: Performance-Driven Design



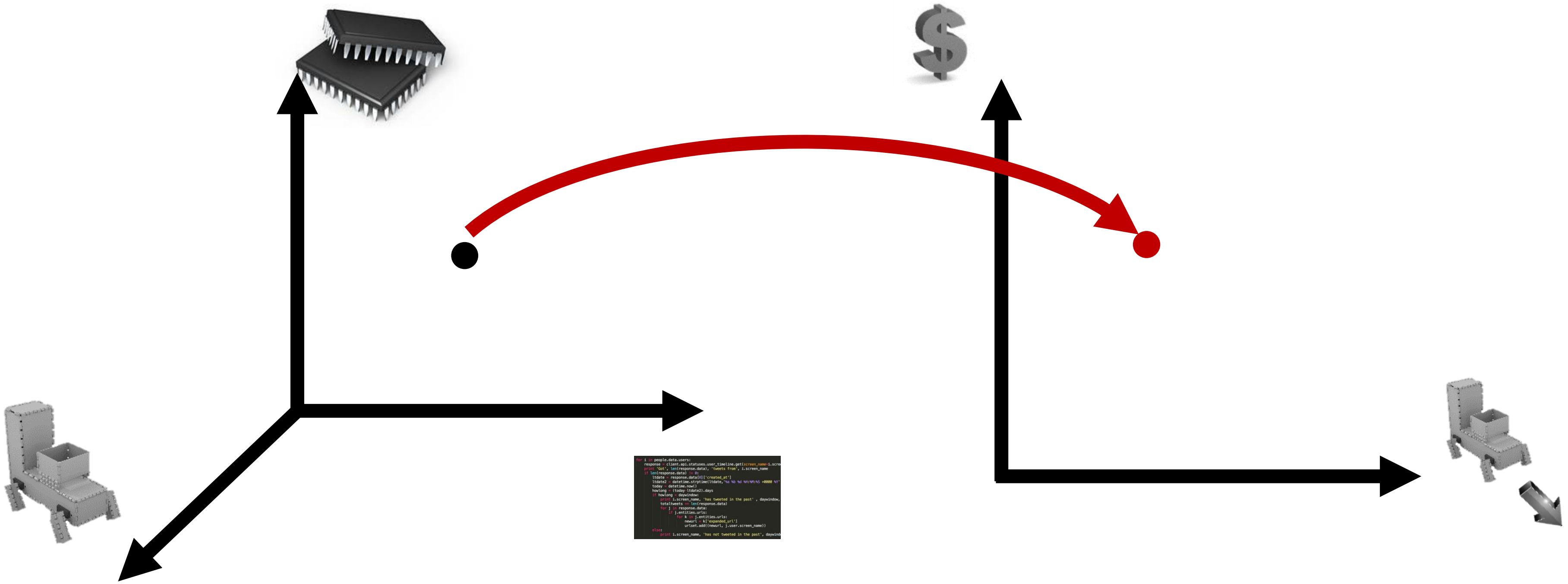
Design Space



Performance Space

From Design Space to Performance Space

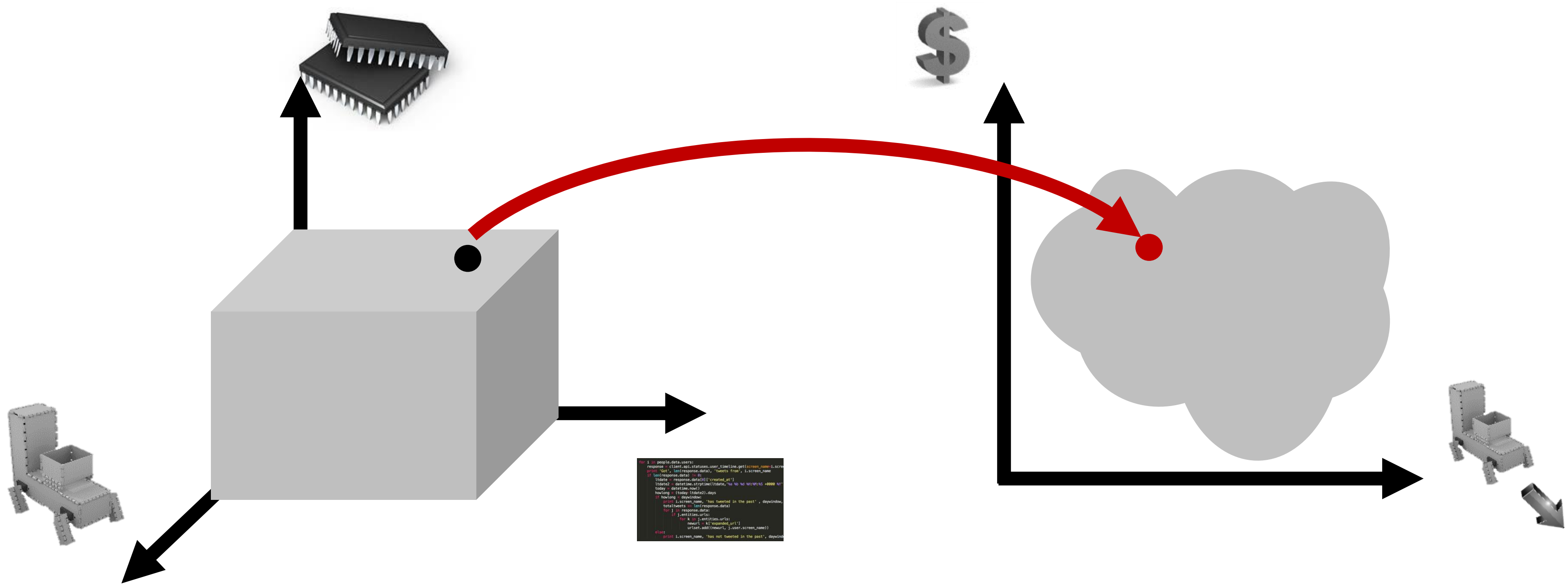
- Numerical simulation maps points from design space to performance space



Design Space

Performance Space

Bounds on Performance

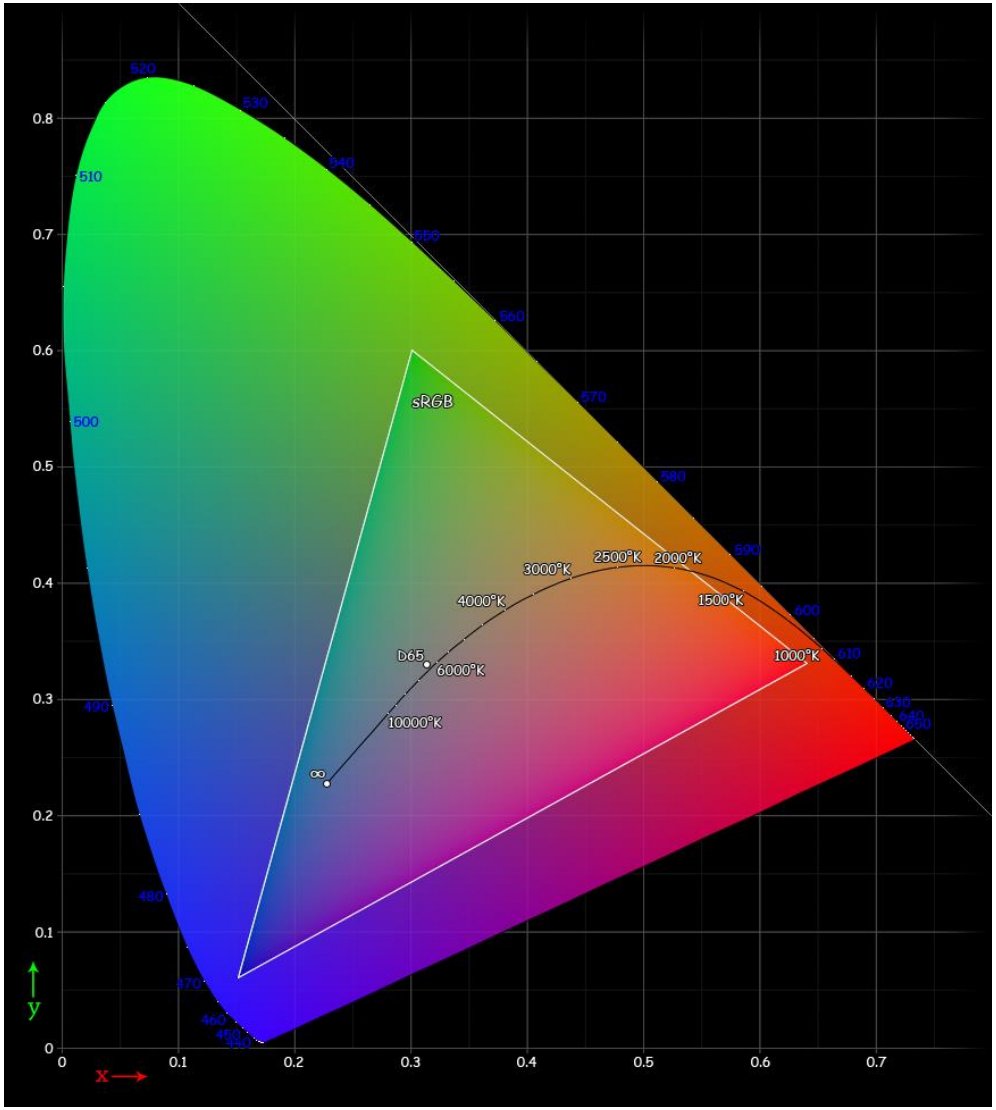


Design Space

Performance Space

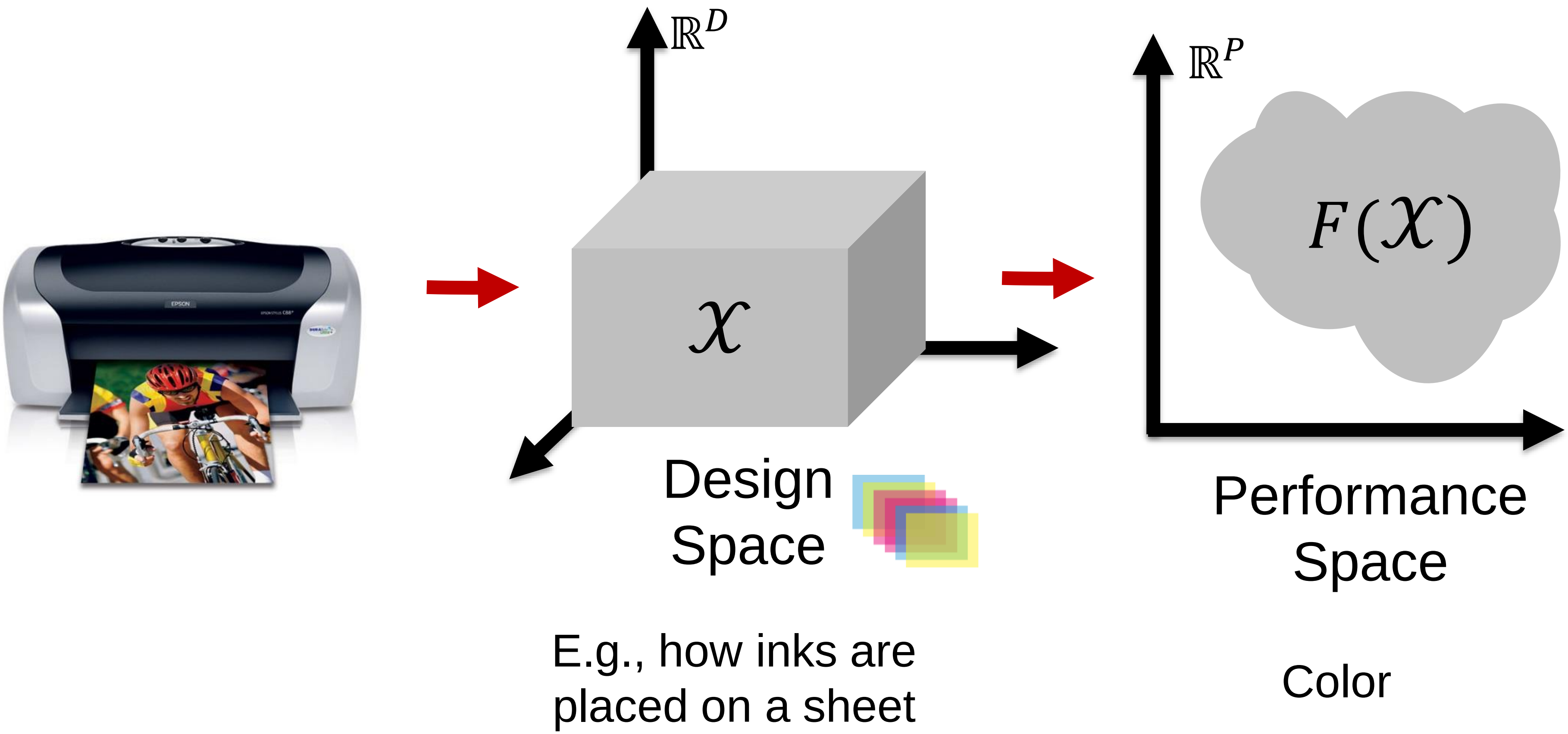
Example I: Color Gamut

- **The subset of colors which can be accurately represented within a given color space or by a certain output device.**



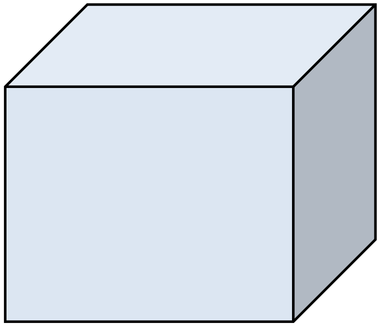
Hardware Capabilities Limit Gamut

- Gamut can be directly tied to capabilities of a given hardware

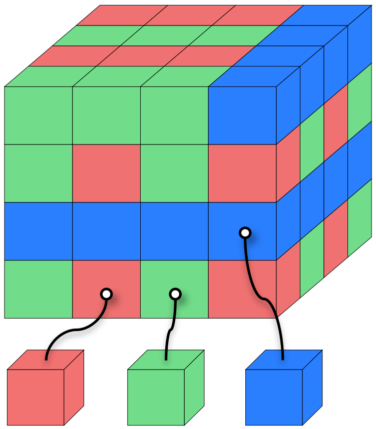


Example II: Mechanical Properties in Printing Microstructures

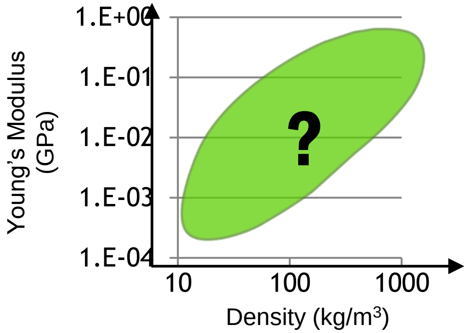
A unit microstructure cell



Heterogeneous material

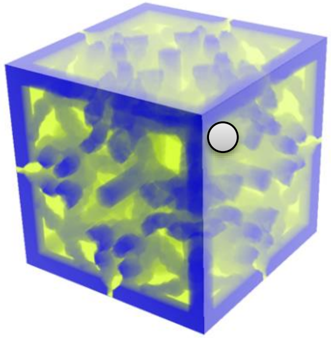


Base homogenous materials

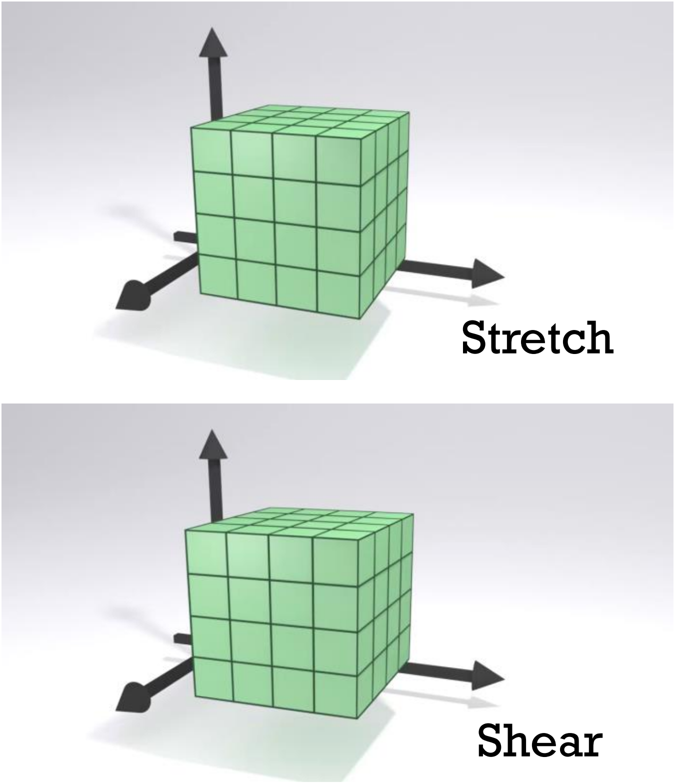


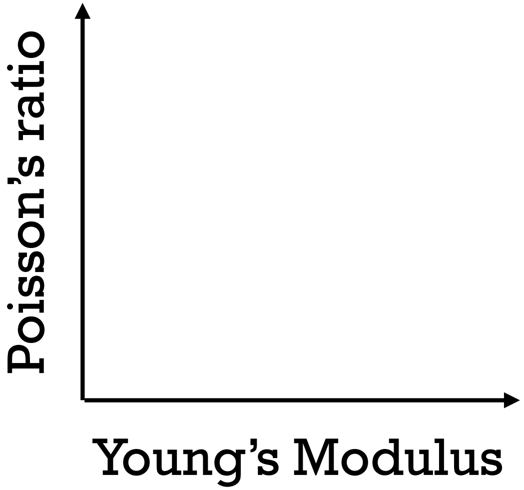
What physical properties can be achieved with microstructures?

Mapping Microstructures to Material Properties



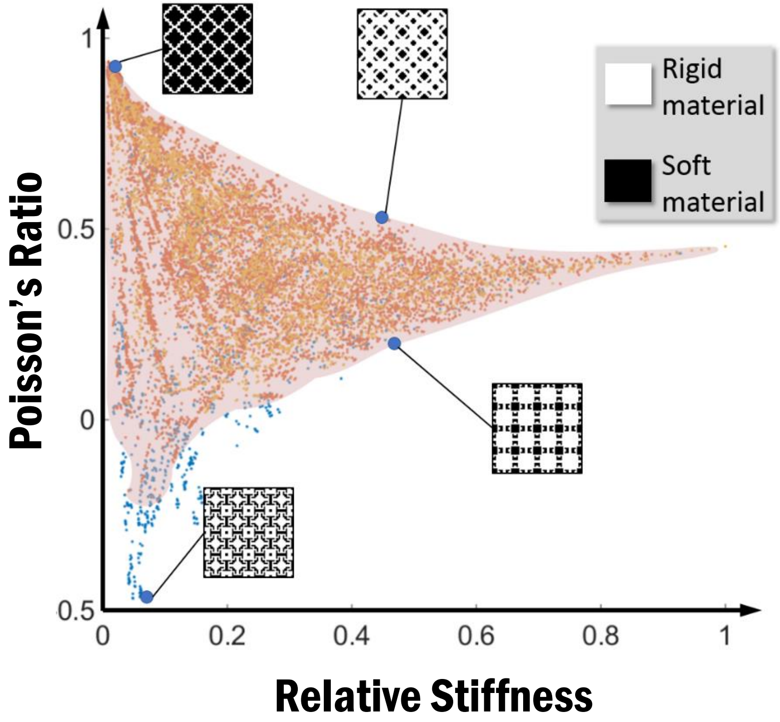
Microstructure





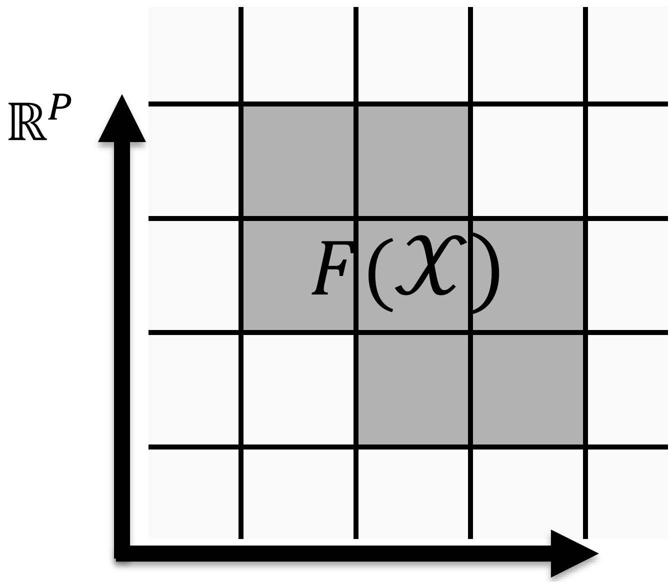
Mechanical Properties Gamut

- **Space of bulk material properties that can be achieved with all material microstructures of a given size**

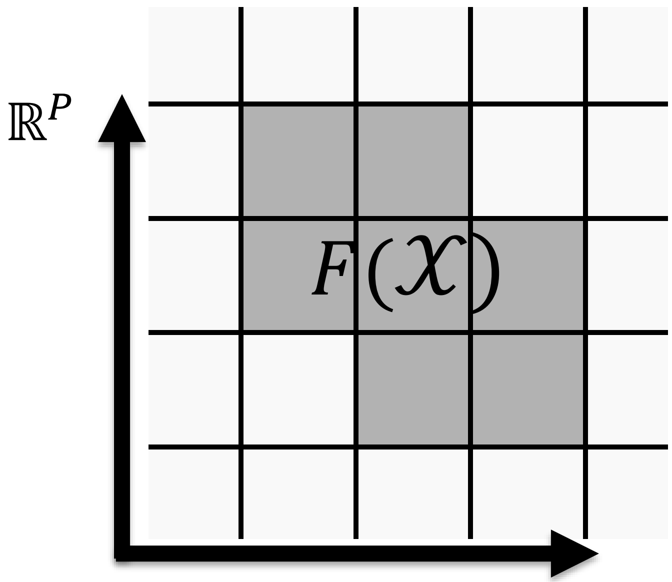


How to Represent Gamut?

- Boundary
  - Mesh/contour
- Volume
  - Grids (e.g., voxels), adaptive grids, points, distance fields

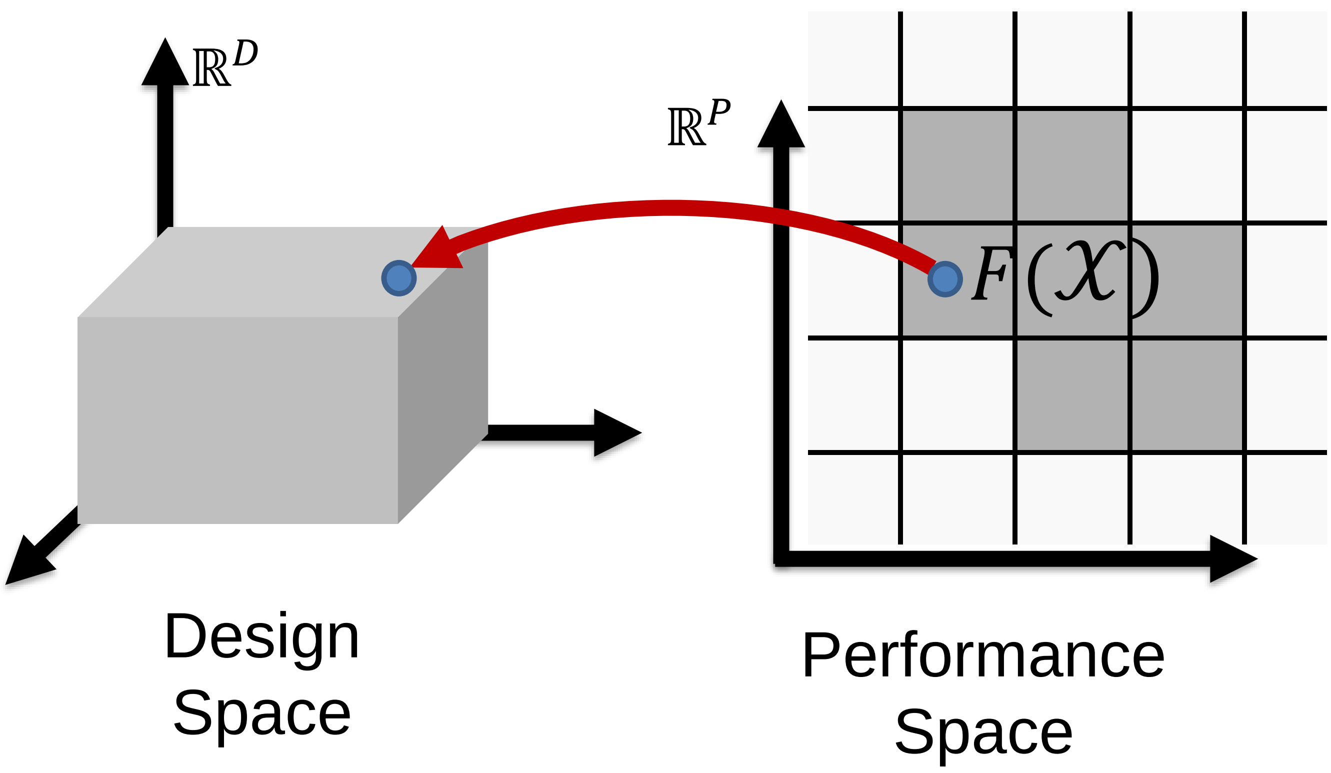


Why Volumetric Gamut Representations?

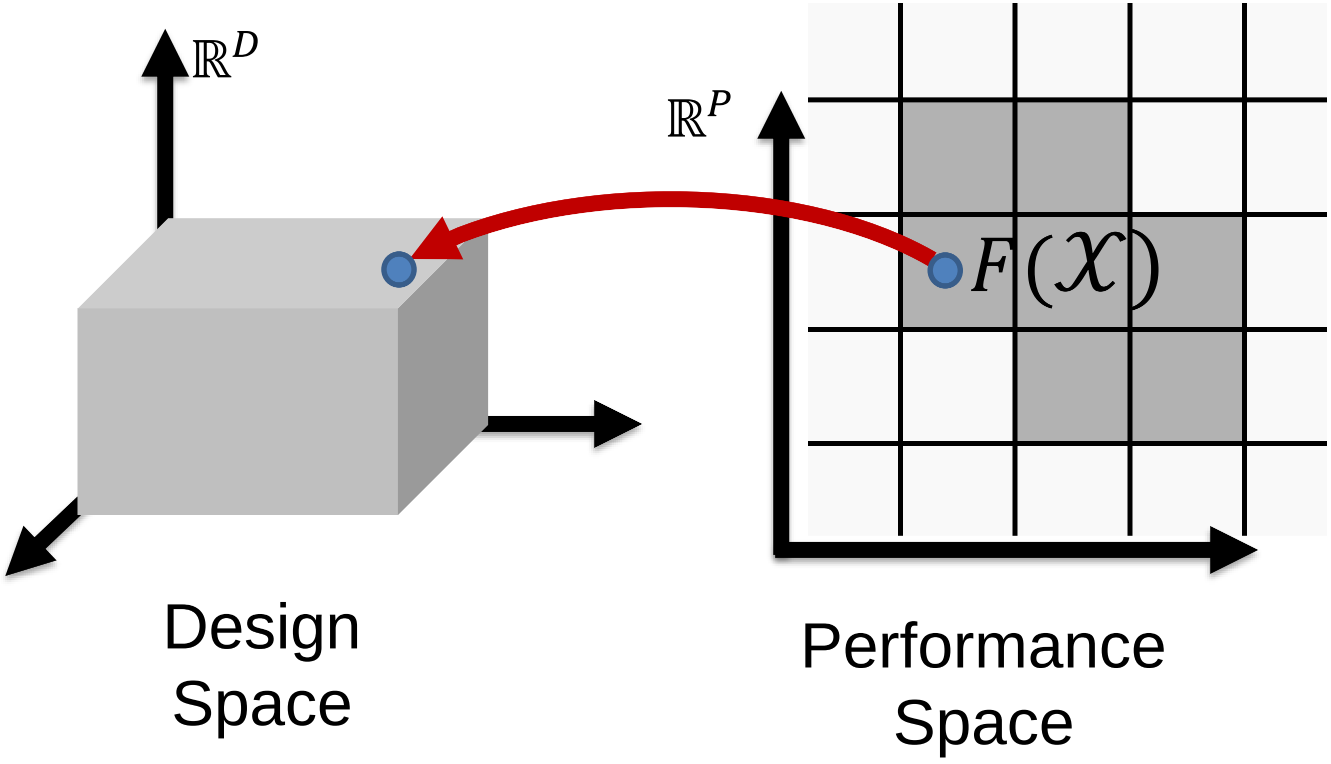


Why Volumetric Gamut Representations?

- Easy to check whether points are inside/outside
- Each cell can store points mapping back to the design space

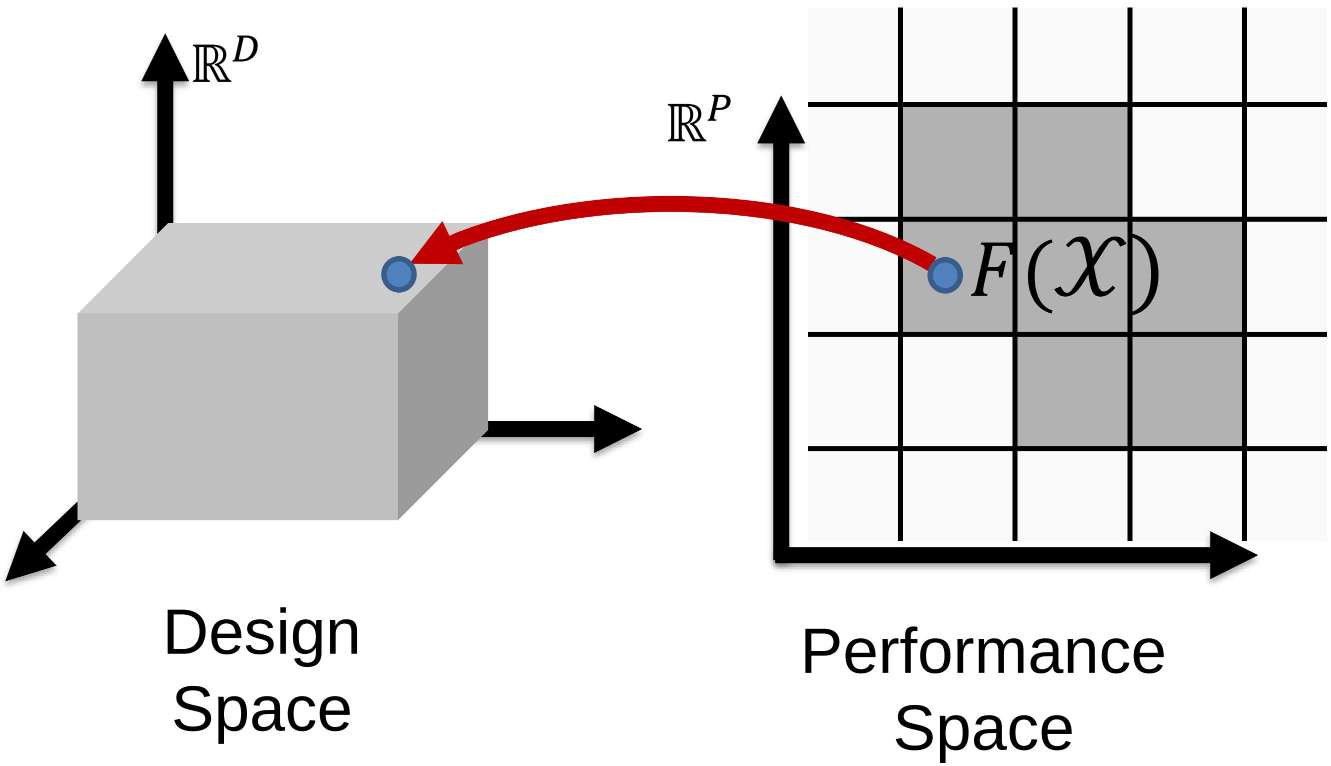


How to Represent Gamut in Higher Dimensions?



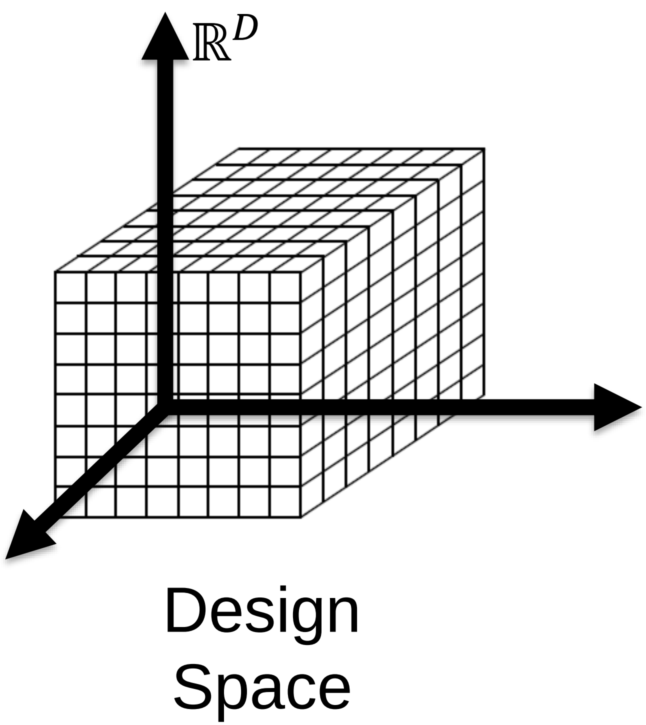
How to Represent Gamut in Higher Dimensions?

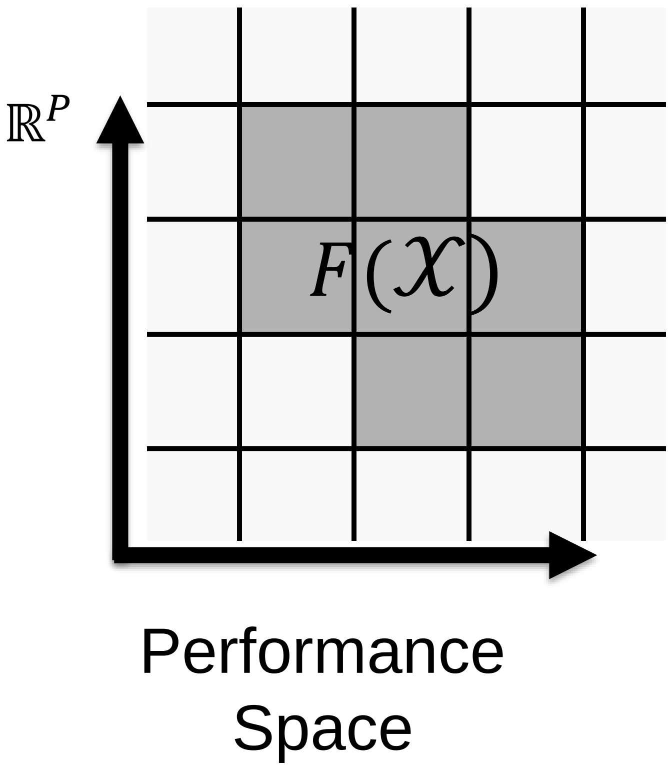
- These representations are useful but have not been explored much
- Possible representations: points, classifiers



How to Compute Gamut?

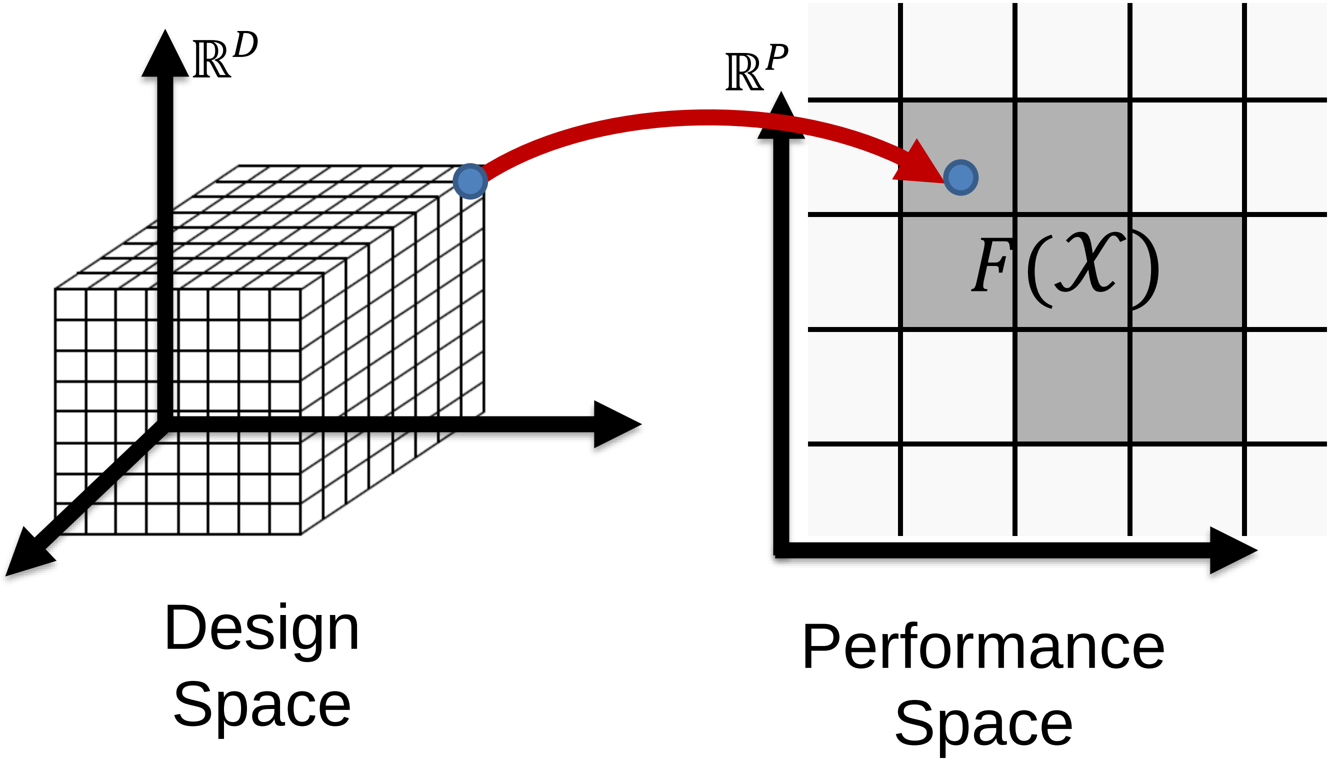
- When design space is low-dimensional





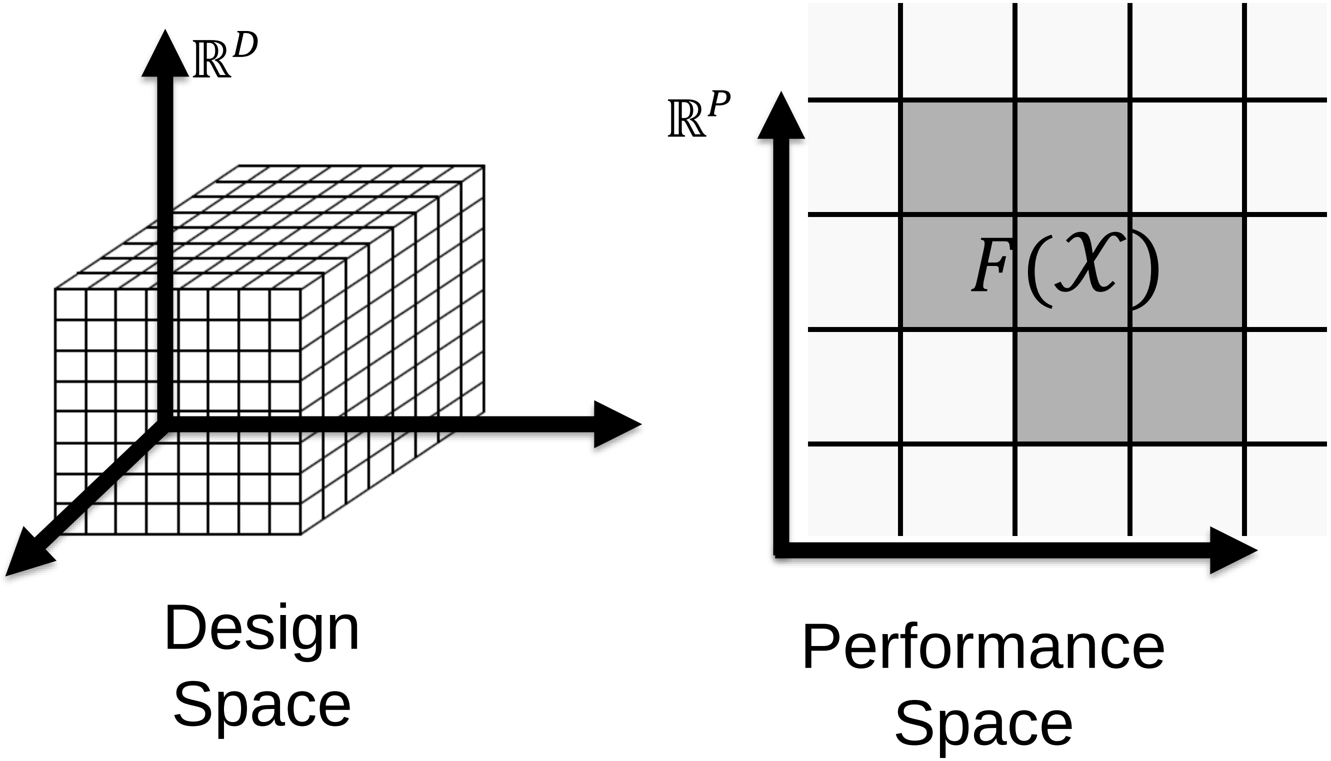
How to Compute Gamut?

- When design space is low-dimensional we can explicitly compute the mapping for all points in design space
- Example: 2D printers/color



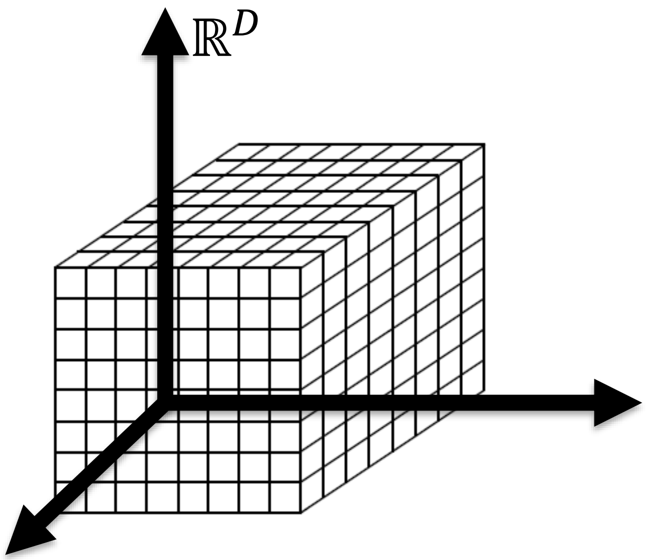
How to Compute Gamut?

- When design space is high dimensional

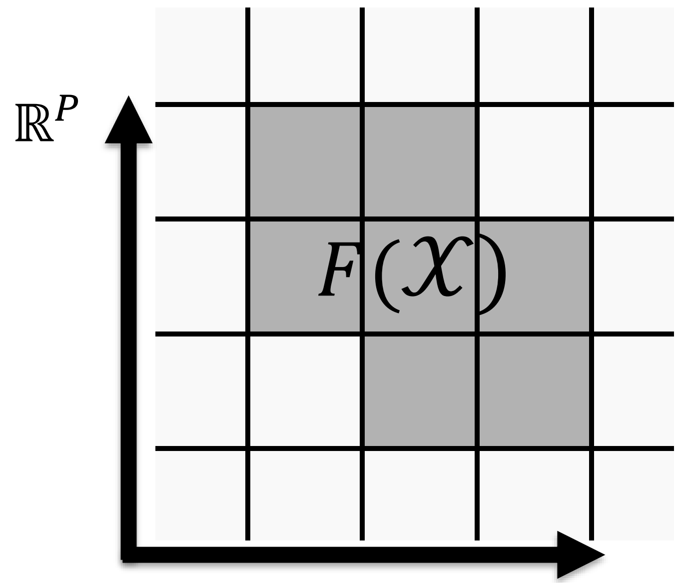


How to Compute Gamut?

- When design space is high dimensional we can use genetic algorithms to expand gamut in all directions

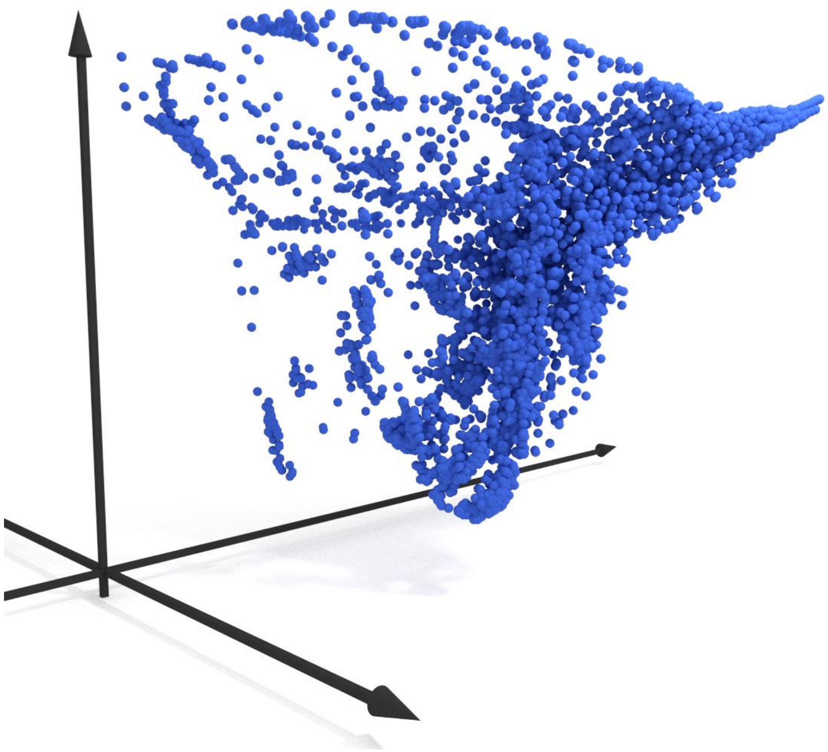


Design Space



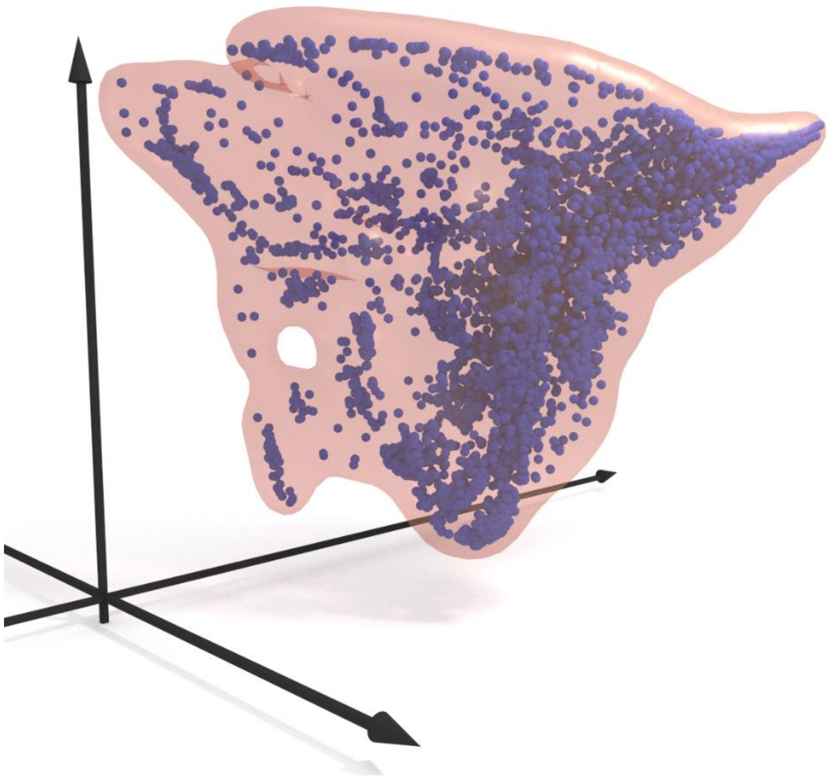
Performance Space

Algorithm: Exploring Microstructure Gamut



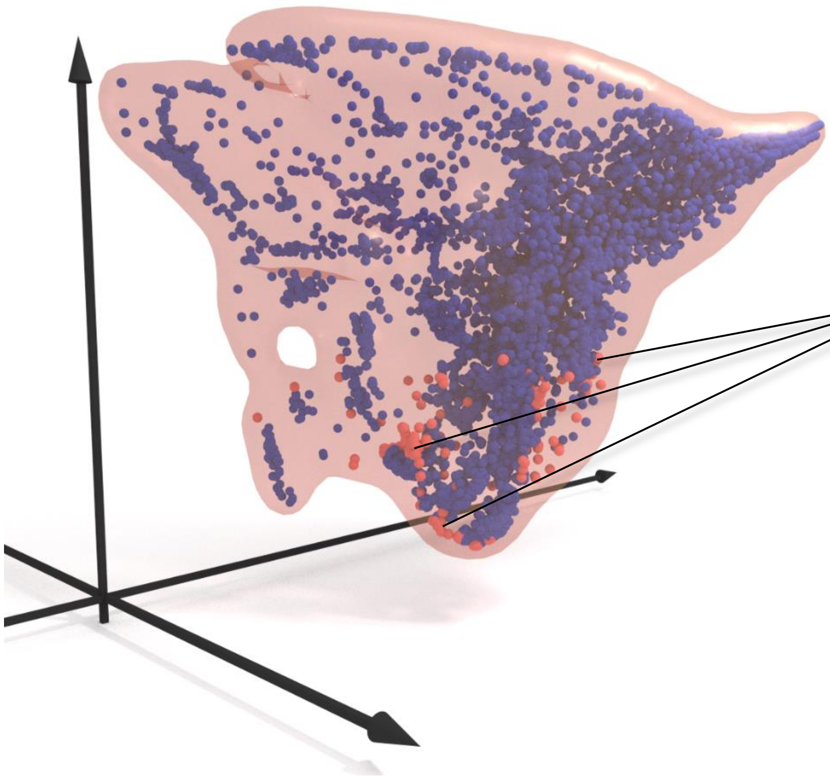
- Microstructure samples

Algorithm: Exploring Microstructure Gamut



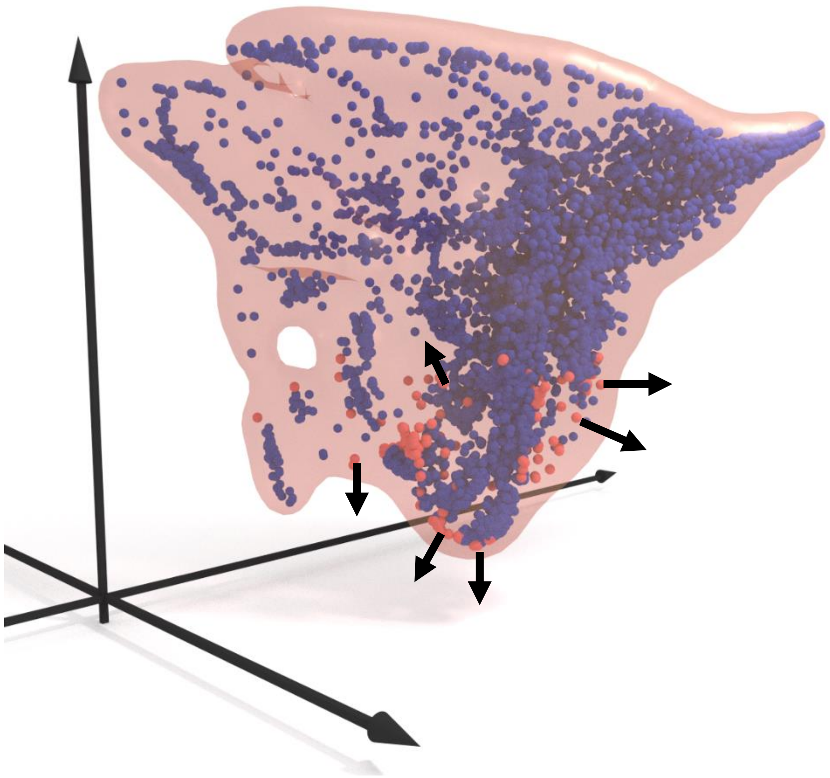
- Microstructure samples
- Compute level set

Algorithm: Exploring Microstructure Gamut



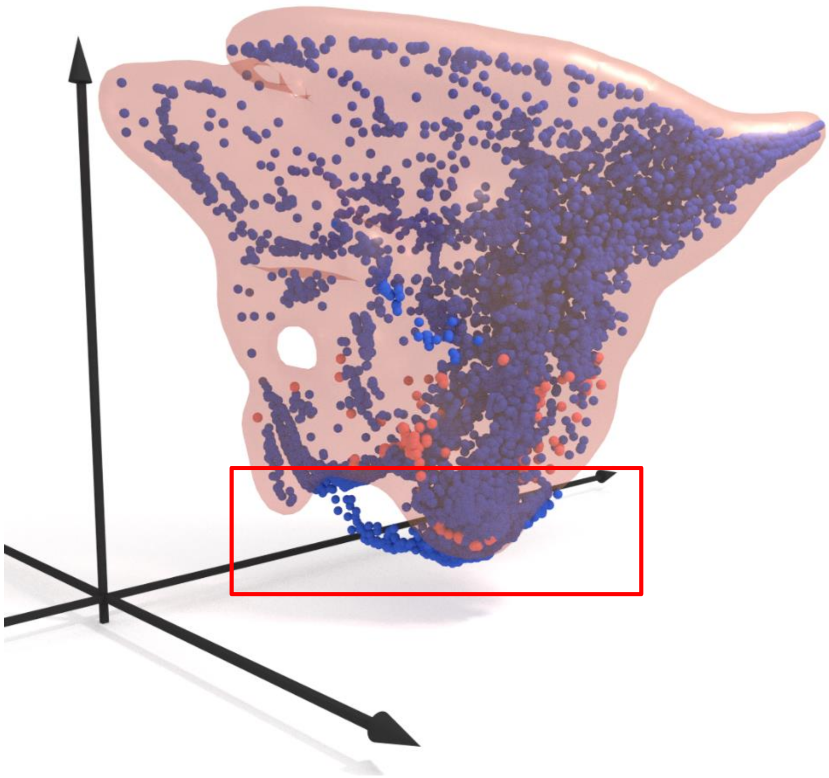
- Microstructure samples
- Compute level set
- Find random seeds near the level set boundary

Algorithm: Exploring Microstructure Gamut



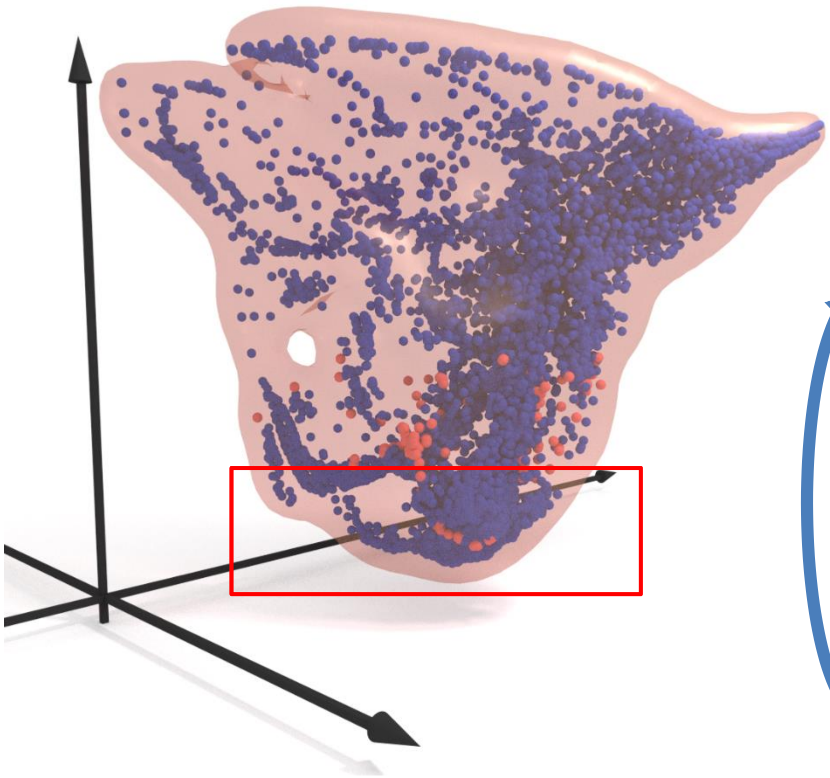
- Microstructure samples
- Compute level set
- Find random seeds near the level set boundary
- Find gradient towards outside of gamut

Algorithm: Exploring Microstructure Gamut



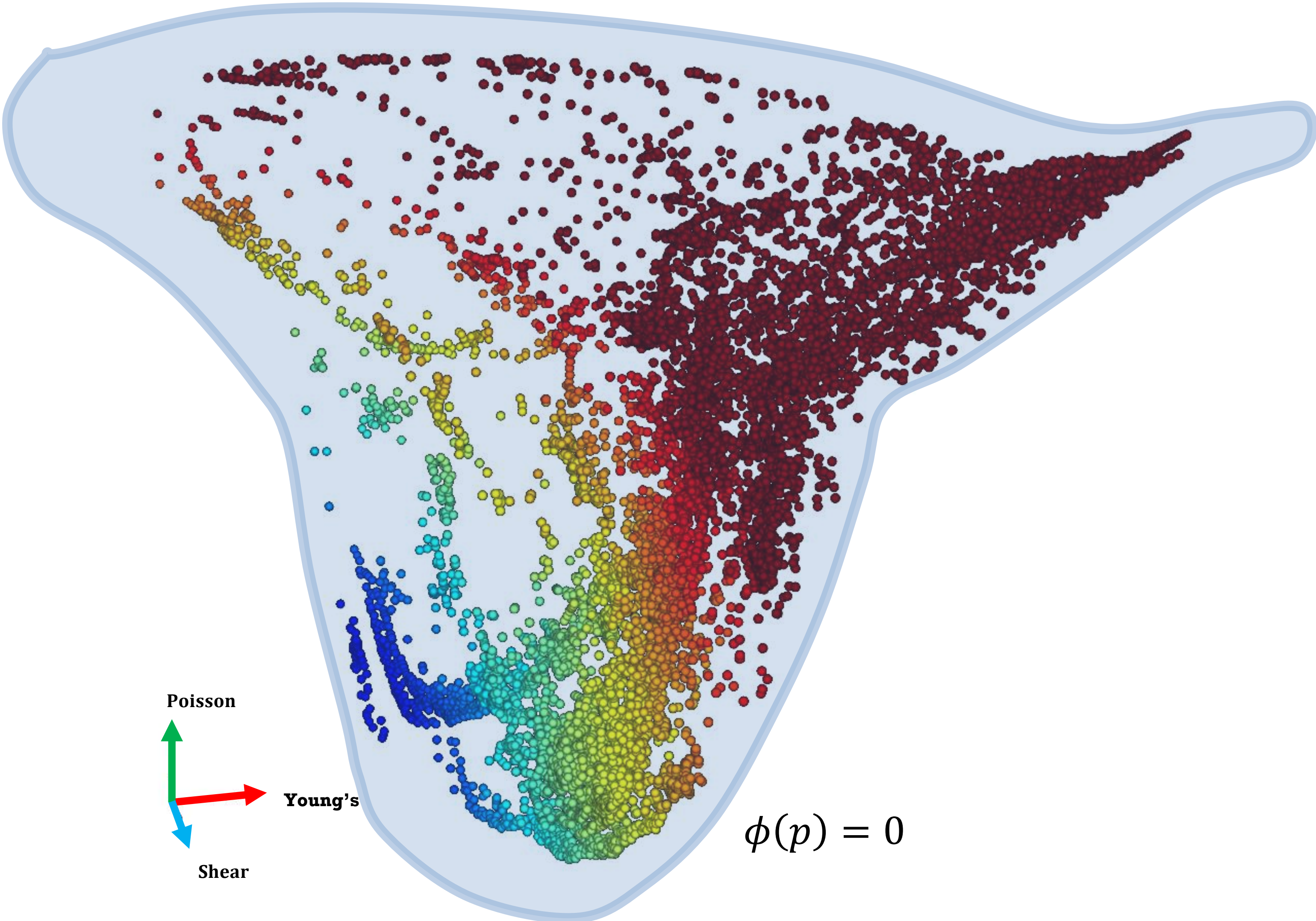
- Microstructure samples
- Compute level set
- Find random seeds near the level set boundary
- Find gradient towards outside of gamut
- Discrete and continuous sampling

Algorithm: Exploring Microstructure Gamut



- Microstructure samples
- Compute level set
- Find random seeds near the level set boundary
- Find gradient towards outside of gamut
- Discrete and continuous sampling
- Update level set

Example: Gamut for Microstructures with Cubic Symmetry



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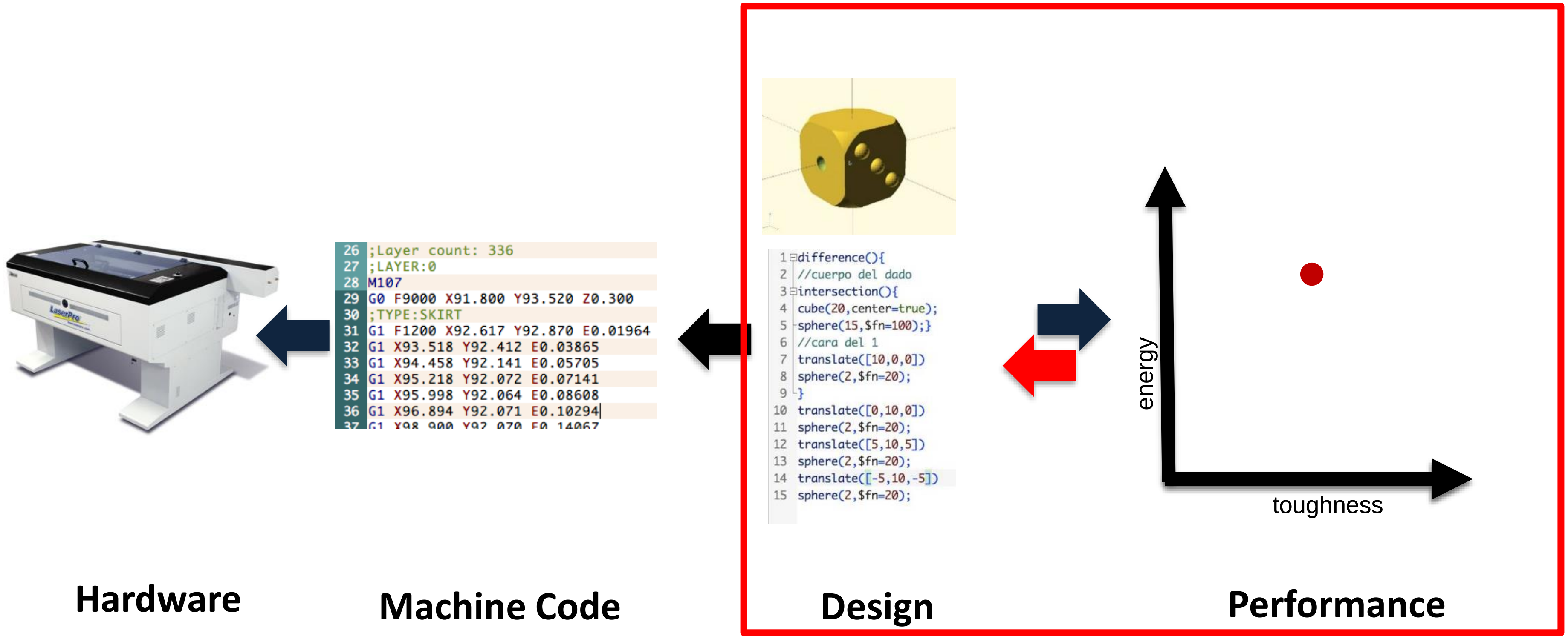
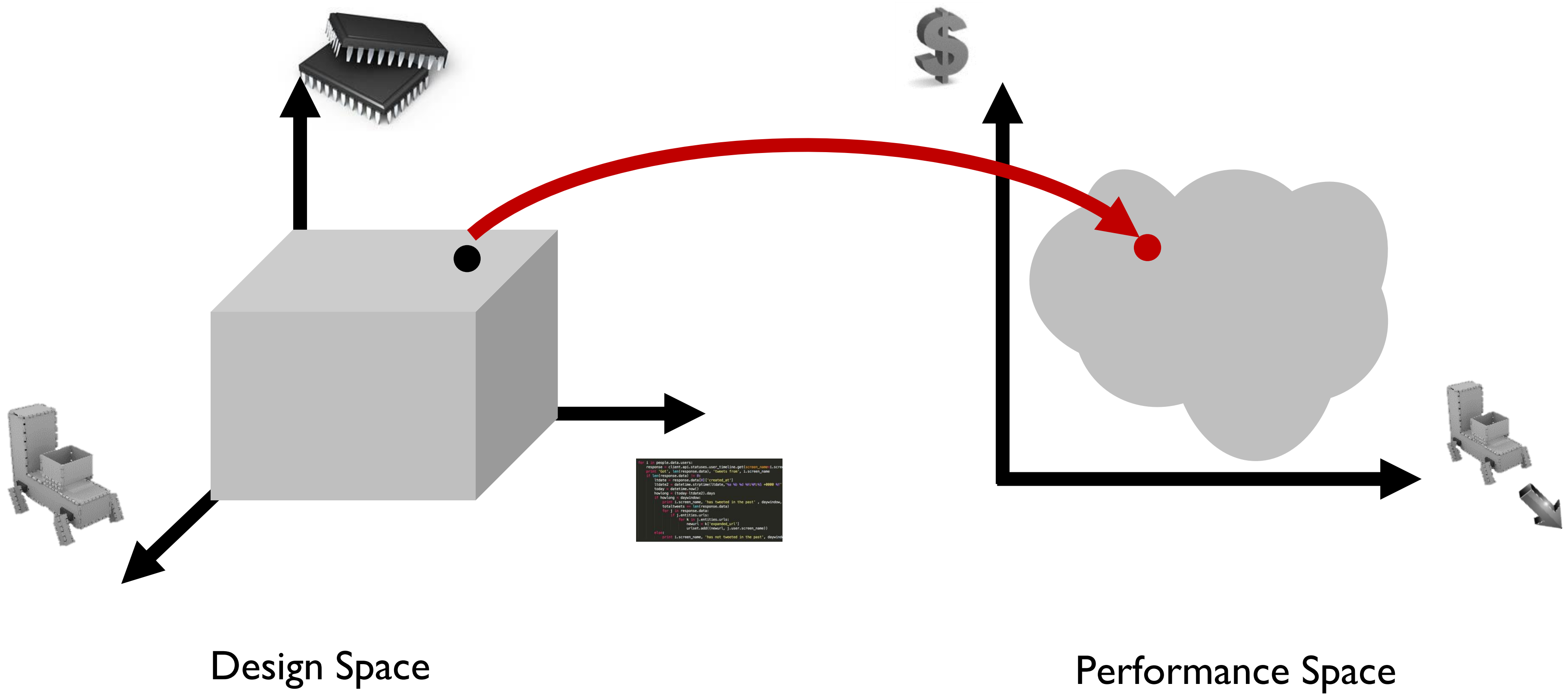
Inverse Methods

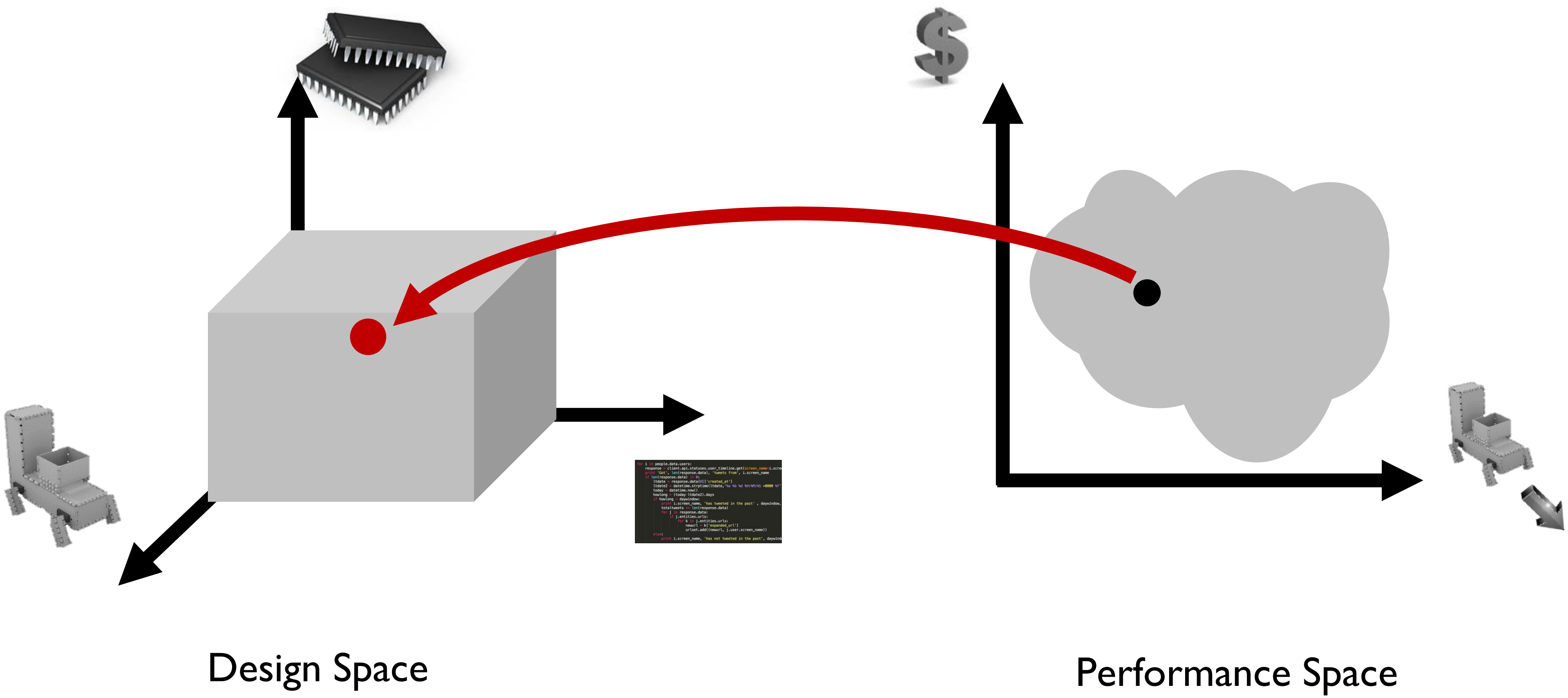


Bounds on Performance



Inverse: From Performance Space to Design Space

- Inverse problem is much more difficult



Inverse: From Performance Space to Design Space

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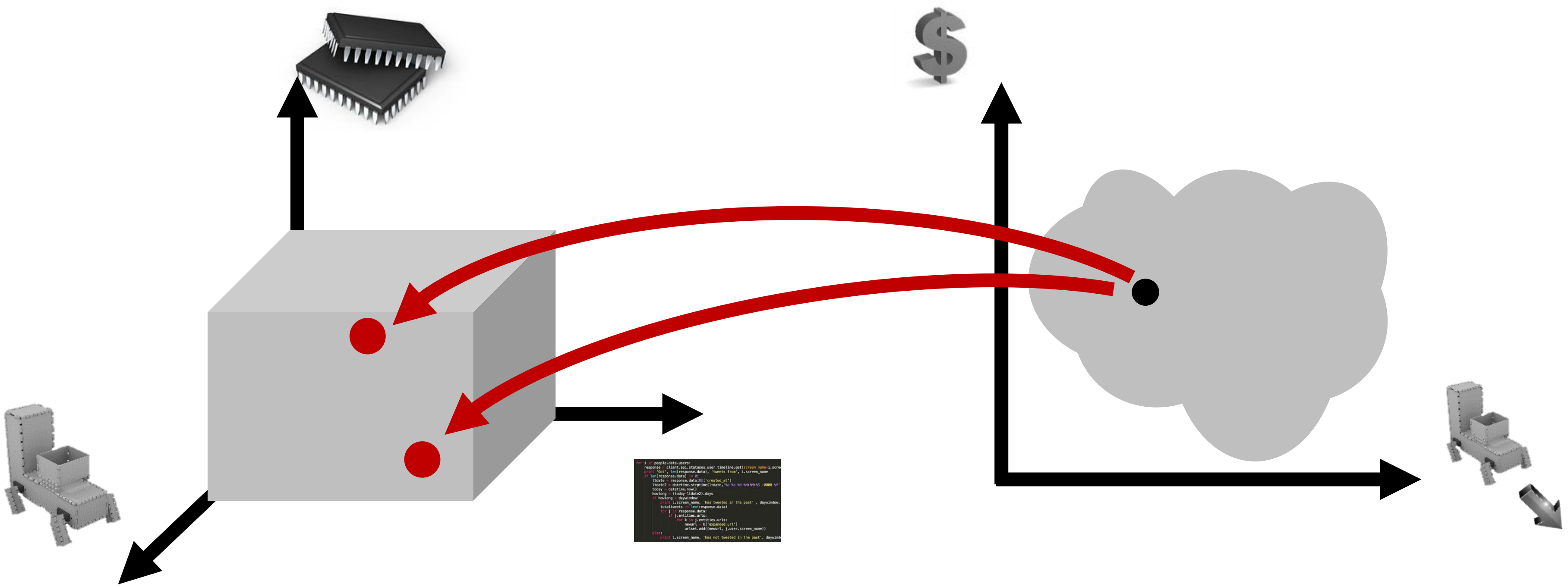
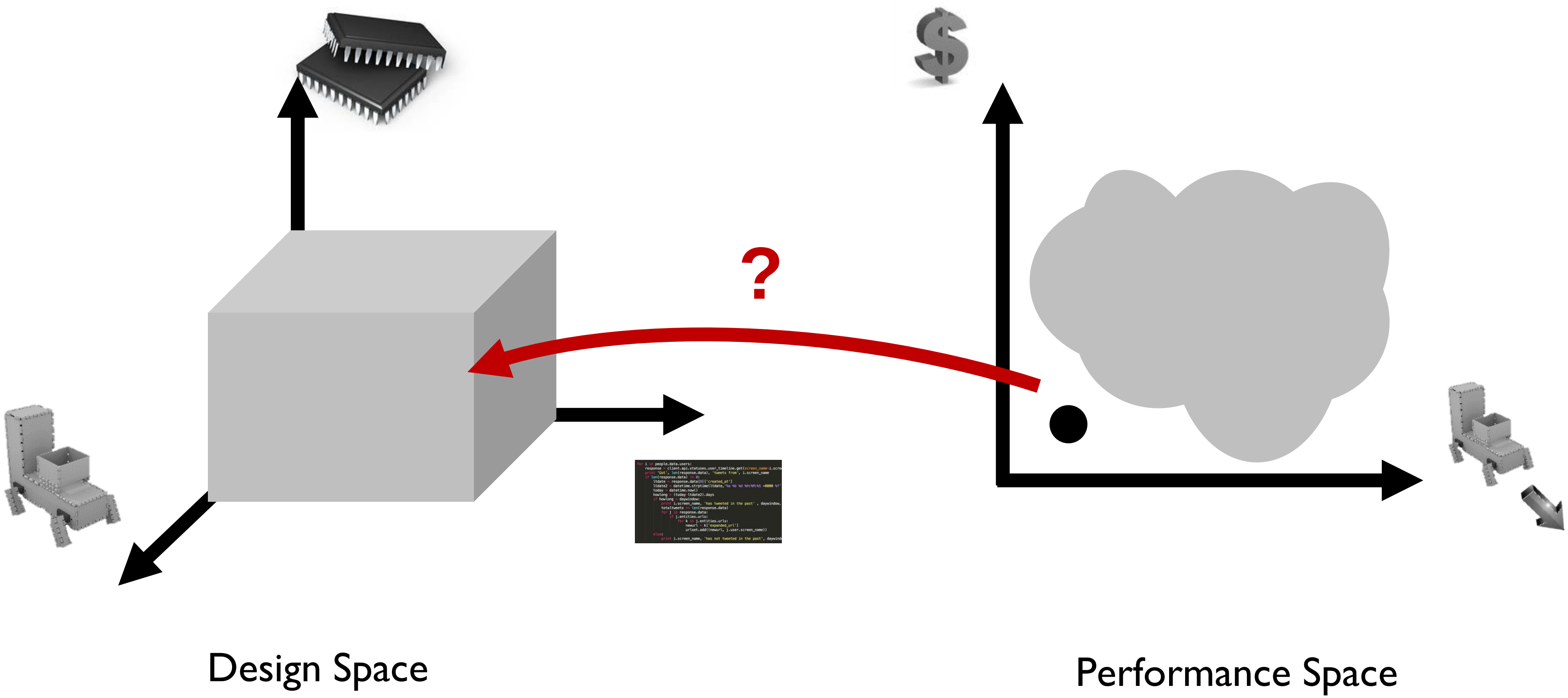


Design Space

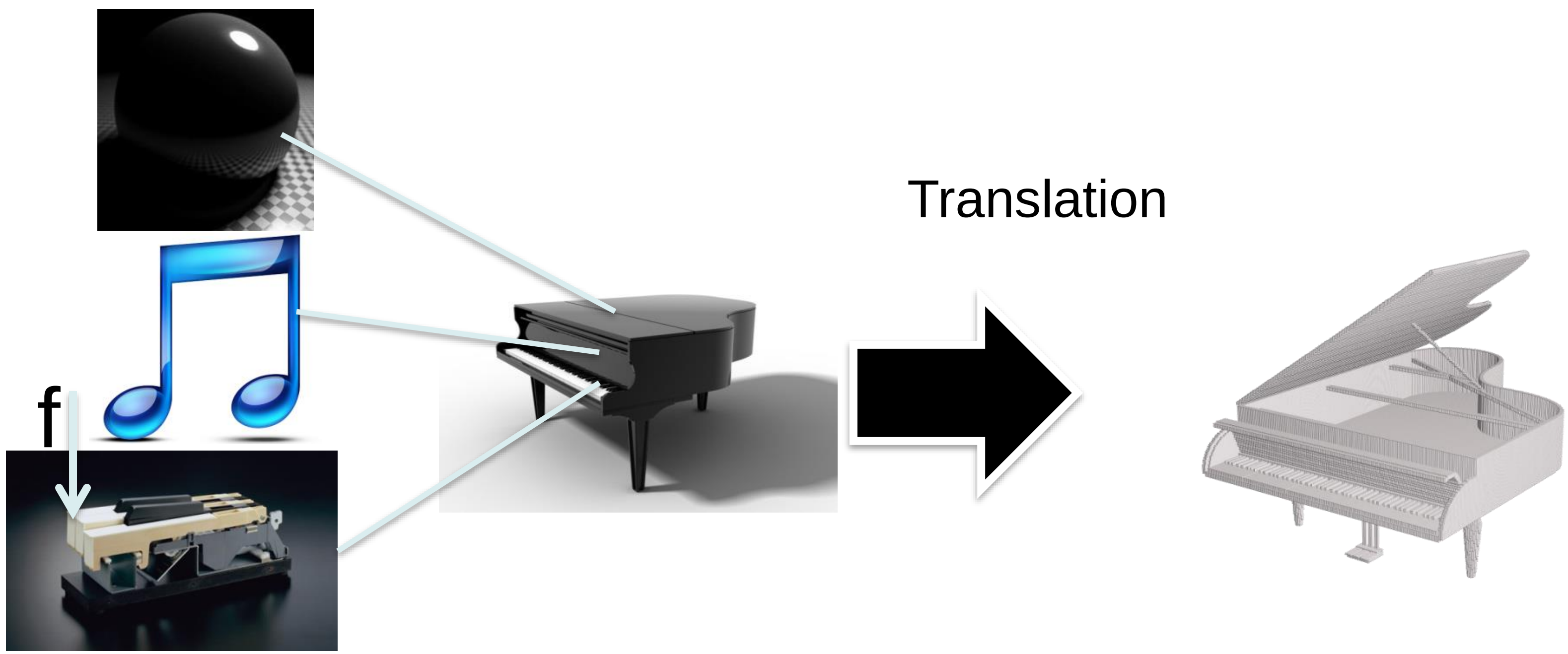
Performance Space

Inverse: From Performance Space to Design Space

- Inverse problem is much more difficult



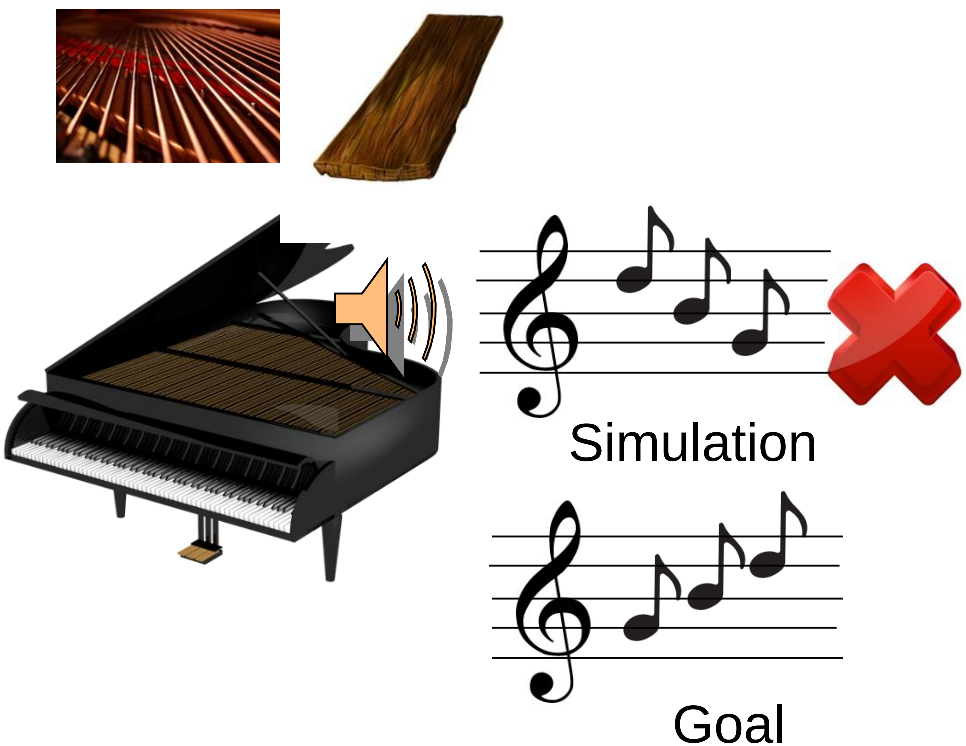
Functional Design/ Generative Design

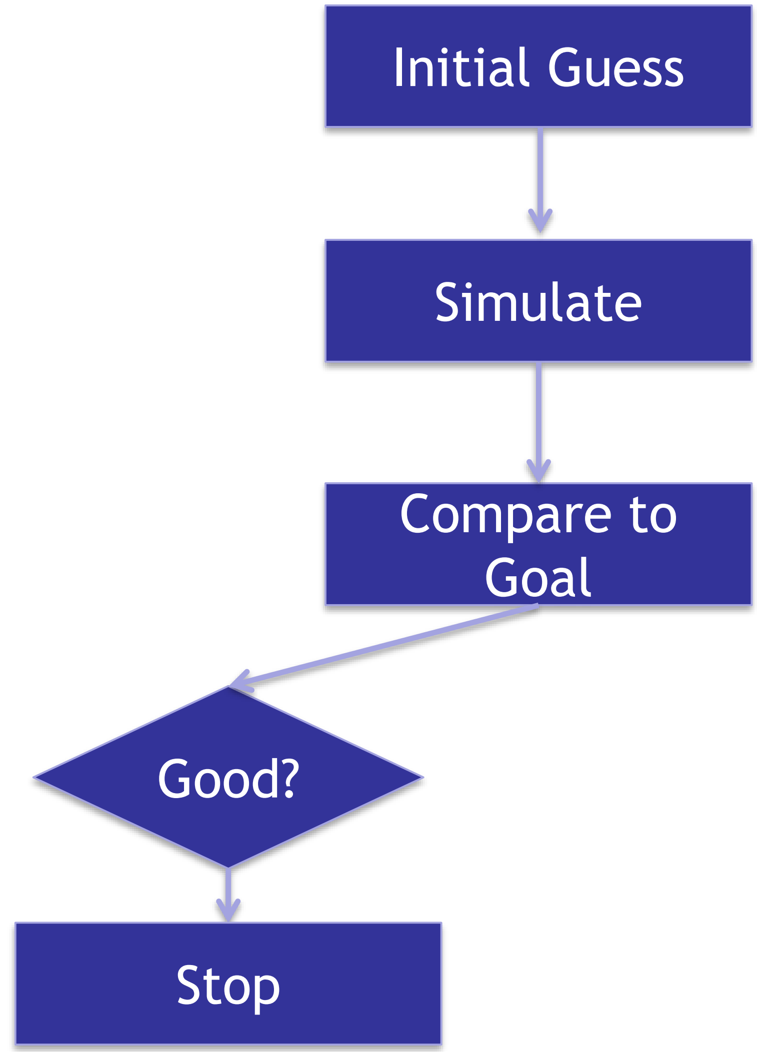


Goal

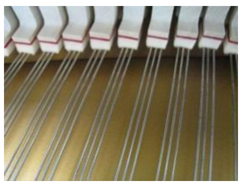
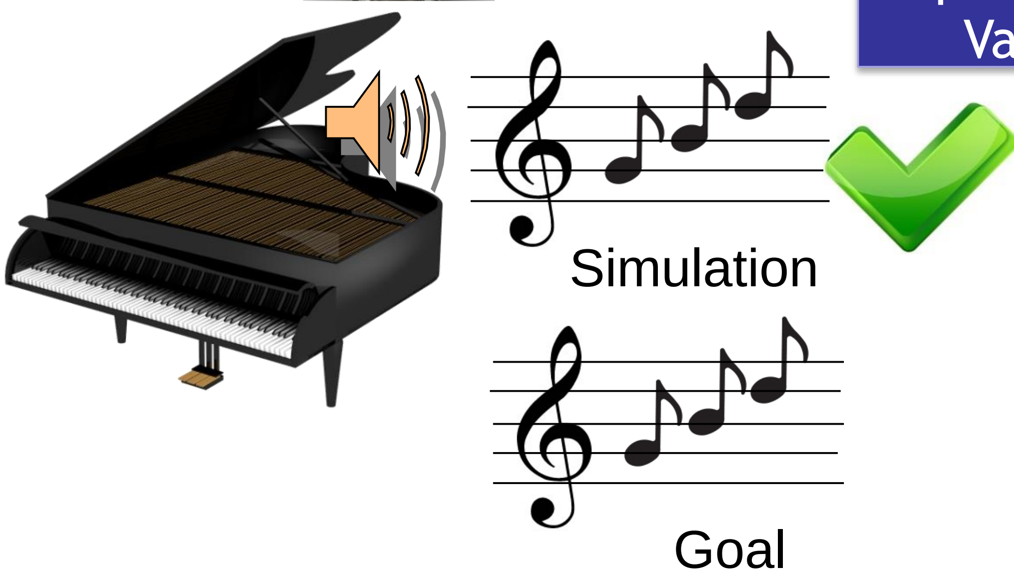
Printable Object

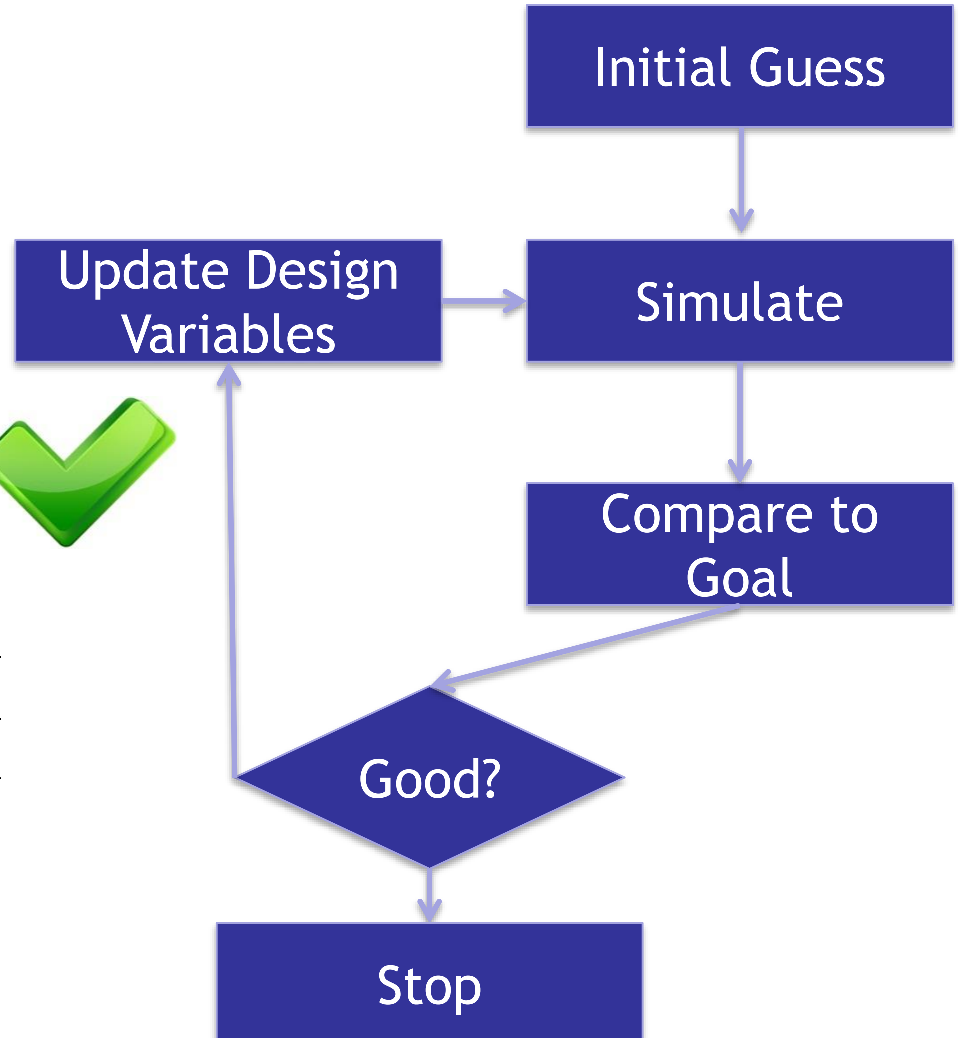
Inverse: From Performance Space to Design Space





Inverse: From Performance Space to Design Space





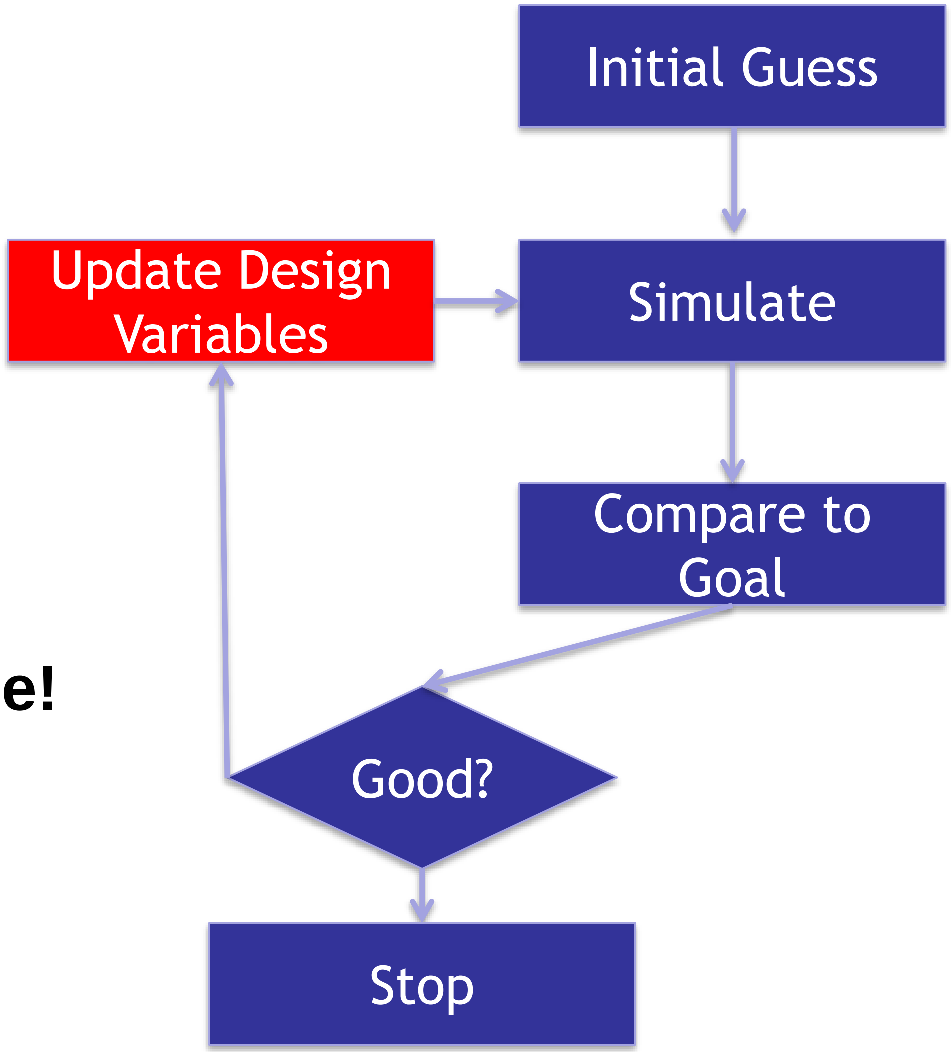
Inverse: From Performance Space to Design Space

How do we update the design variables?

✓converge to a good solutions quickly

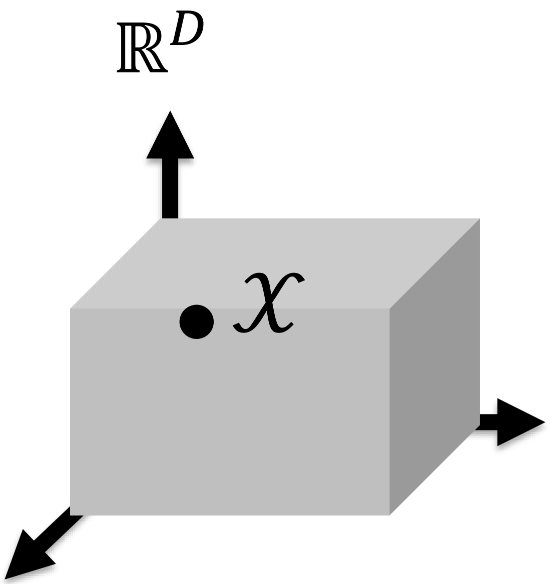
✓not get stuck in local minima

Depends on the Design Space!



Design Space

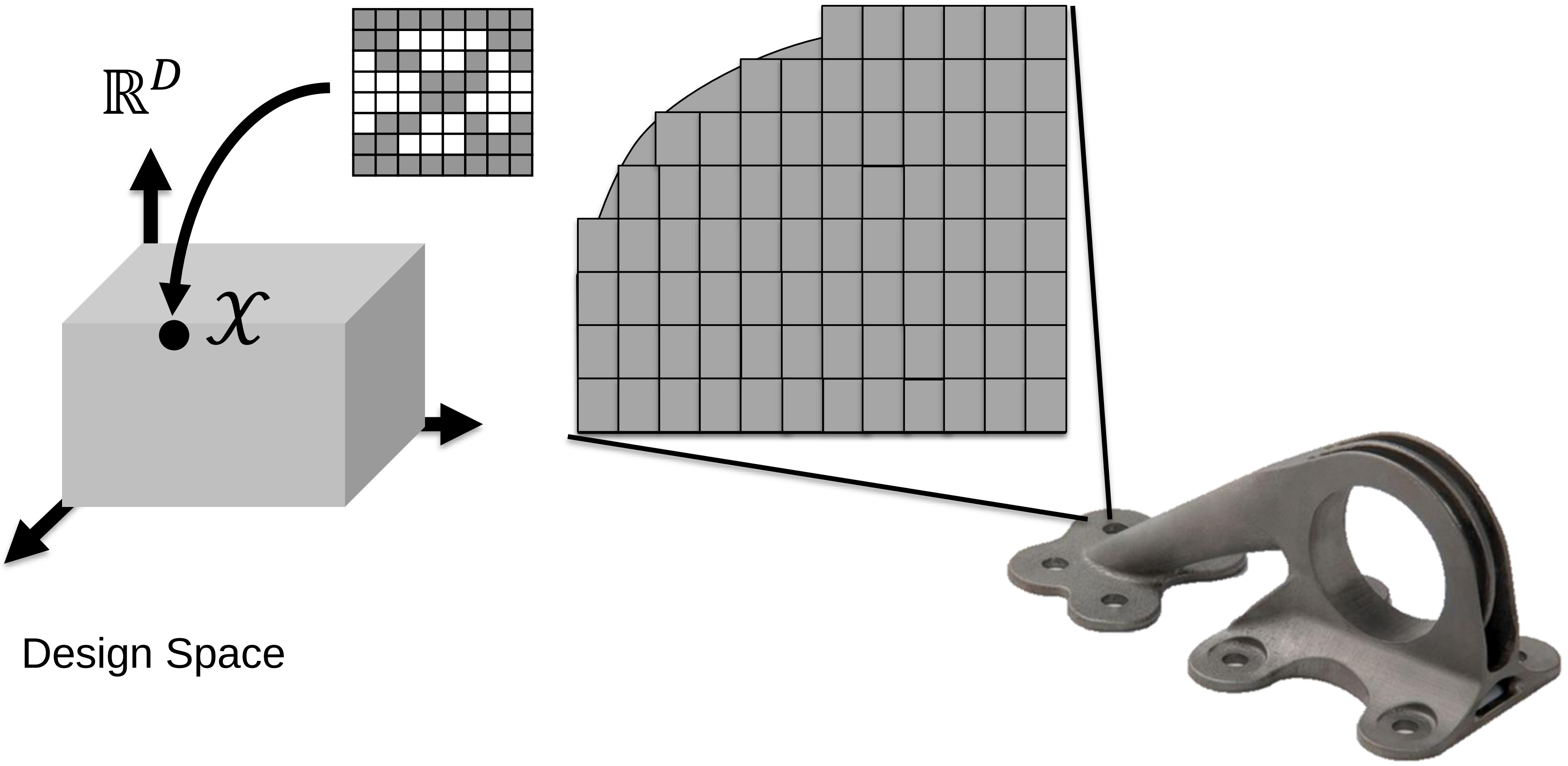
- Each design can be mathematically represented as a point in $\mathbb{R}^D$



Design Space

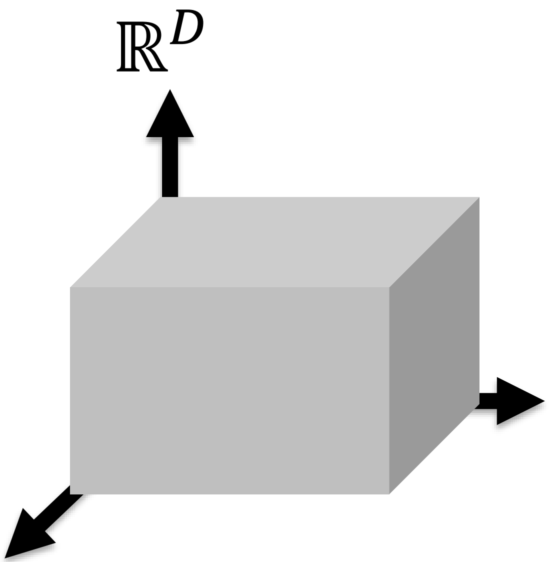
Design Space for Additive Manufacturing

- Each design can be mathematically represented as a point in $\mathbb{R}^D$, where D = number of voxels in a build volume

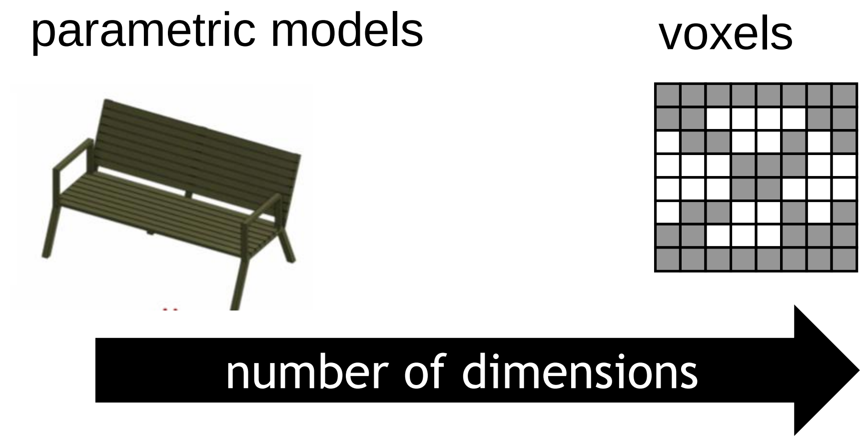


Reducing Design Space

- Each design can be mathematically represented as a point in $\mathbb{R}^D$



Design Space



Example

Design target

fabrication

Example

Design target

fabrication

fabrication

Rest shape

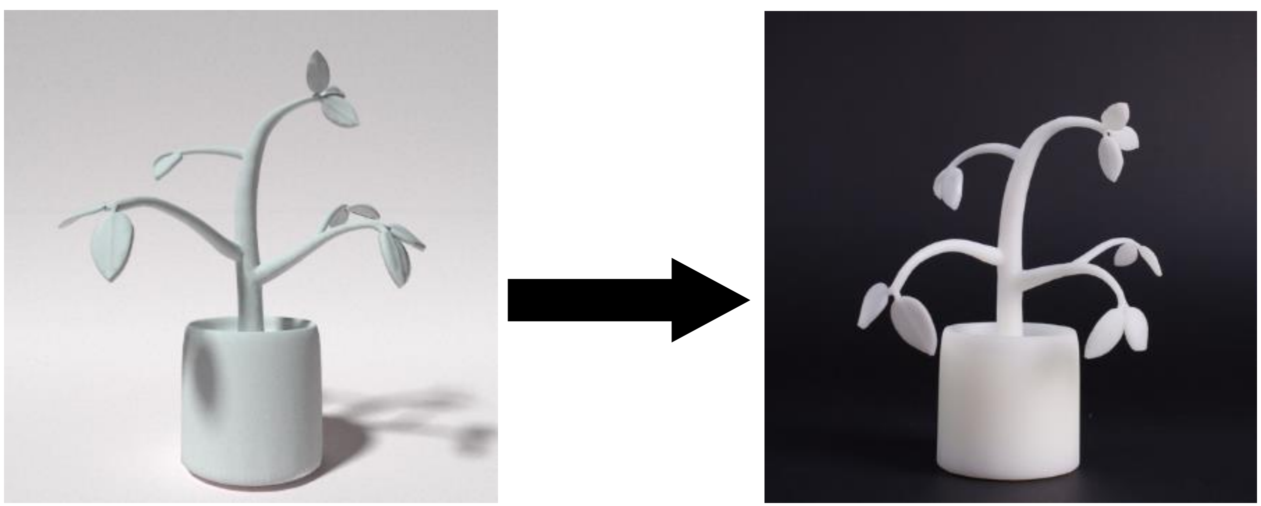
An Inverse Elastic Shape Design

x Reduced Parameters

- Mesh Vertices
- Mesh deformation “knobs”
  - e.g cages

An Inverse Elastic Shape Design

$\boldsymbol{x}$ | Reduced Parameters | $\rightarrow$ | Simulate | $f(\boldsymbol{x})$



simulated result

An Inverse Elastic Shape Design

$\boldsymbol{x}$ Reduced Parameters → Simulate $f(\boldsymbol{x})$

↓

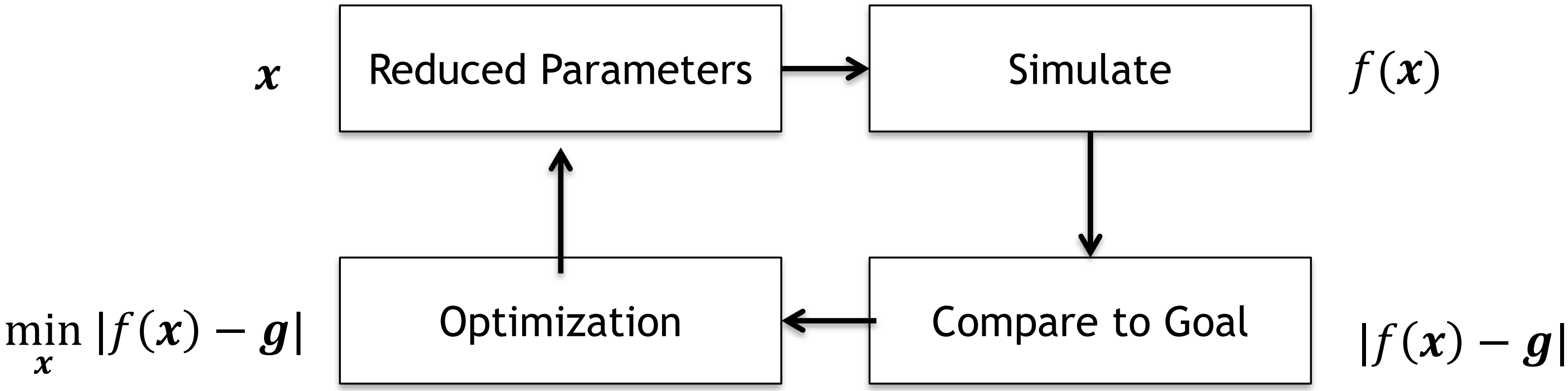
Compare to Goal $|f(\boldsymbol{x}) - \boldsymbol{g}|$

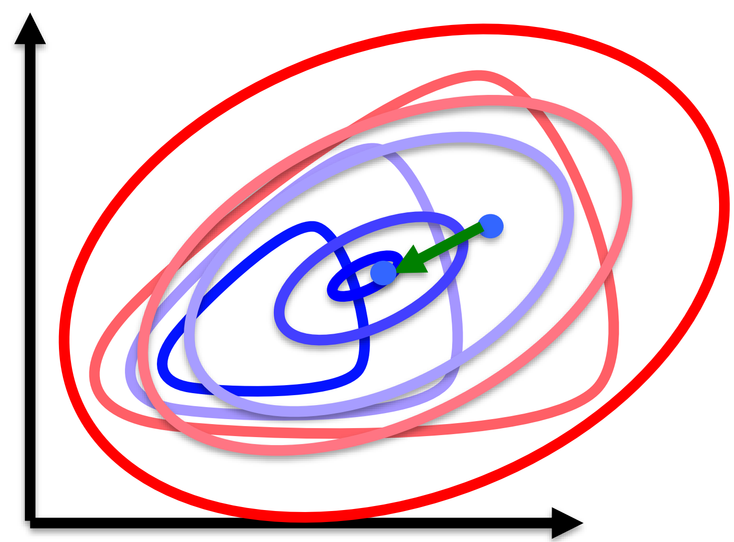
simulated result

? =

goal

An Inverse Elastic Shape Design

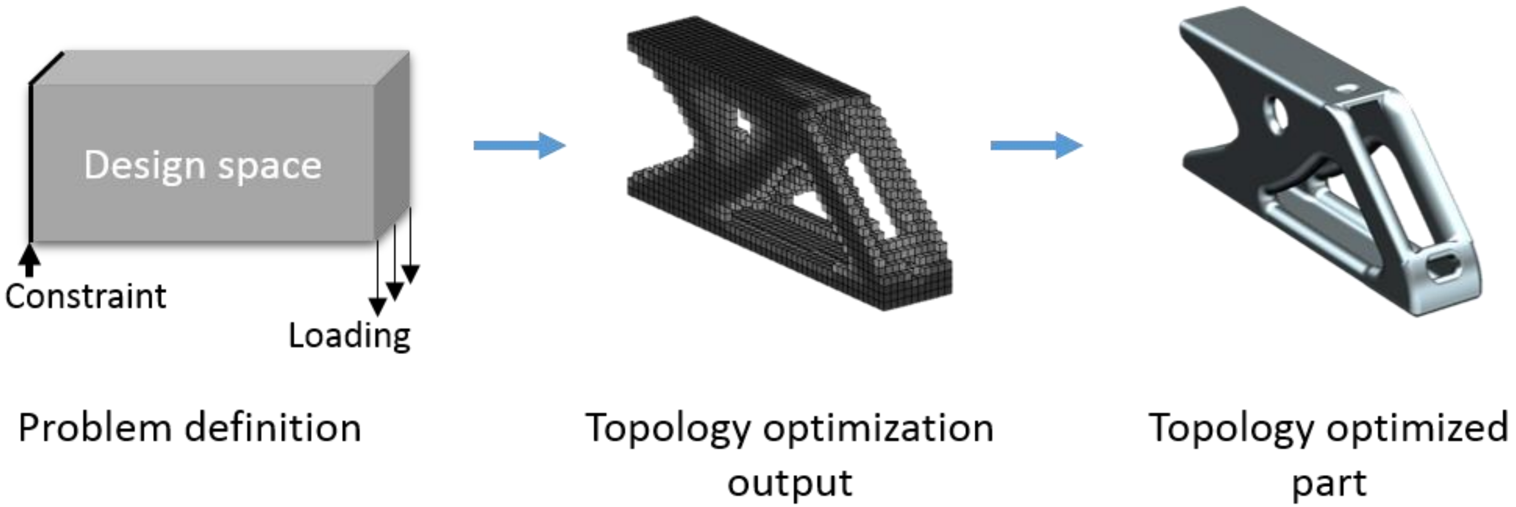




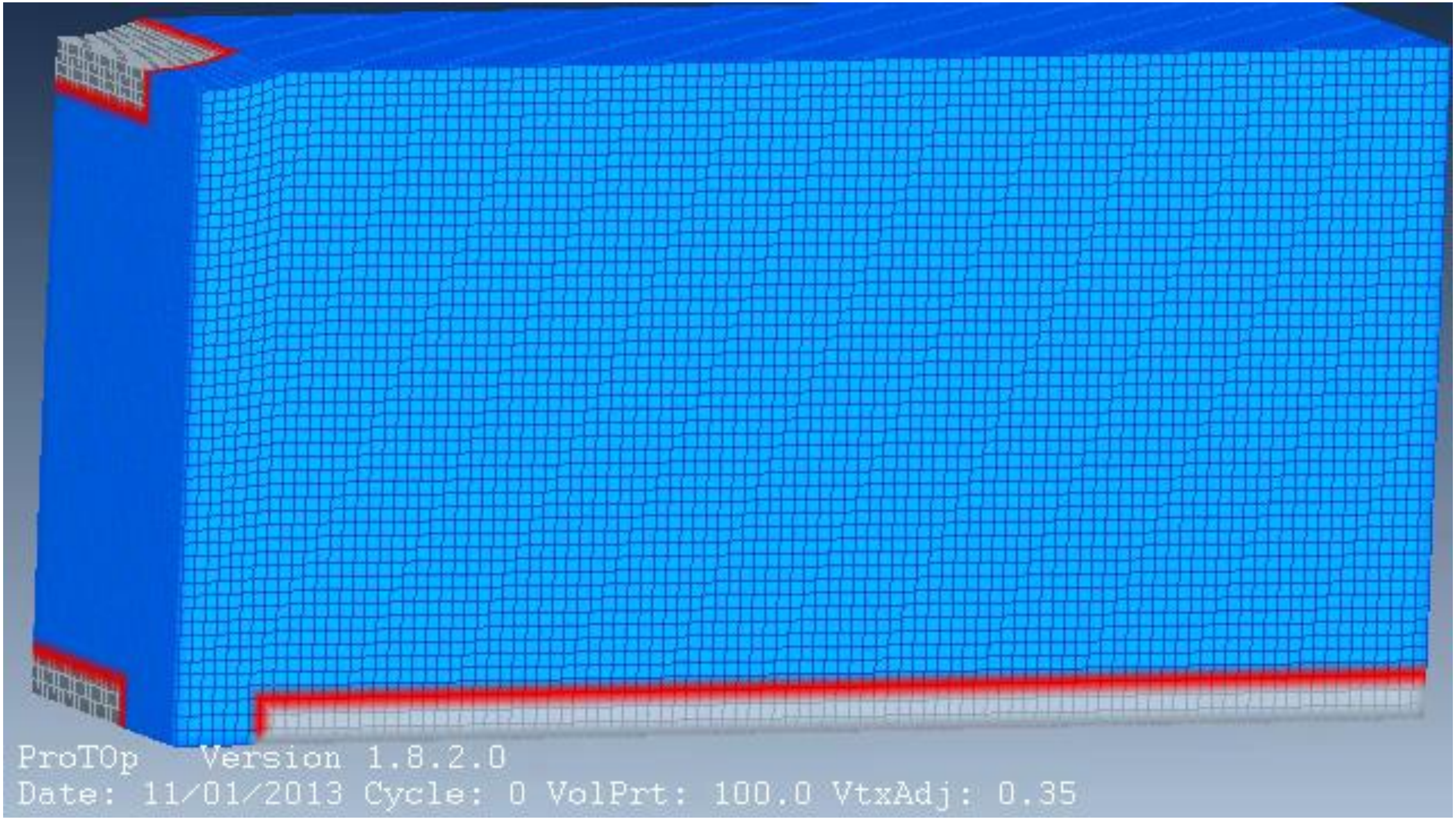
e.g., Newton’s Method

Inverse Methods: Topology Optimization

Topology Optimization

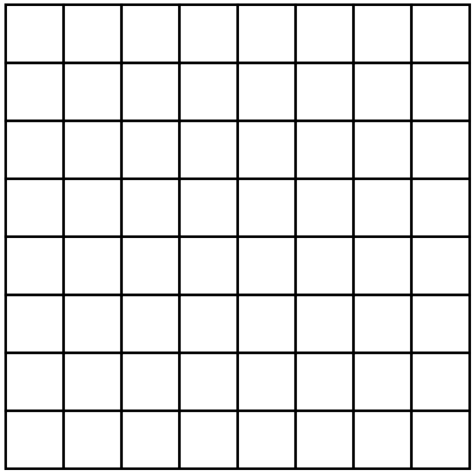


Topology Optimization

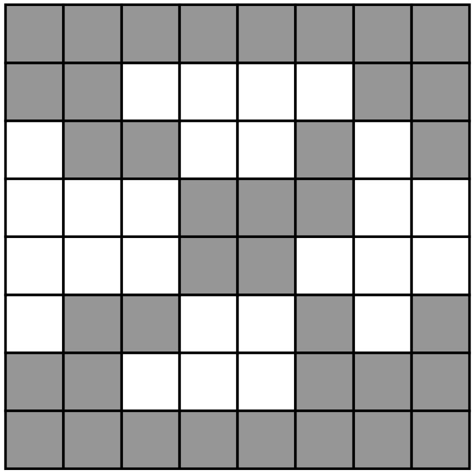


Topology Optimization

- Objectives:
  - Structure should be as stiff as possible (i.e. the compliance should be minimal) when a load is applied
  - The total amount of material should be equal to V_{max}



Initial layout



Output:
Voxels with material assignment (no material, full)

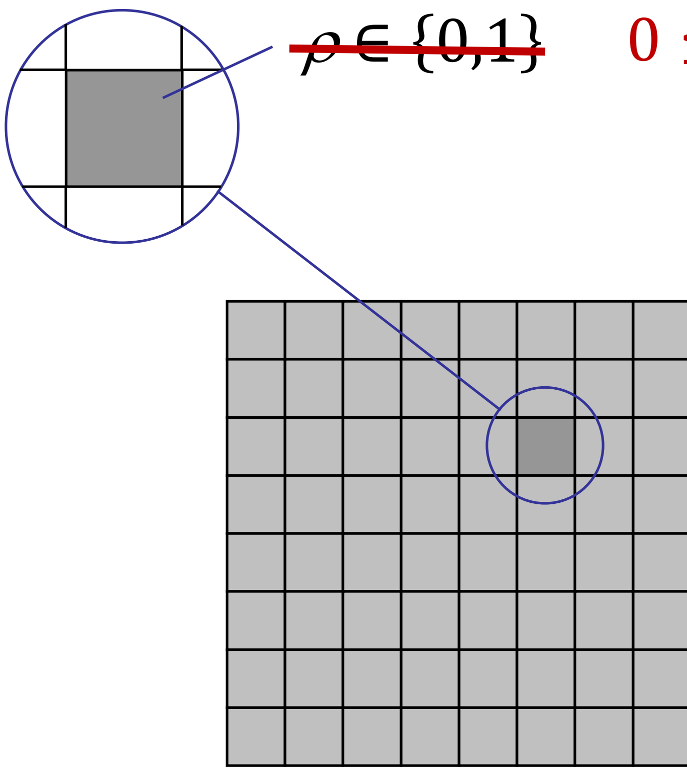
Large discrete space: $\{0,1\}^N$

Topology Optimization

- Design variables

Material property $\cancel{\mathbf{C} = \rho \mathbf{C}_0}$ $\mathbf{C} = \rho^p \mathbf{C}_0$

$\cancel{\rho \in \{0,1\}}$ $0 \leq \rho \leq 1$



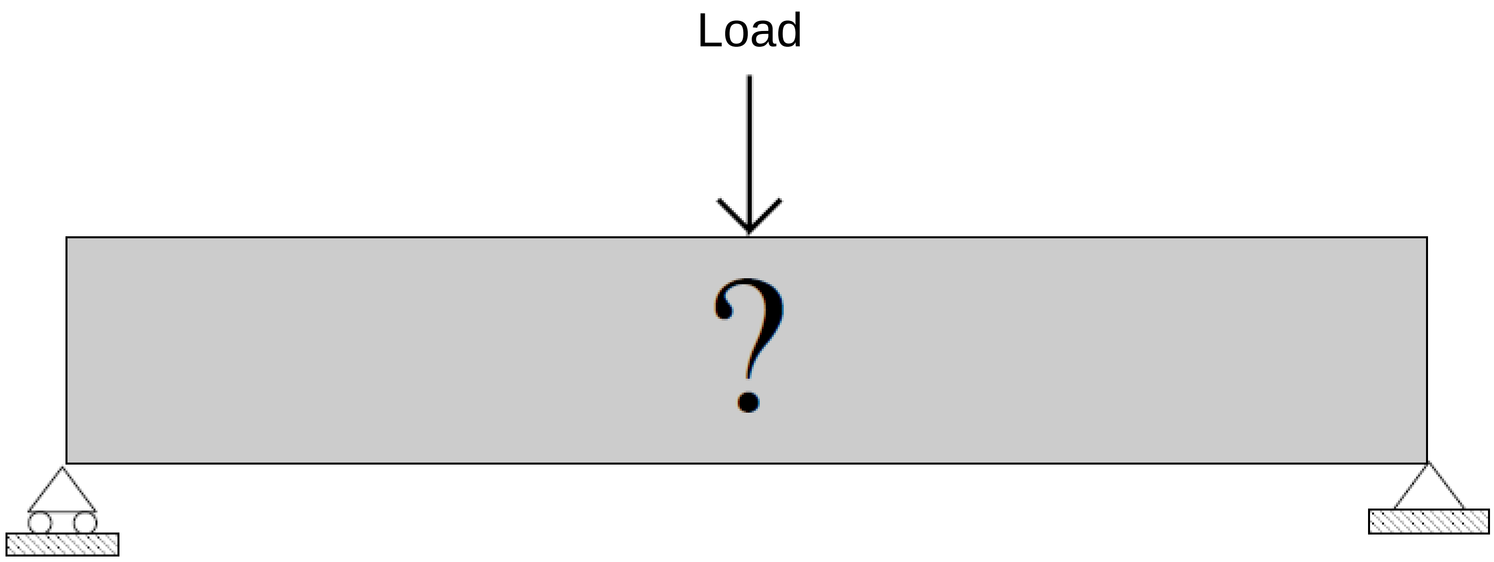
the method is called SIMP, power-law or density approach.

[Bendsøe, 1989]

Large discrete space: $\{0,1\}^N$

Topology Optimization: Boundary Conditions

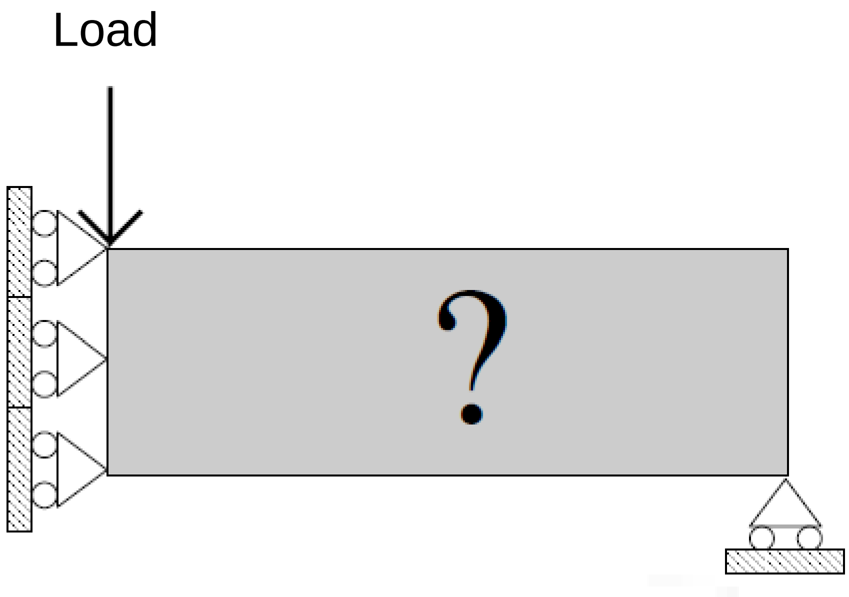
- Default boundary conditions: MMB Beam



Full domain

Topology Optimization: Boundary Conditions

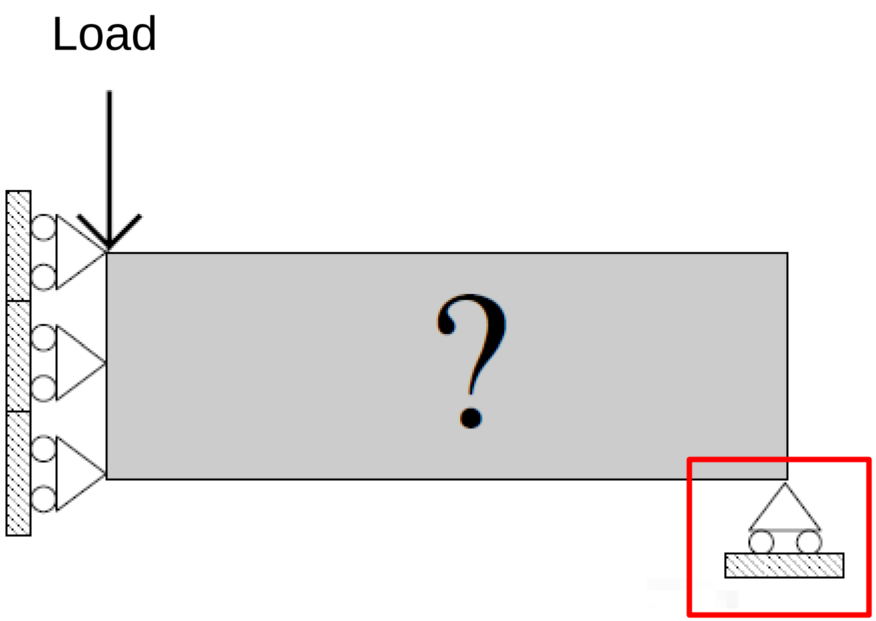
- Default boundary conditions: MMB Beam



Half design domain

Topology Optimization: Boundary Conditions

- Default boundary conditions: MMB Beam



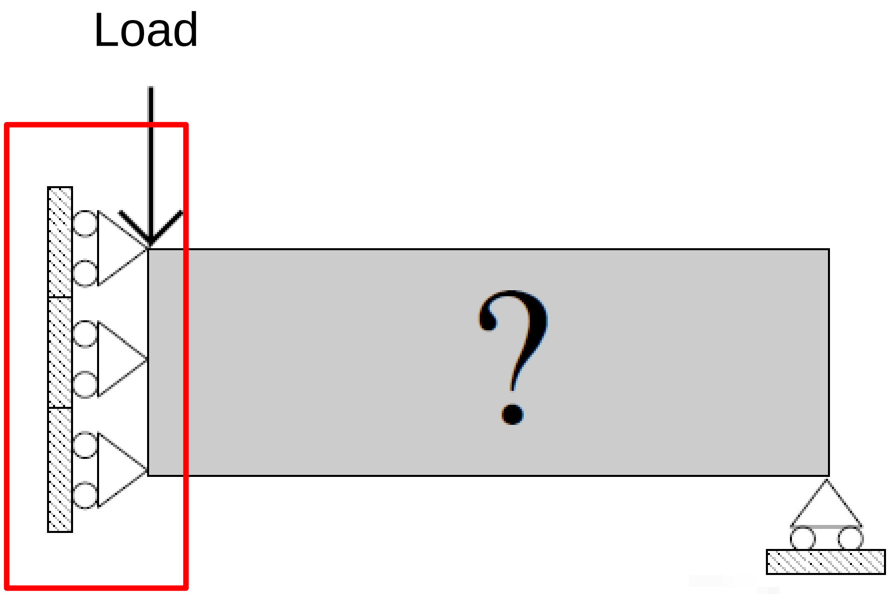
Structure is supported horizontally

Half design domain

Topology Optimization: Boundary Conditions

- Default boundary conditions: MMB Beam

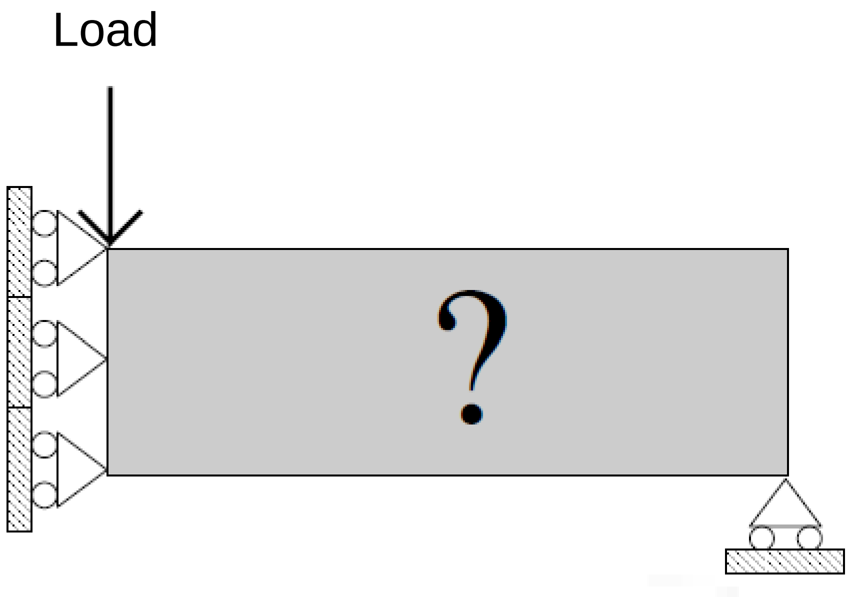
Structure is symmetric



Half design domain

Topology Optimization: Boundary Conditions

- How can we measure compliance?



Compute static equilibrium: $\mathbf{KU} = \mathbf{F}$

Measure Energy of the System: $\mathbf{U}^T\mathbf{KU}$

Topology Optimization: Mathematical Formulation

- Minimum compliance problem

$$\min_{\mathbf{x}} c(\mathbf{x}) = \mathbf{U}^T\mathbf{K}\mathbf{U} = \sum_{e=1}^{N} (x_e)^p \mathbf{u}_e^T \mathbf{k}_0 \mathbf{u}_e$$

$$\text{subject to} \quad \frac{V(\mathbf{x})}{V_0} = f$$

$$\mathbf{K}\mathbf{U} = \mathbf{F}$$

$$\mathbf{0} < \mathbf{x}_{\min} \leq \mathbf{x} \leq \mathbf{1}$$

Topology Optimization: Mathematical Formulation

- Minimum compliance problem

Densities

$$\min_{\boxed{\mathbf{x}}} c(\mathbf{x}) = \mathbf{U}^T\mathbf{K}\mathbf{U} = \sum_{e=1}^{N}(x_e)^p\mathbf{u}_e^T\mathbf{k}_0\mathbf{u}_e$$

$$\text{subject to} \quad \frac{V(\mathbf{x})}{V_0} = f$$

$$\mathbf{K}\mathbf{U} = \mathbf{F}$$

$$\mathbf{0} < \mathbf{x}_{\min} \leq \mathbf{x} \leq \mathbf{1}$$

Topology Optimization: Mathematical Formulation

- Minimum compliance problem

$$\min_{\mathbf{x}} c(\mathbf{x}) = \mathbf{U}^T \mathbf{K} \mathbf{U} = \sum_{e=1}^{N} (x_e)^p \mathbf{u}_e^T \mathbf{k}_0 \mathbf{u}_e$$

$$\text{subject to} \quad \frac{V(\mathbf{x})}{V_0} = f$$

$$\mathbf{K}\mathbf{U} = \mathbf{F}$$

$$\boxed{\mathbf{0} < \mathbf{x}_{\min} \leq \mathbf{x} \leq \mathbf{1}}$$

Valid range for densities

Topology Optimization: Mathematical Formulation

- Minimum compliance problem

Energy of the system

$$\min_{\mathbf{x}} c(\mathbf{x}) = \boxed{\mathbf{U}^T\mathbf{K}\mathbf{U}} = \sum_{e=1}^{N} (x_e)^p \mathbf{u}_e^T \mathbf{k}_0 \mathbf{u}_e$$

$$\text{subject to} \quad \frac{V(\mathbf{x})}{V_0} = f$$

$$\mathbf{K}\mathbf{U} = \mathbf{F}$$

$$\mathbf{0} < \mathbf{x}_{\min} \leq \mathbf{x} \leq \mathbf{1}$$

Topology Optimization: Mathematical Formulation

- Minimum compliance problem

$$\min_{\mathbf{x}} c(\mathbf{x}) = \mathbf{U}^T\mathbf{K}\mathbf{U} = \sum_{e=1}^{N}(x_e)^p \mathbf{u}_e^T \mathbf{k}_0 \mathbf{u}_e$$

$$\text{subject to} \quad \frac{V(\mathbf{x})}{V_0} = f$$

$$\boxed{\mathbf{K}\mathbf{U} = \mathbf{F}}$$ Static equilibrium

$$\mathbf{0} < \mathbf{x}_{\min} \le \mathbf{x} \le \mathbf{1}$$

Topology Optimization: Mathematical Formulation

- Minimum compliance problem

$$\min_{\mathbf{x}} c(\mathbf{x}) = \mathbf{U}^T\mathbf{K}\mathbf{U} = \sum_{e=1}^{N} (x_e)^p \mathbf{u}_e^T \mathbf{k}_0 \mathbf{u}_e$$

subject to $\boxed{\frac{V(\mathbf{x})}{V_0} = f}$ Desired volume fraction

$$\mathbf{K}\mathbf{U} = \mathbf{F}$$

$$\mathbf{0} < \mathbf{x}_{\min} \leq \mathbf{x} \leq \mathbf{1}$$

Result

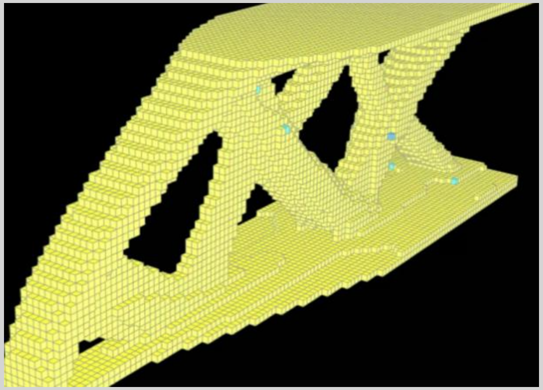
- Based on the paper:

  "A 99 line topology optimization code in Matlab" by Ole Sigmund, Structural and Multidisciplinary Optimization 21(2), 2001, pp. 120-127

- Code can be find here:
  - http://www.topopt.mek.dtu.dk/apps-and-software

Challenges

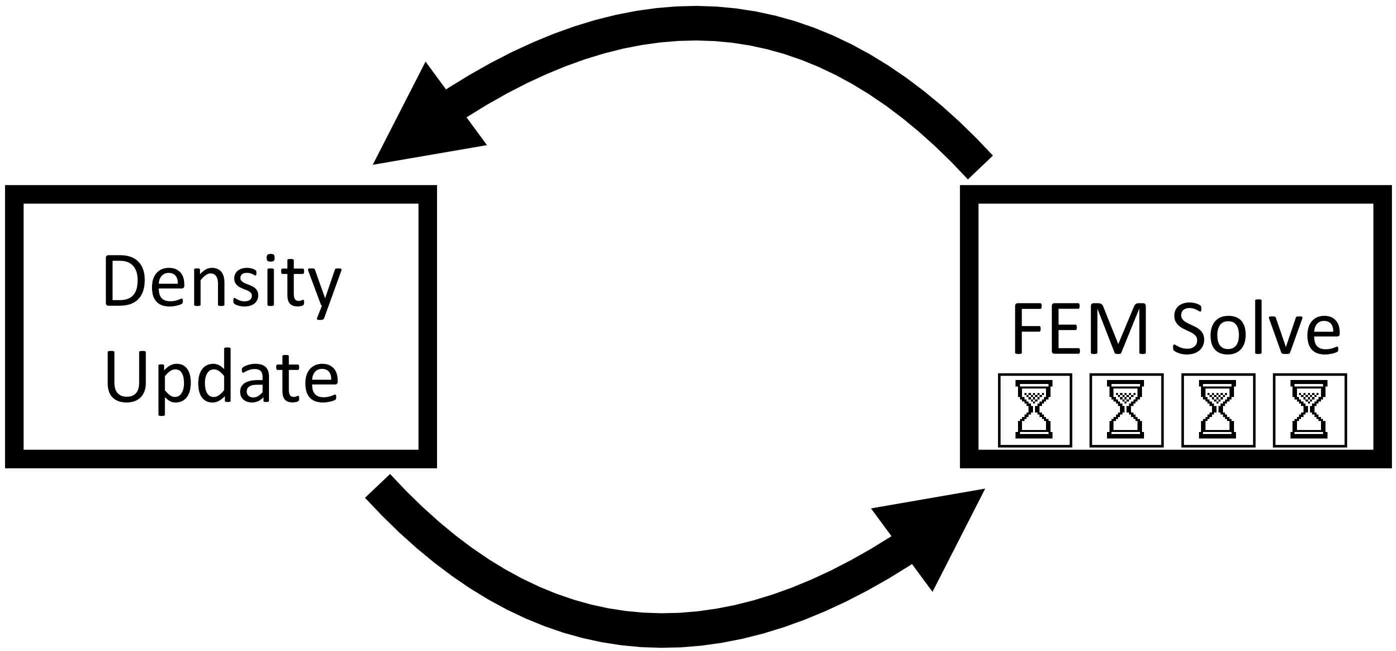
Hardware: Object-1000 Plus
- Up to 39.3 x 31.4 x 19.6 in.
- 600dpi (~40 microns)
- 5 trillion voxels

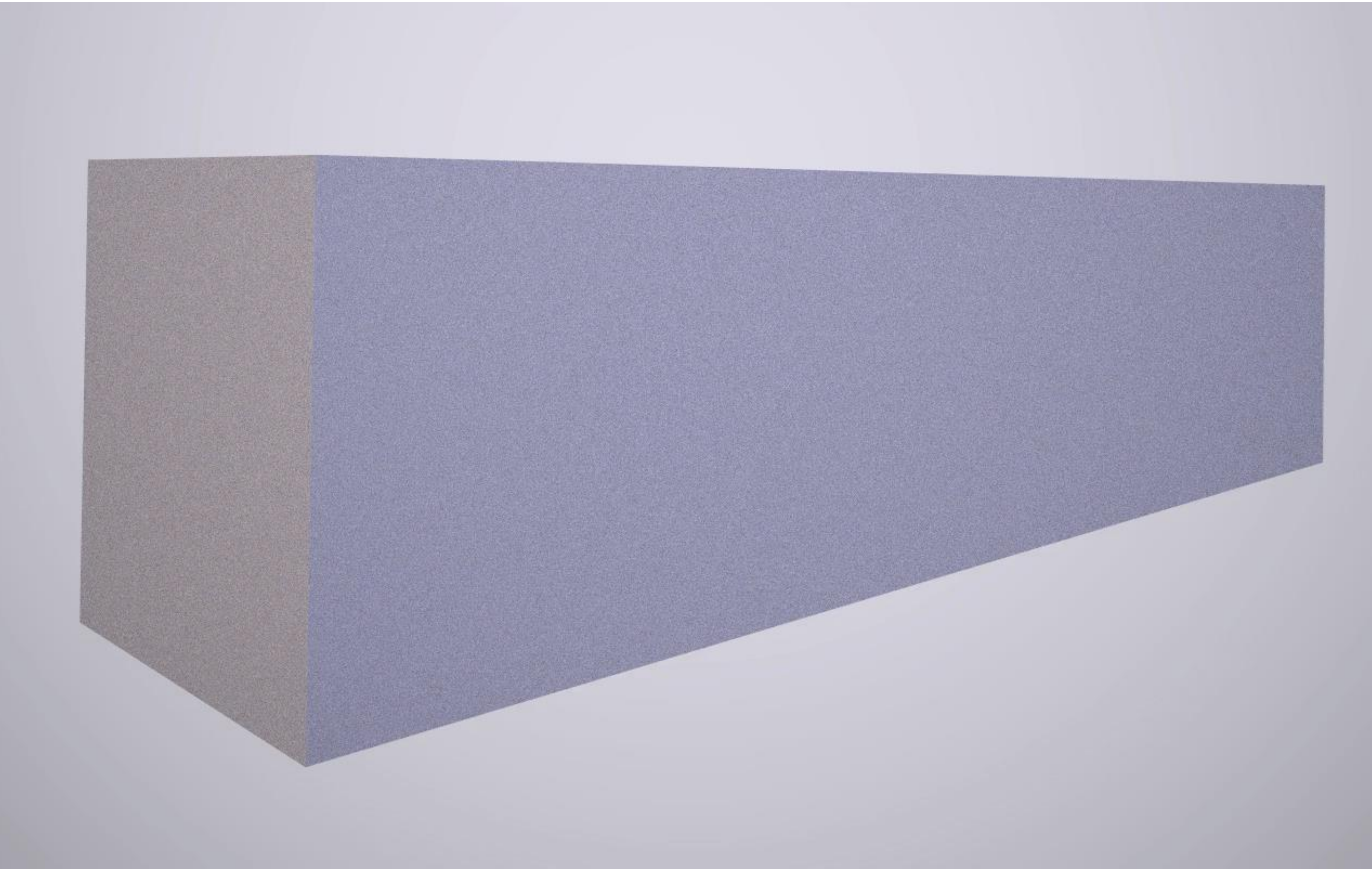


Software: SIMP Topology Optimization

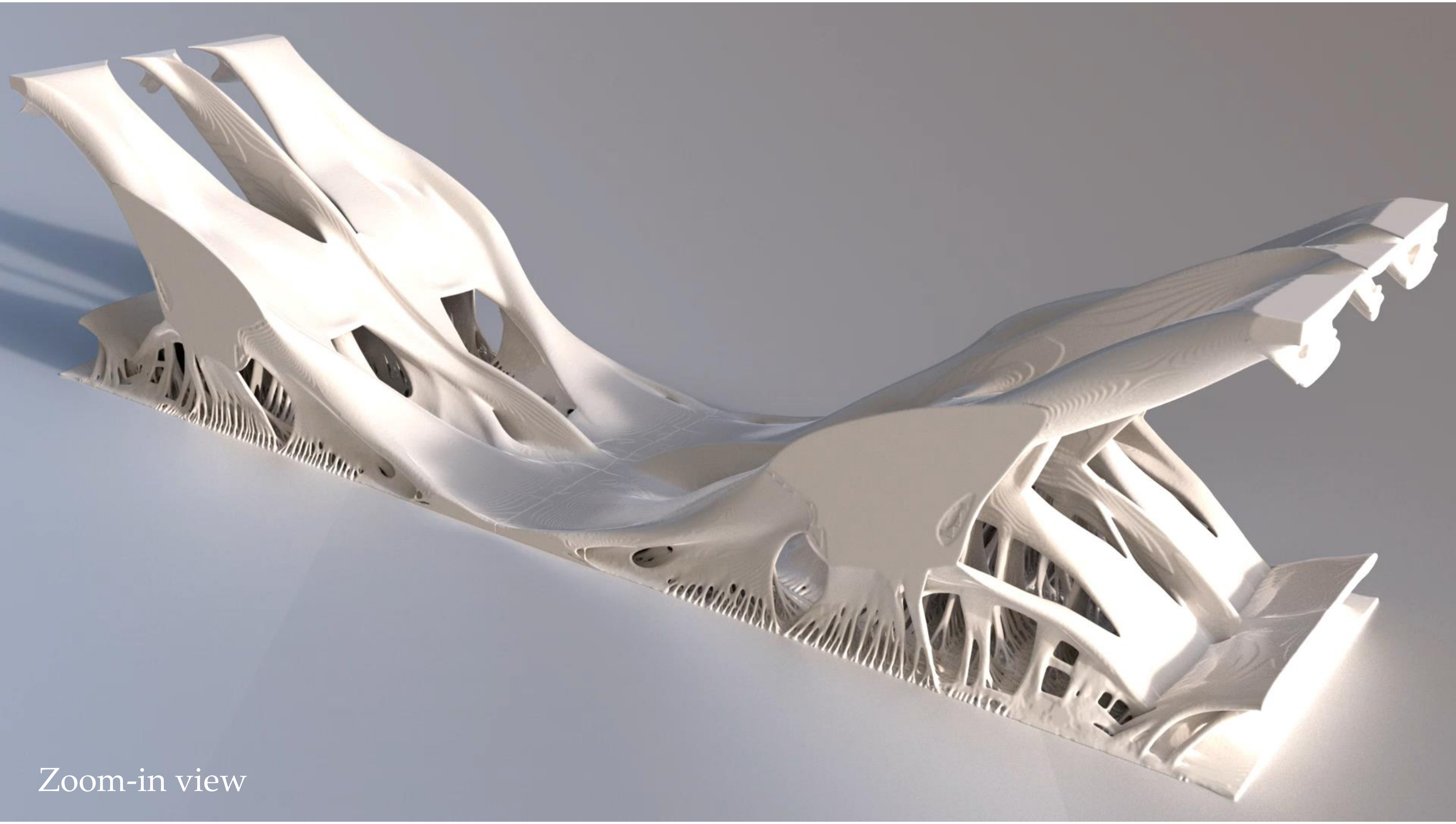
- Up to millions of elements
- Difficult to handle multiple materials

Topology Optimization





Source: Liu et al 2018



Source: Liu et al 2018

Course Schedule

9:00 am – 9:10 am	Introduction
9:10 am – 9:25 am	Hardware Review
9:25 am – 9:50 am	From Design to Machine Code
9:50 am – 10:15 am	Design Space Representations
10:15 am – 10:25 am	Performance Driven Design
10:25 am - 10:40 am	Break
10:40 am – 10:55 am	Performance Space Representation
10:55 am - 11:15 am	Inverse Methods
11:15 am – 11:35 am	Multi-objective Inverse Methods
11:35 am - 12:00 pm	Advanced Performance-Driven Design
12:00 pm - 12:15 pm	Course Review

Multiple Performance Objectives

Performance metric:
flexibility

Performance metric:
weight

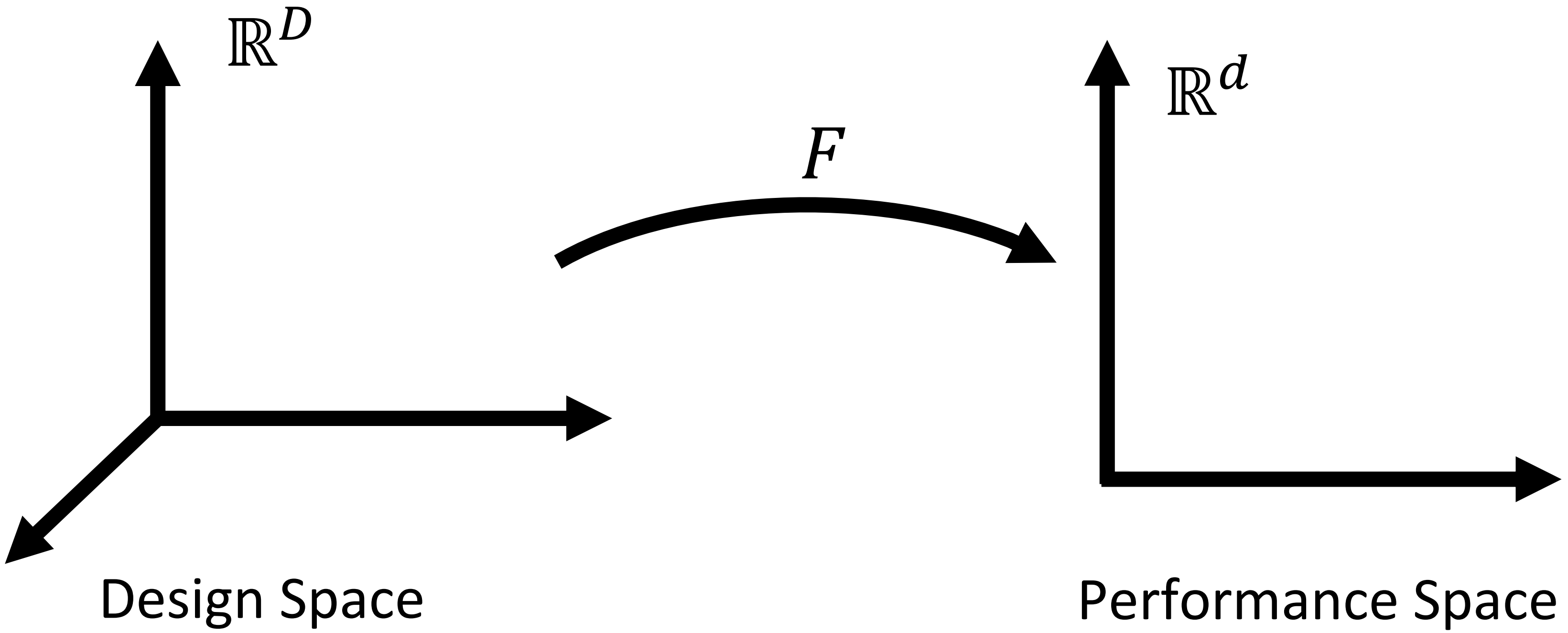
Performance metric:
stability

Multi-Objective Optimization

$$\min f_i(x), \quad i = 1, \ldots, d \quad x \in \mathbb{R}^D$$

Subject to $\quad g(x) \geq, \quad h(x) = 0$

$$F(x) = [f_1(x), \ldots . f_d(x)]$$



Multi-Objective Optimization

$$\min f_i(x), \qquad i = 1, \dots, d$$

Subject to $\quad g(x) \geq, \quad h(x) = 0$

$$F(x) = [f_1(x), \dots . f_d(d)]$$

We know how to do this: $\boxed{\min f(x)}$

Multi-Objective Optimization

$$\min f_i(x), \qquad i = 1, \ldots, d$$

Subject to $\quad g(x) \geq, \quad h(x) = 0$

$$F(x) = [f_1(x), \ldots . f_d(d)]$$

We know how to do this: $\boxed{\min f(x)}$

Solution: $f(x) = \sum_i w_i f_i(x)$

Multi-Objective Optimization

$$\min f_i(x), \qquad i = 1, \dots, d$$

Subject to $\quad g(x) \geq, \quad h(x) = 0$

$$F(x) = [f_1(x), \dots . f_d(d)]$$

We know how to do this: $\boxed{\min f(x)}$

Solution: $f(x) = \sum_i \boxed{w_i} f_i(x)$

How do you pick the weights?

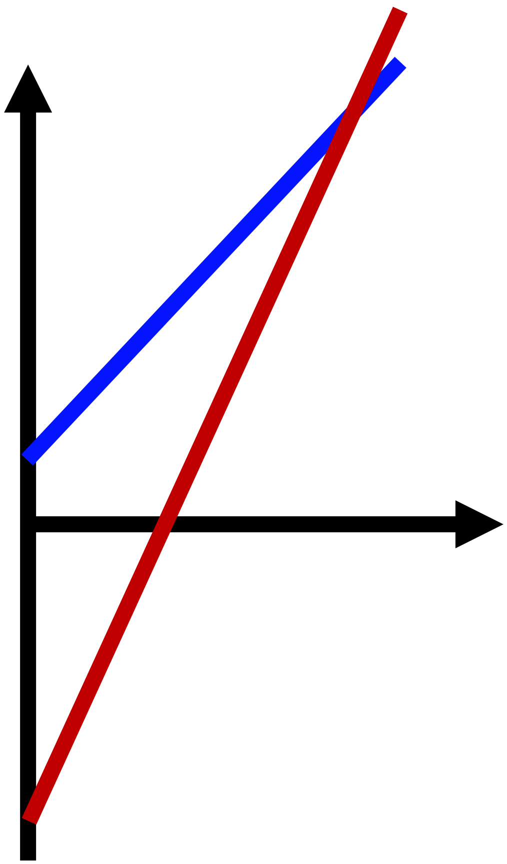
Do the Weights Mater?

Example:

$$f_1(x) = 2x - 5$$

$$f_2(x) = x + 3$$

$$0 \leq x \leq 1$$



$$f(x) = w_1 f_1(x) + w_2 f_2(x)$$

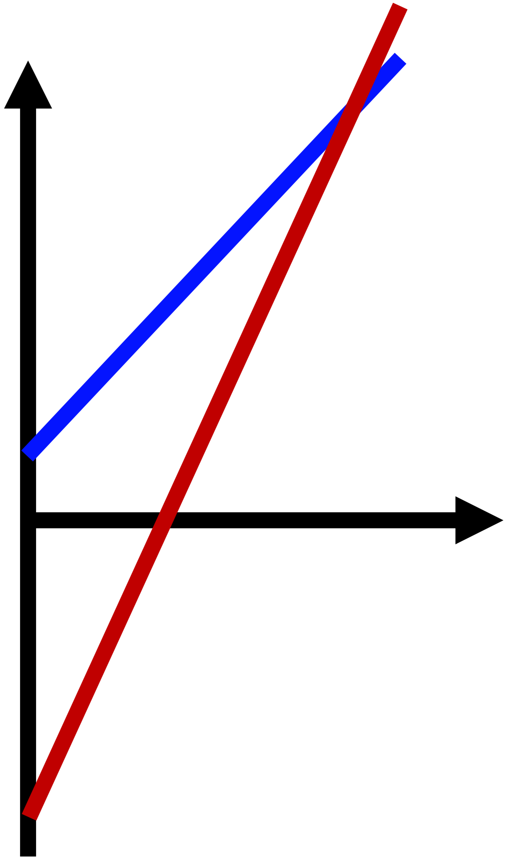
Do the Weights Mater?

Example:

$$f_1(x) = 2x - 5$$

$$f_2(x) = x + 3$$

$$0 \leq x \leq 1$$

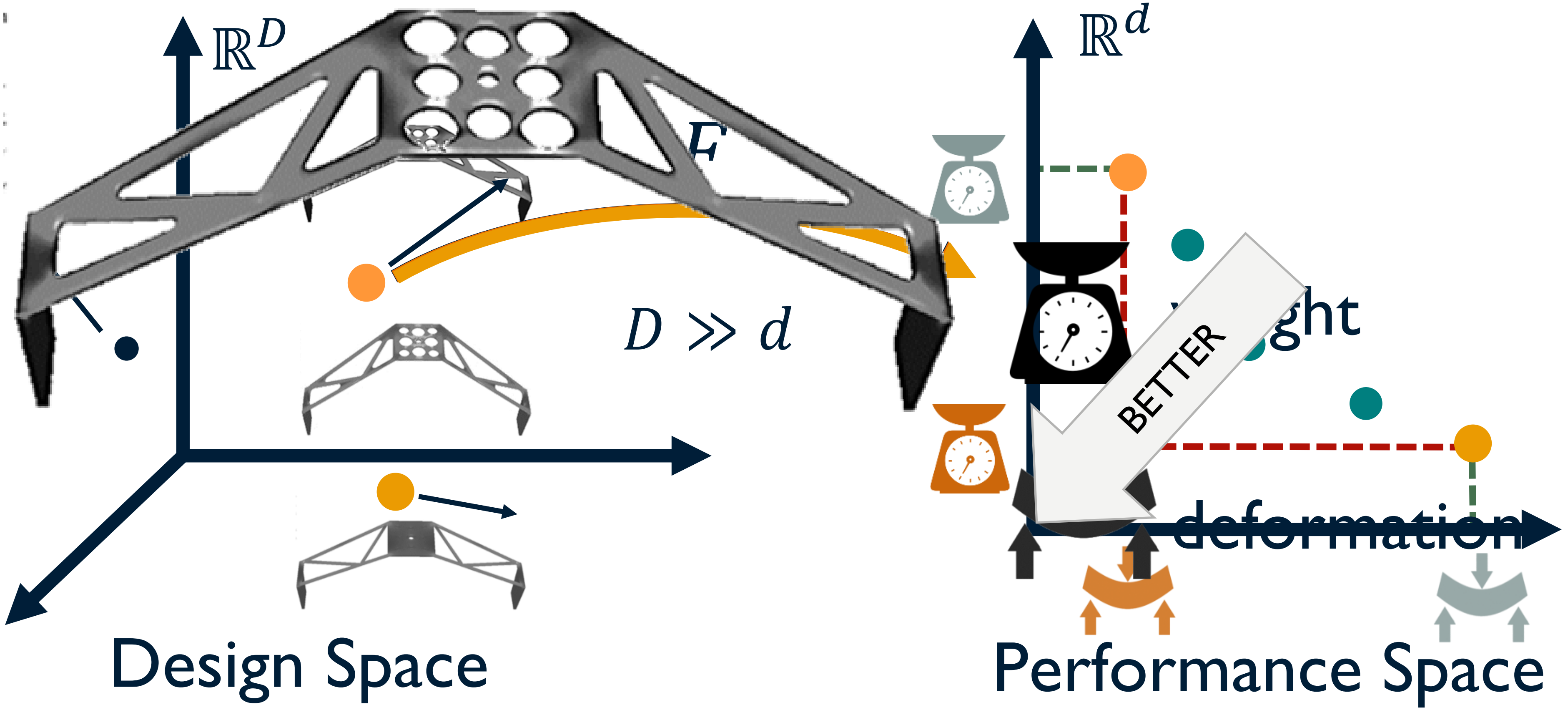


$$f(x) = w_1 f_1(x) + w_2 f_2(x)$$

No matter what weights you pick

$\arg\min f(x) = 0$

When Objectives are Conflicting



Experiment

(A)

3 carrots
8 candies

(B)

6 carrots
6 candies

~~(C)~~

~~6 carrots~~
~~4 candies~~

Experiment

~~(A)~~

~~3 carrots~~
~~8 candies~~

(B)

6 carrots
6 candies

~~(C)~~

~~6 carrots~~
~~4 candies~~

(D)

7 carrots
3 candies

(E)

5 carrots
7 candies

(F)

4 carrots
9 candies

Definition: Dominance

(A)

3 carrots
8 candies

(B)

6 carrots
6 candies

(C)

6 carrots
4 candies

(D)

7 carrots
3 candies

(E)

5 carrots
7 candies

(F)

4 carrots
9 candies

Definition: Dominance

(A)

3 carrots
8 candies

(B)

6 carrots
6 candies

(C)

6 carrots
4 candies

(D)

7 carrots
3 candies

(E)

5 carrots
7 candies

(F)

4 carrots
9 candies

Pareto Optimality

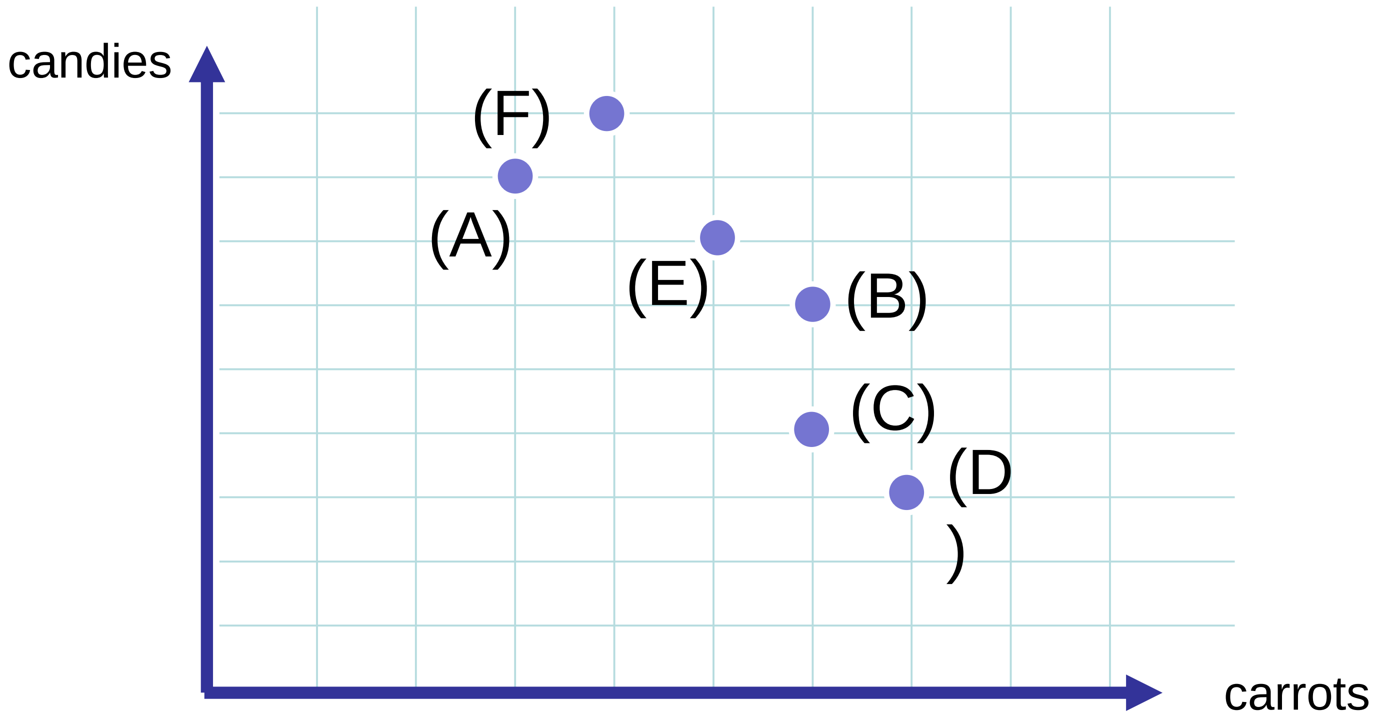
A solution x_1 is said to dominate the other solution x_2, if both the following conditions are true:

1. The solution x_1 is no worse than x_2 in all objectives.

2. The solution x_1 is strictly better than x_2 in at least one objective.

A point is Pareto optimal if it in not dominated by any point: called non-dominated point

Let’s Plot this



(A)

3 carrots
8 candies

(B)

6 carrots
6 candies

(C)

6 carrots
4 candies

(D)

7 carrots
3 candies

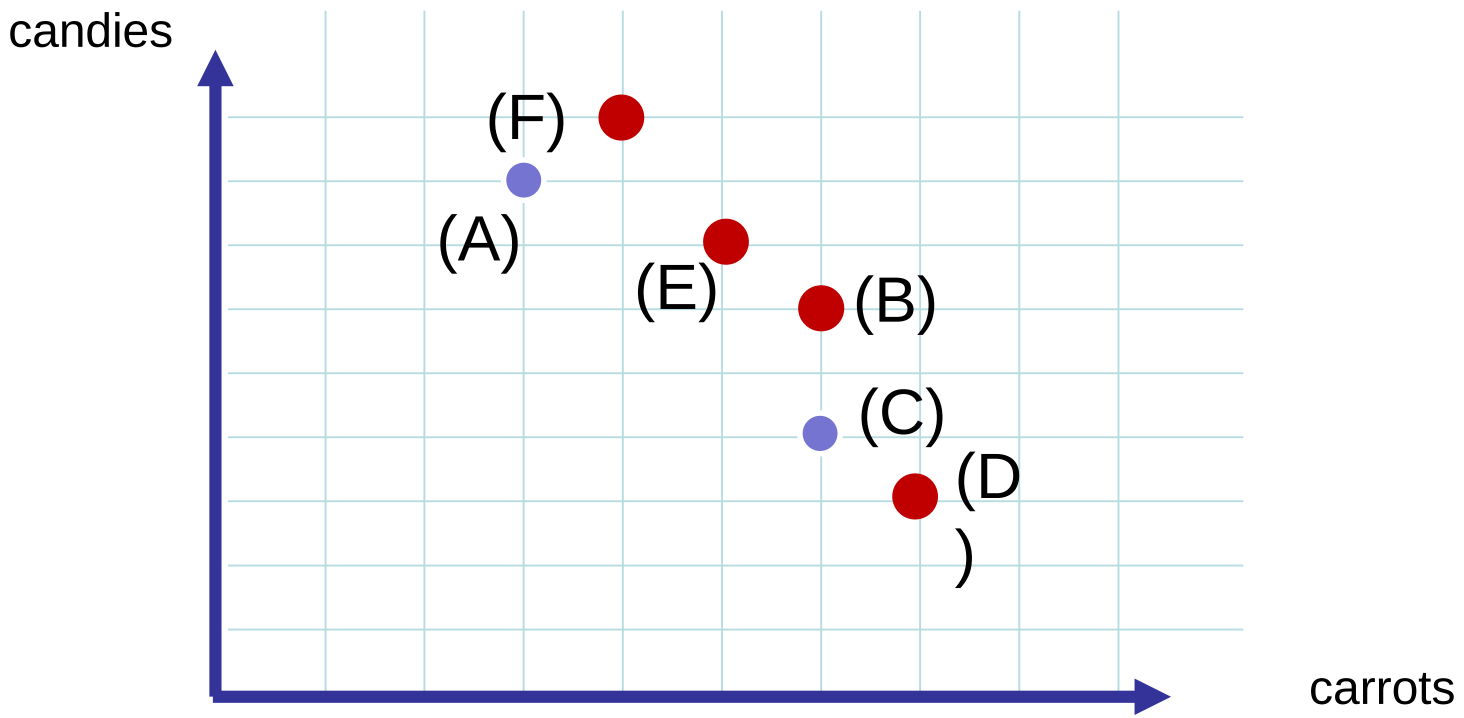
(E)

5 carrots
7 candies

(F)

4 carrots
9 candies

Pareto Front



(A)

3 carrots
8 candies

(B)

6 carrots
6 candies

(C)

6 carrots
4 candies

(D)

7 carrots
3 candies

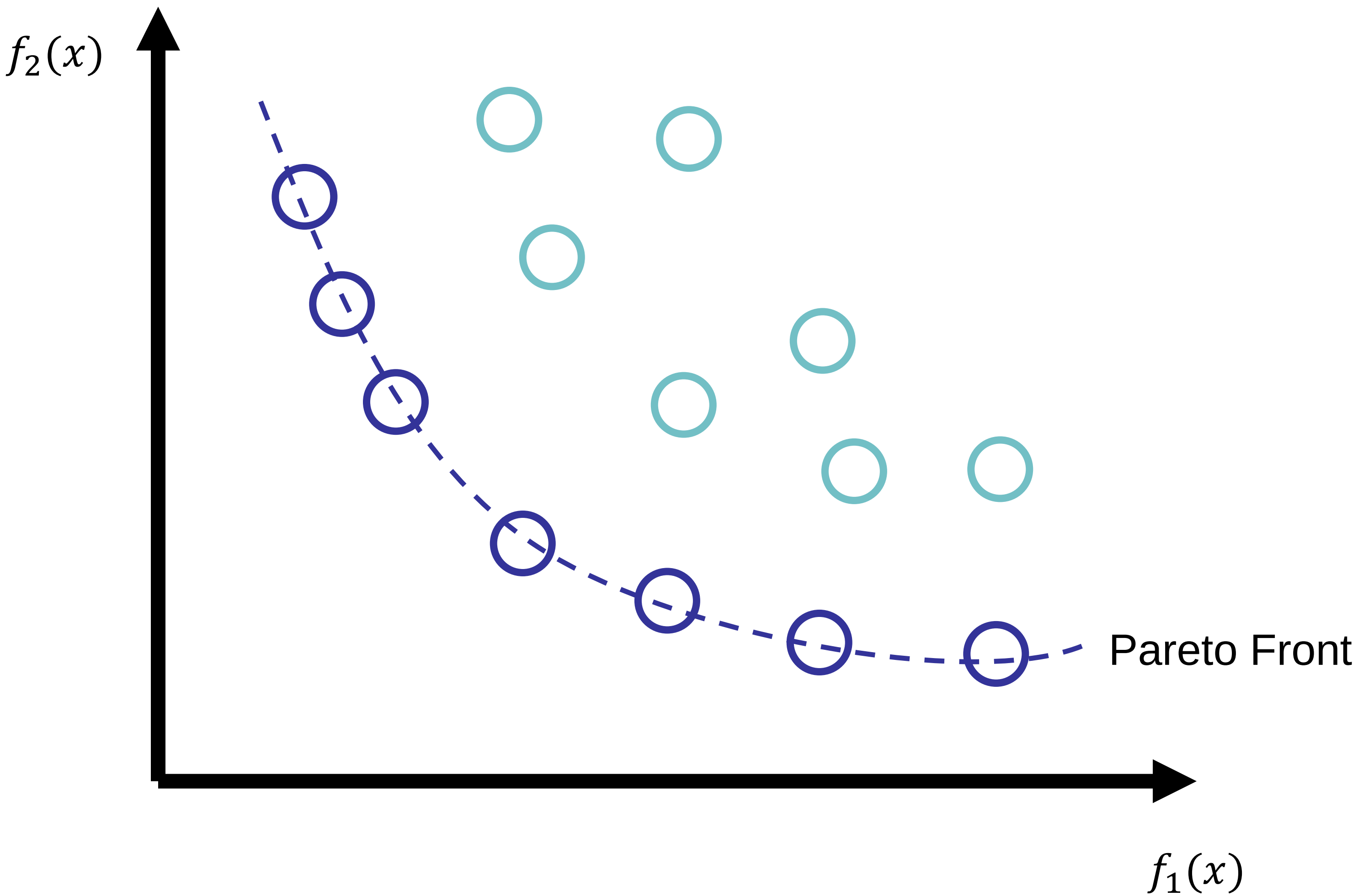
(E)

5 carrots
7 candies

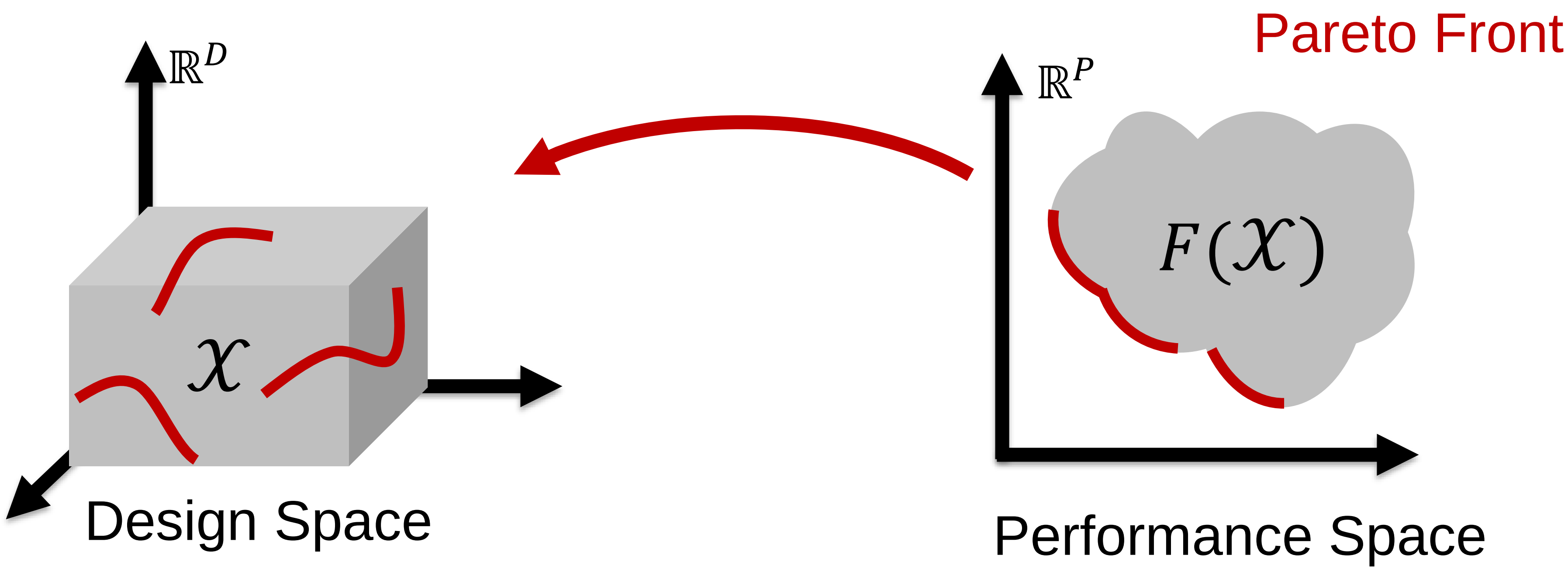
(F)

3 carrots
9 candies

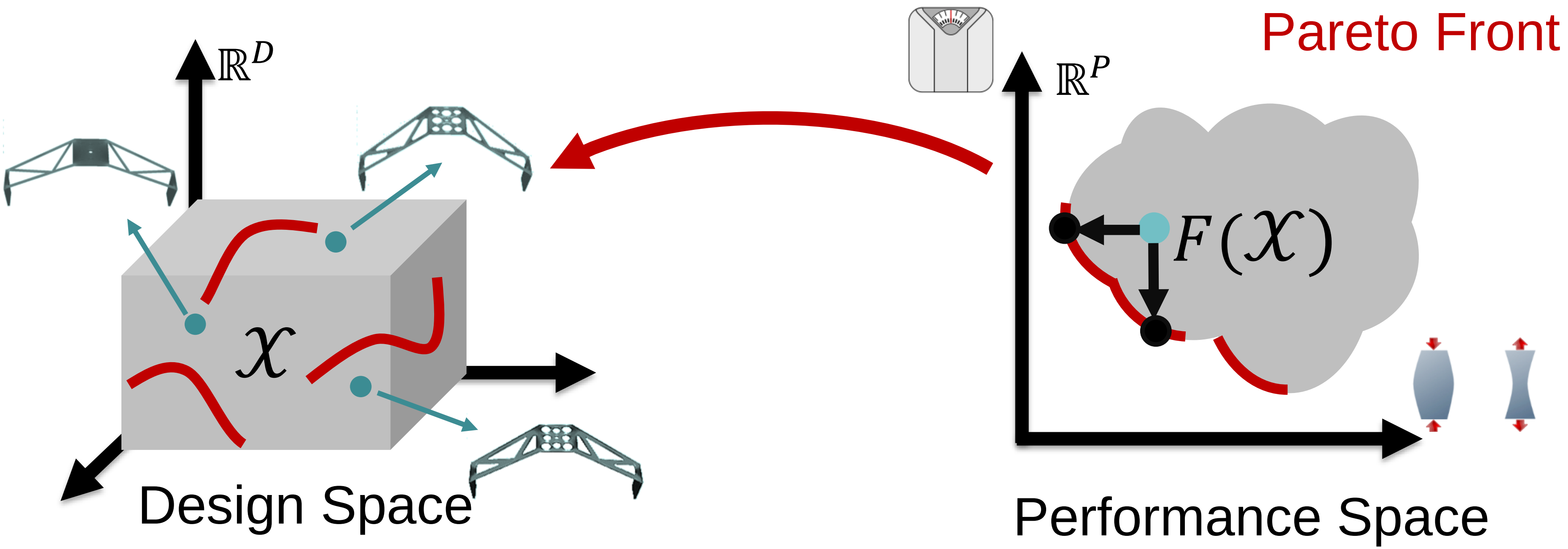
For Minimization



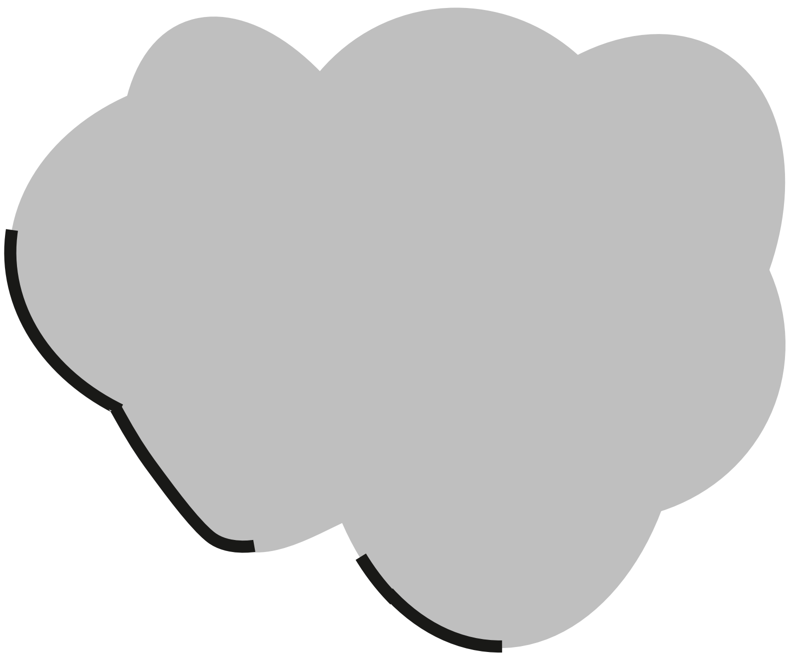
Space of Optimal Solutions



Space of Optimal Solutions



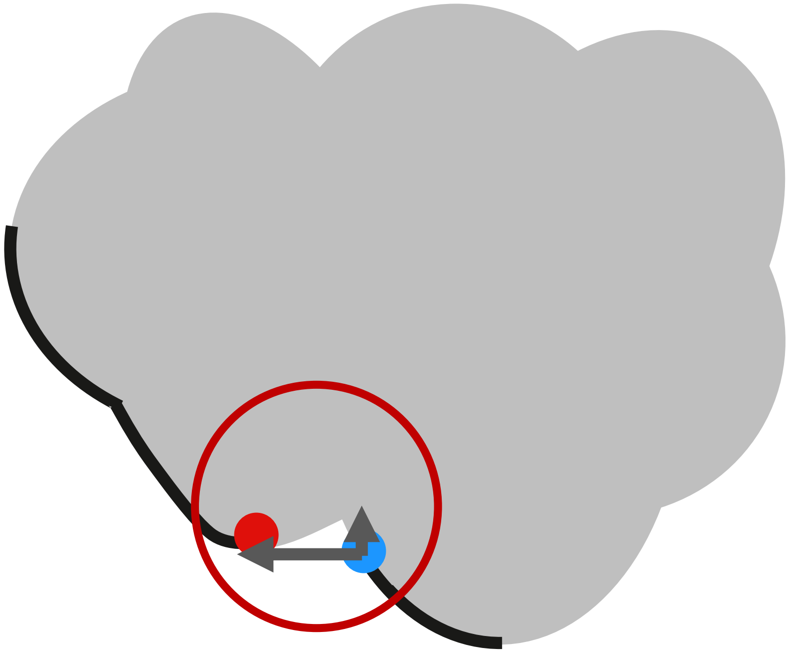
The Geometry of the Front



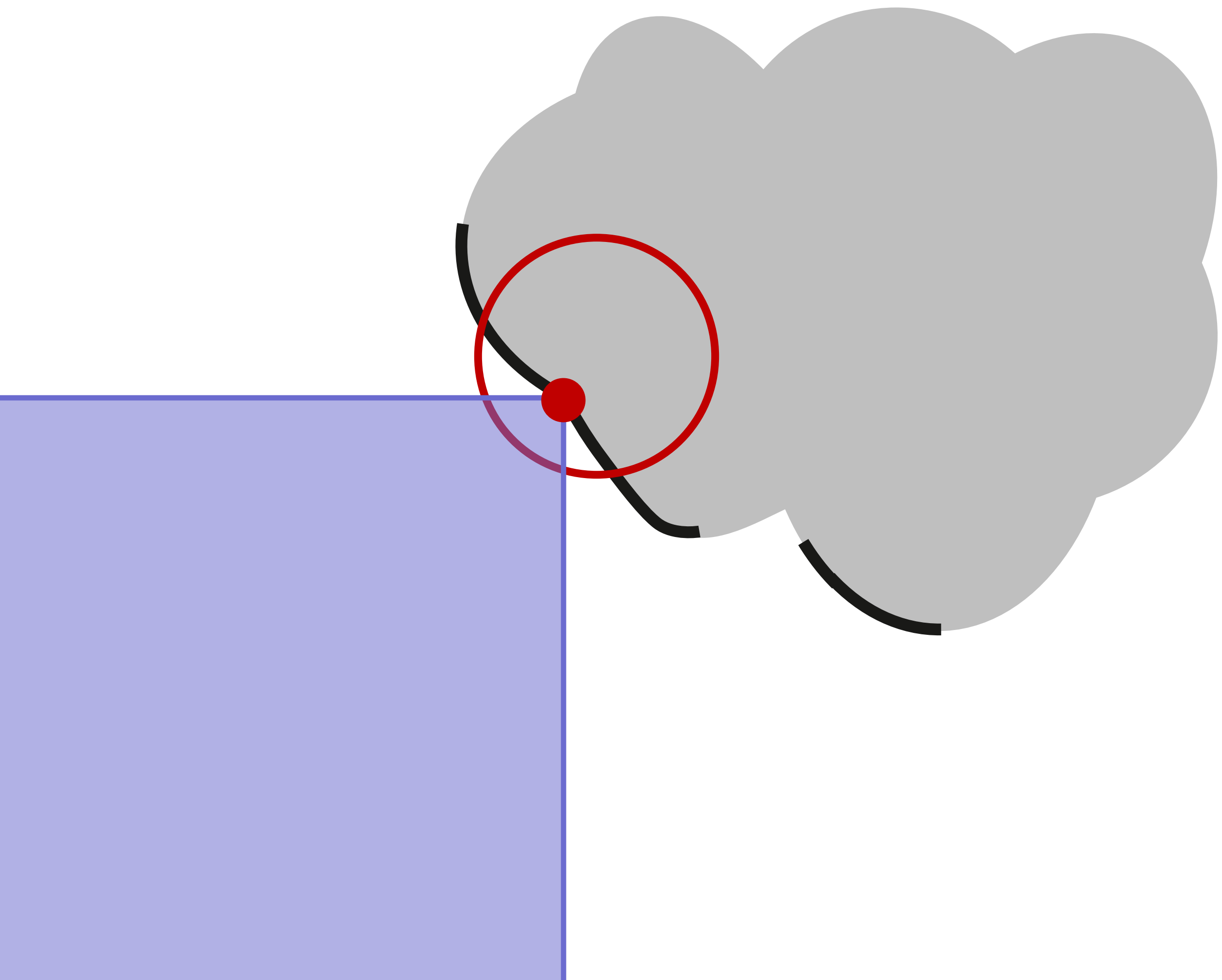
Not a straight line!

Solution: $f(x) = \sum_i w_i f_i(x)$ ☹

The Front Can Have Gaps



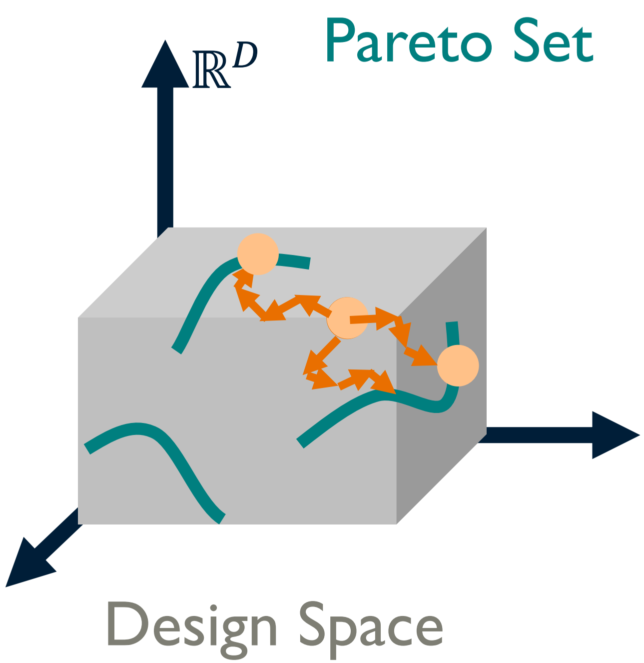
The Front Can Have Non-Convex Regions

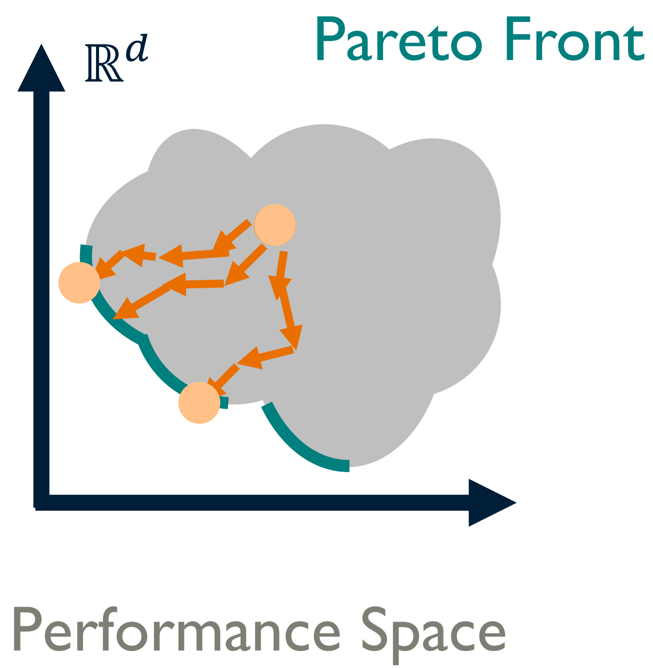


Pareto Front Discovery

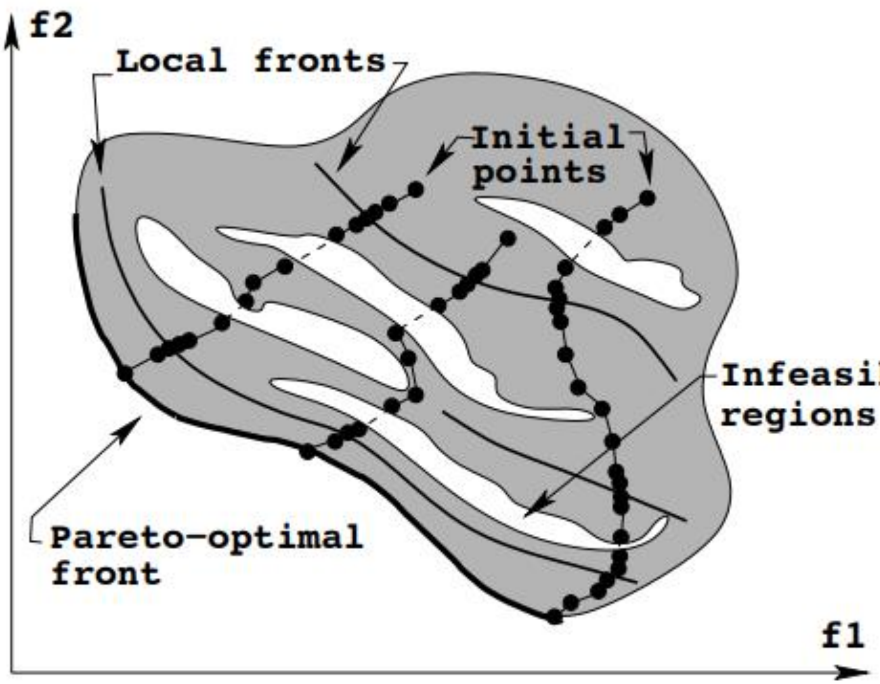
Main Challenge:

- Converge to optimal solutions
- Diverse set that describes the full front





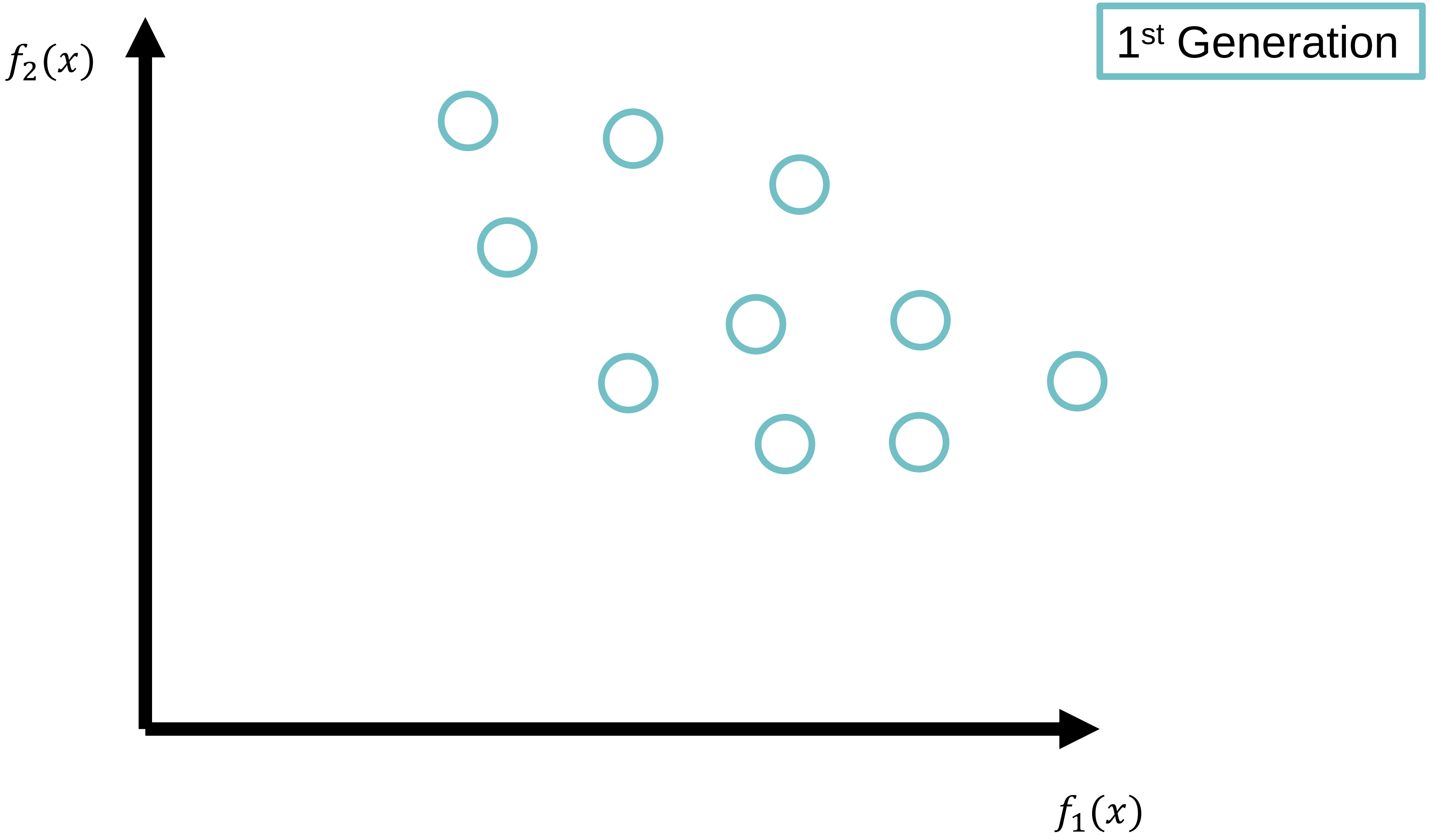
Problem: Each Single Objective Optimization is not SIMPLE!



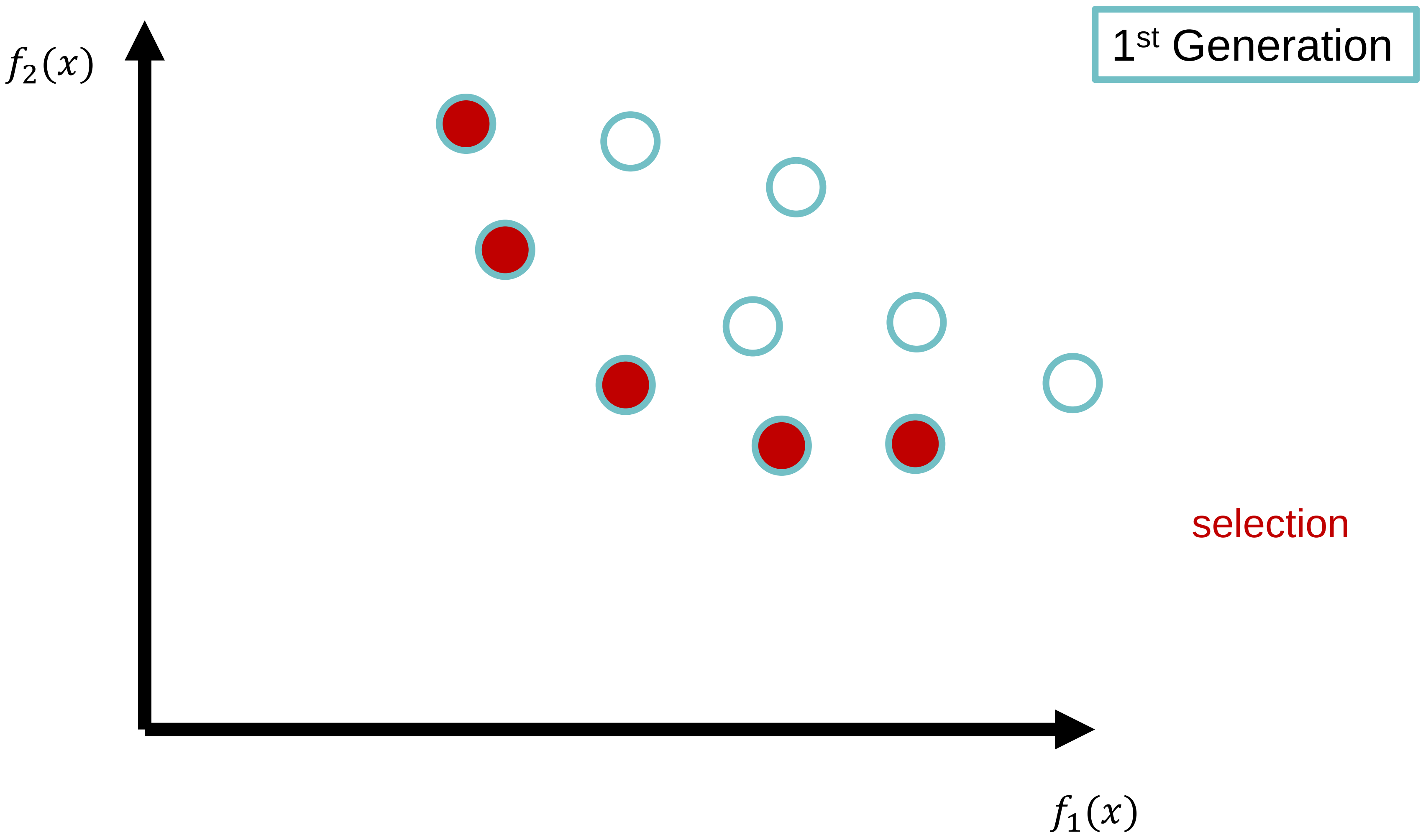
Move many points in parallel towards the front at the same time?

Source: Deb et al 2002

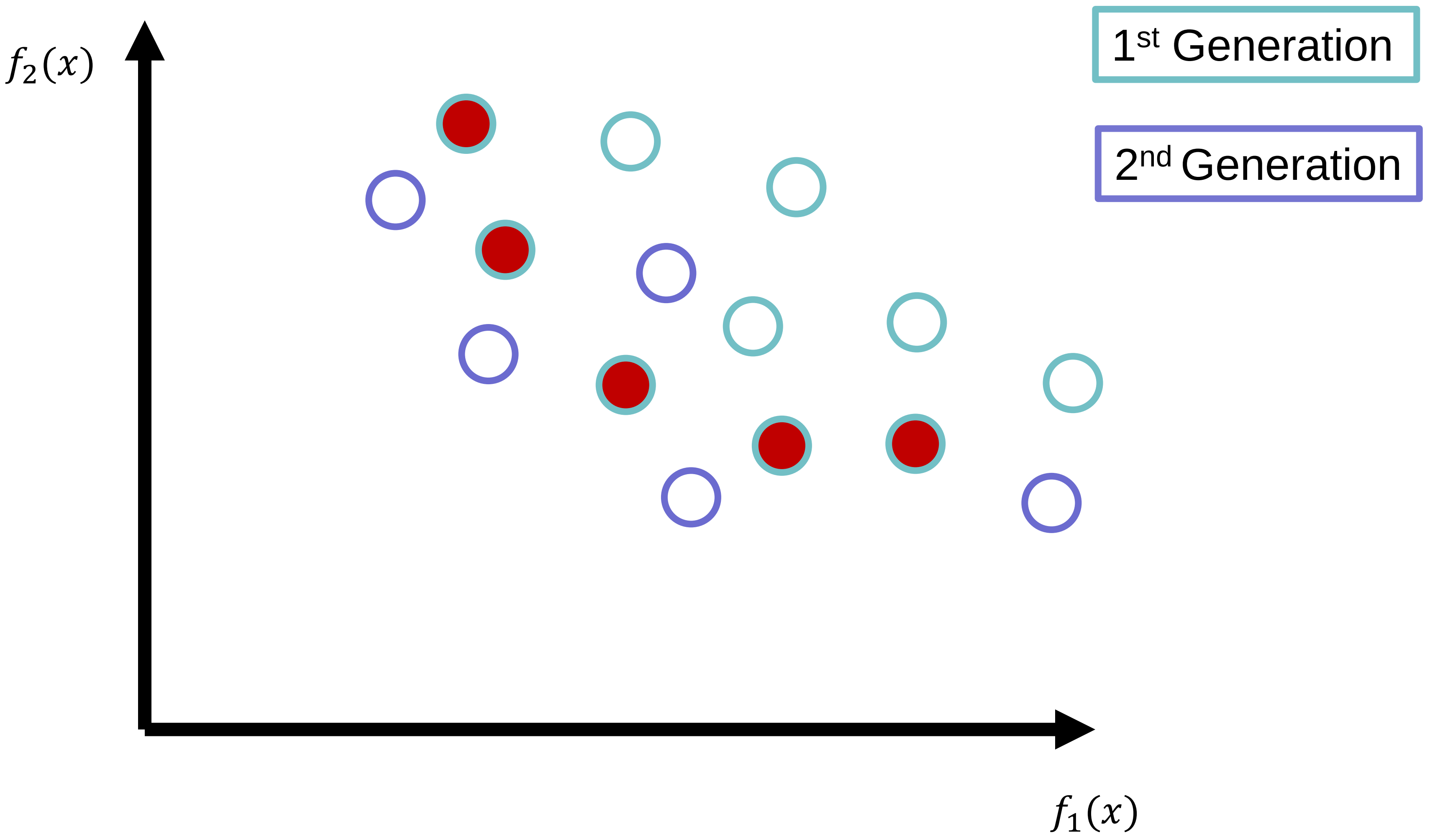
Evolutionary Algorithms



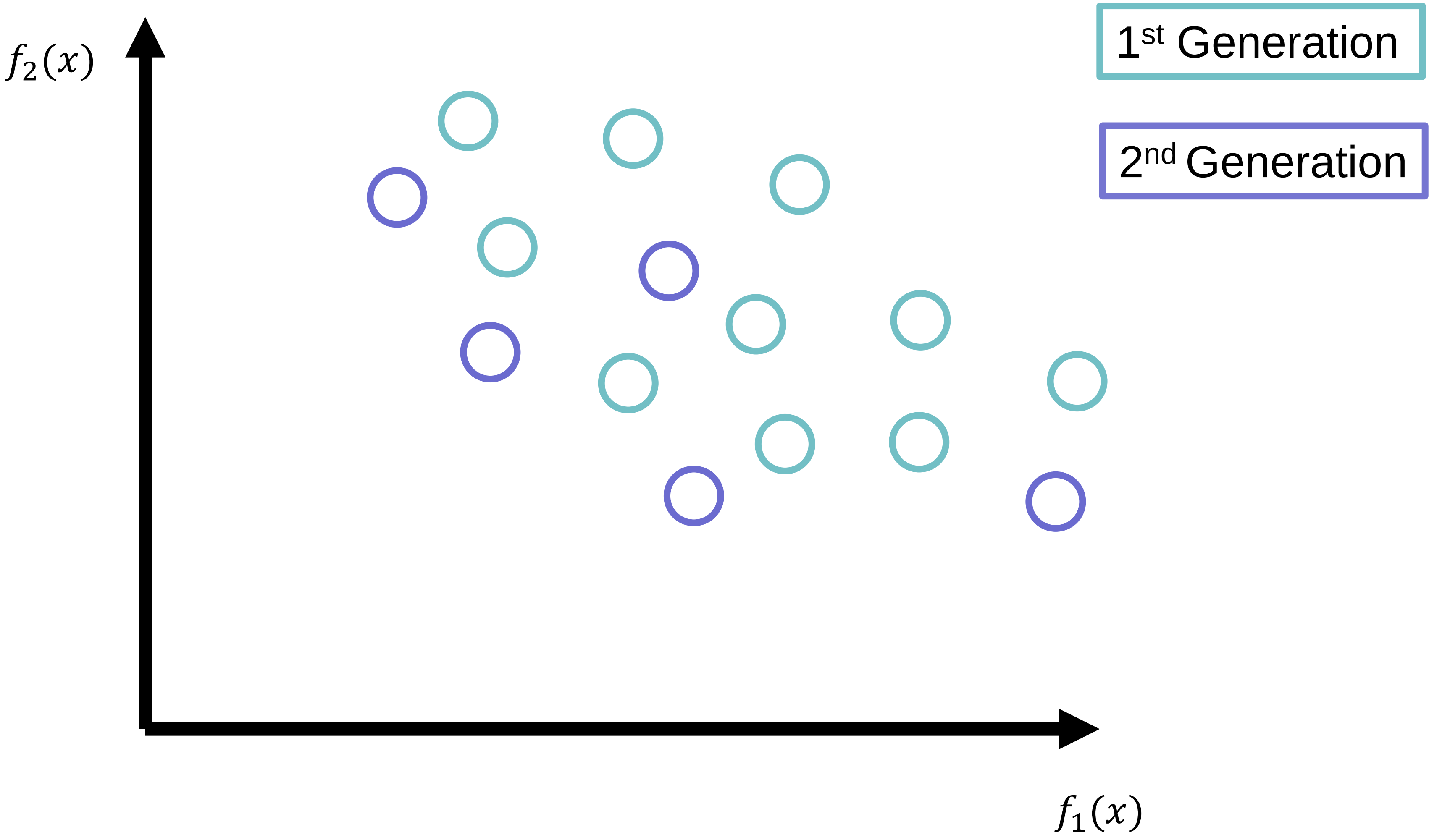
Evolutionary Algorithms



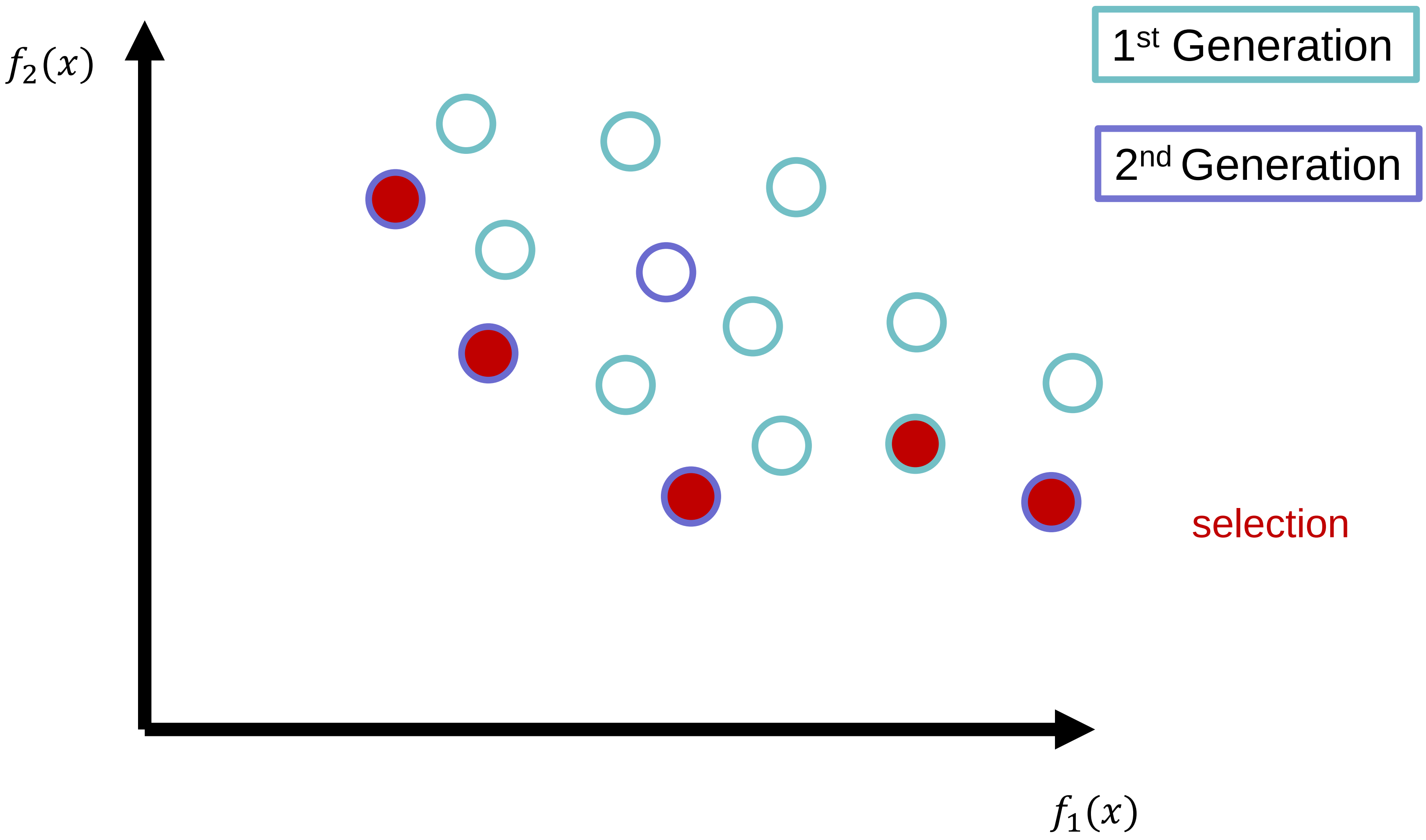
Evolutionary Algorithms



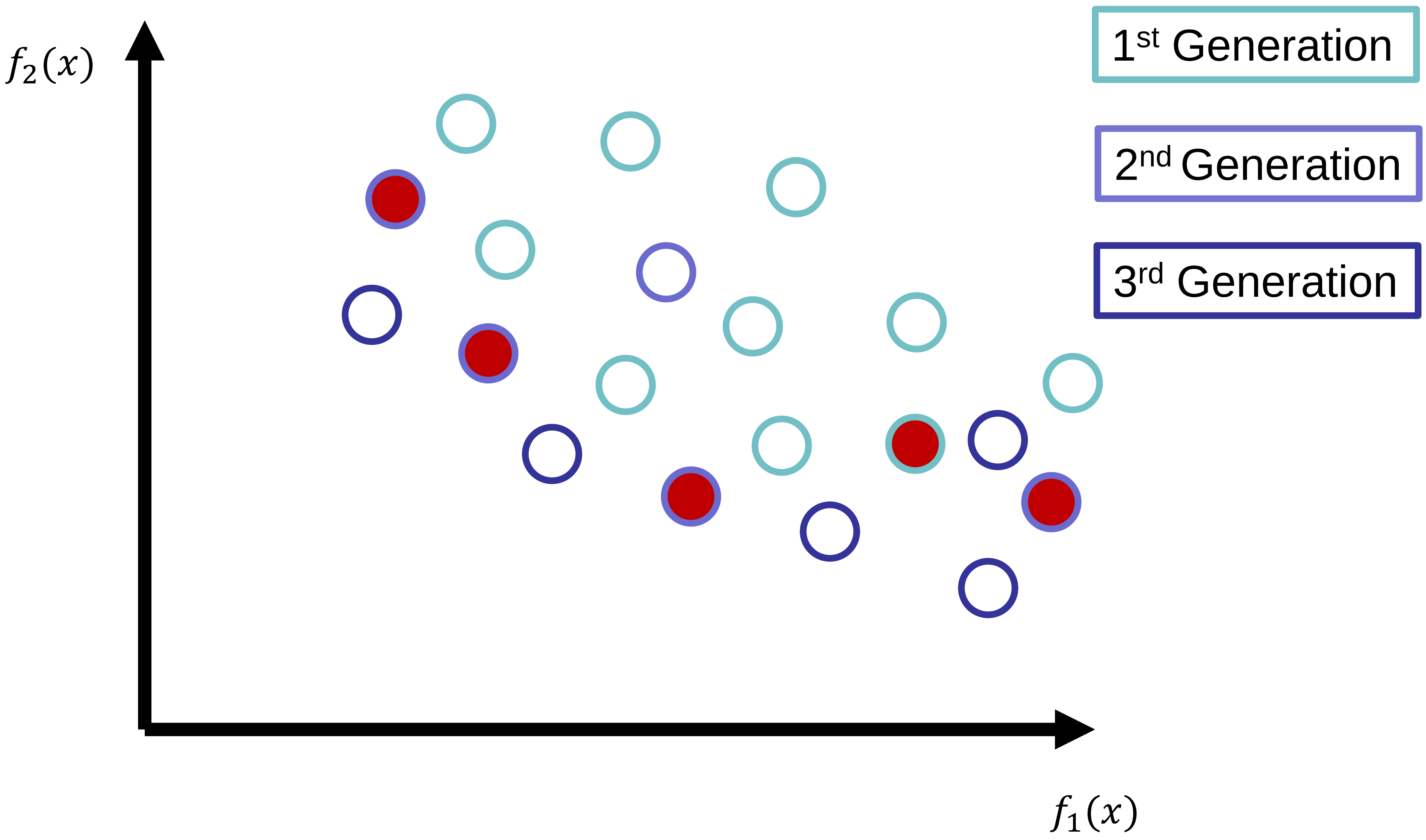
Evolutionary Algorithms



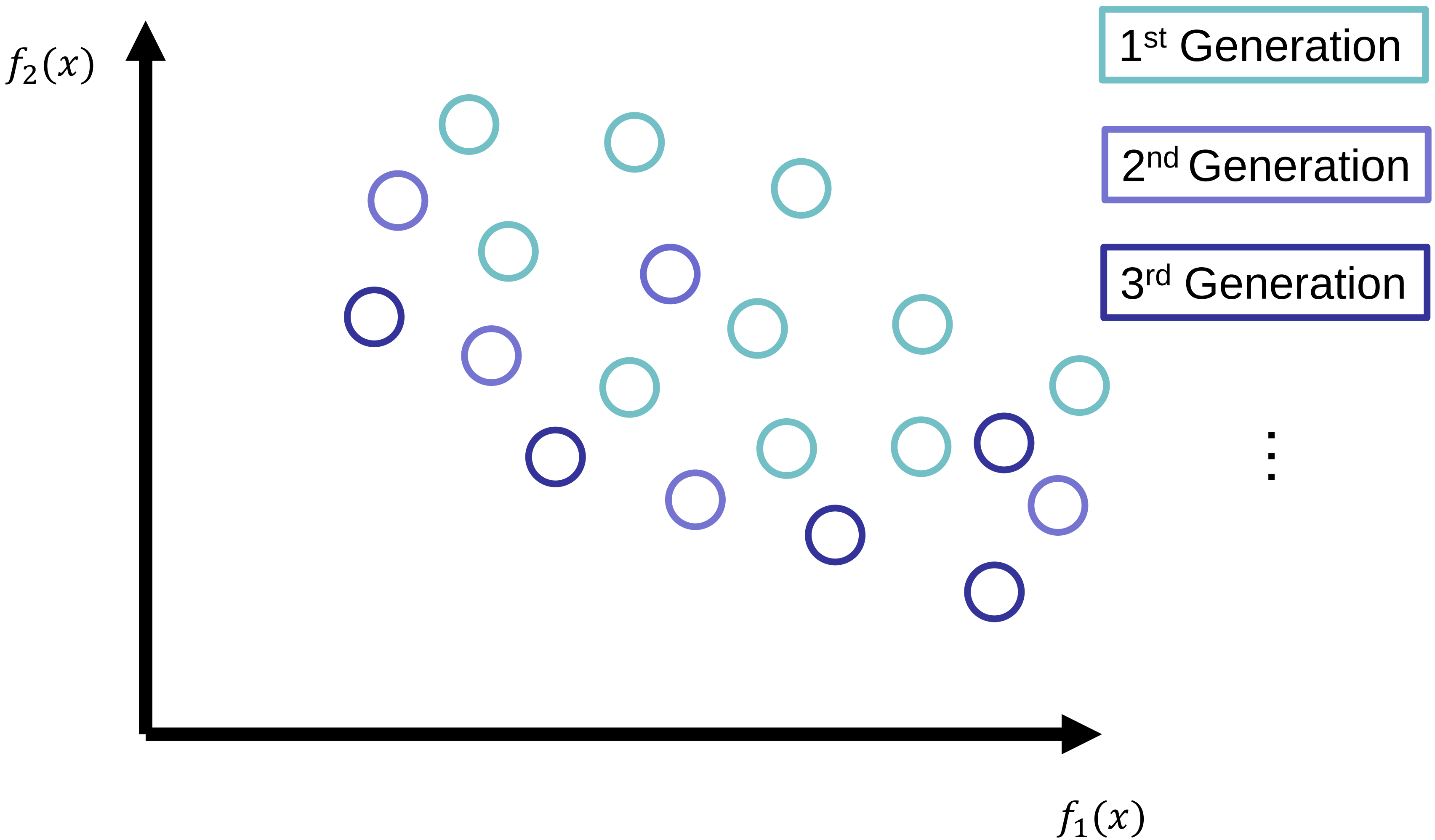
Evolutionary Algorithms



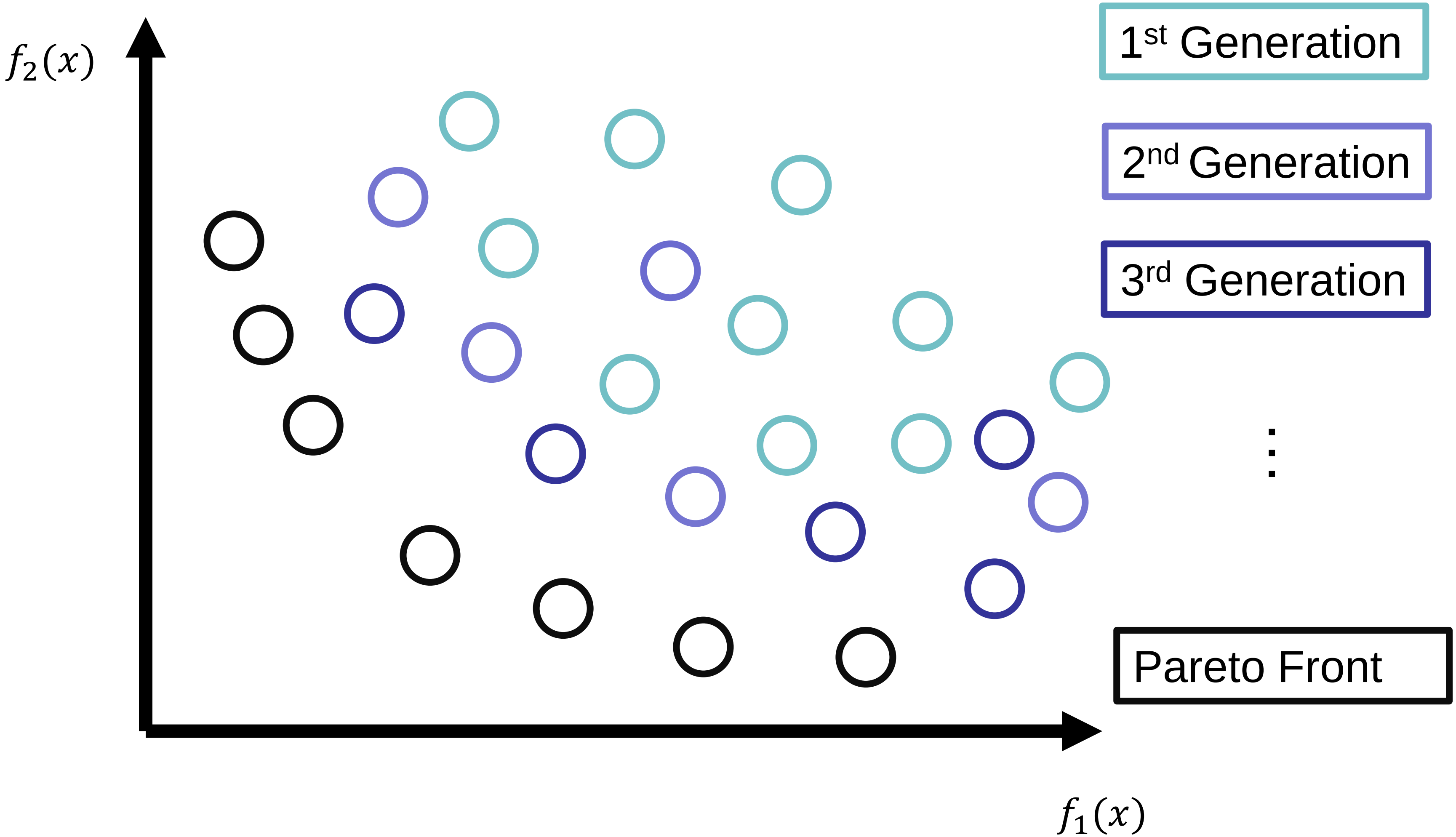
Evolutionary Algorithms



Evolutionary Algorithms



Evolutionary Algorithms



Elitist Non-dominated Sorting GA or NSGA-II

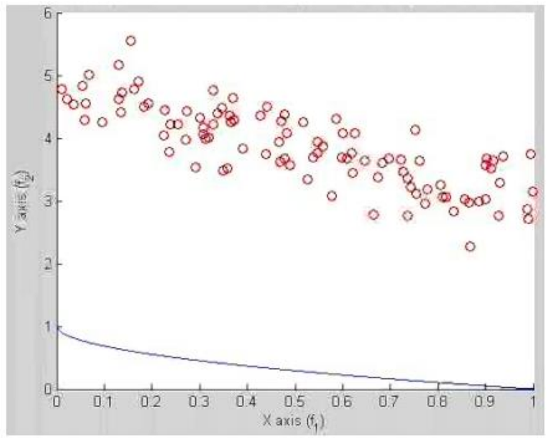


Figure 10: Initial population.

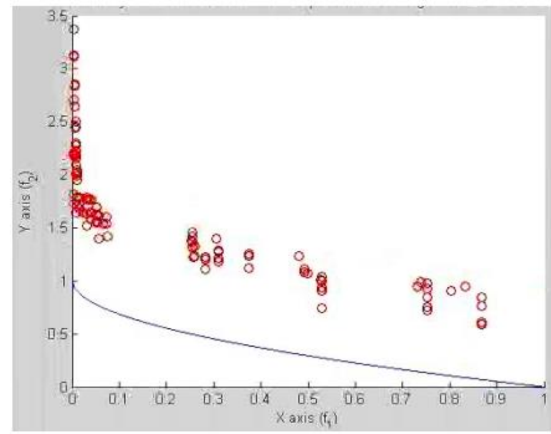


Figure 11: Population at generation 10.

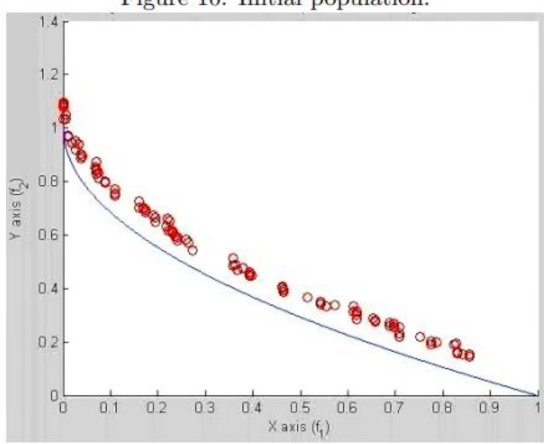


Figure 12: Population at generation 30.

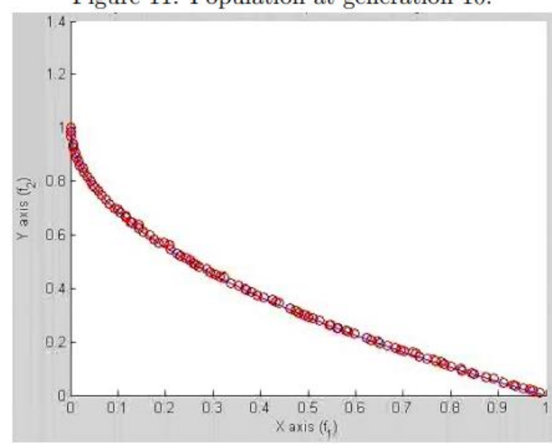
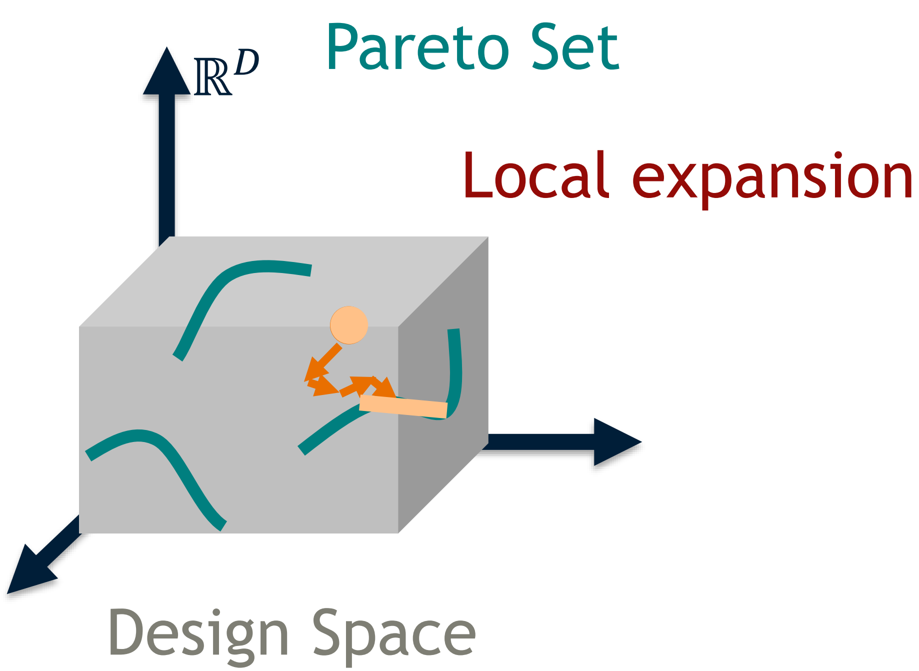
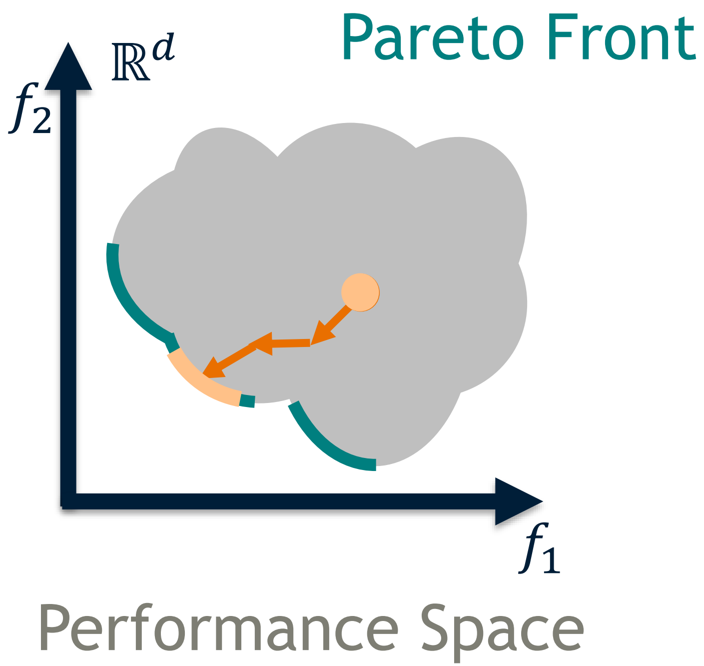


Figure 13: Population at generation 100.

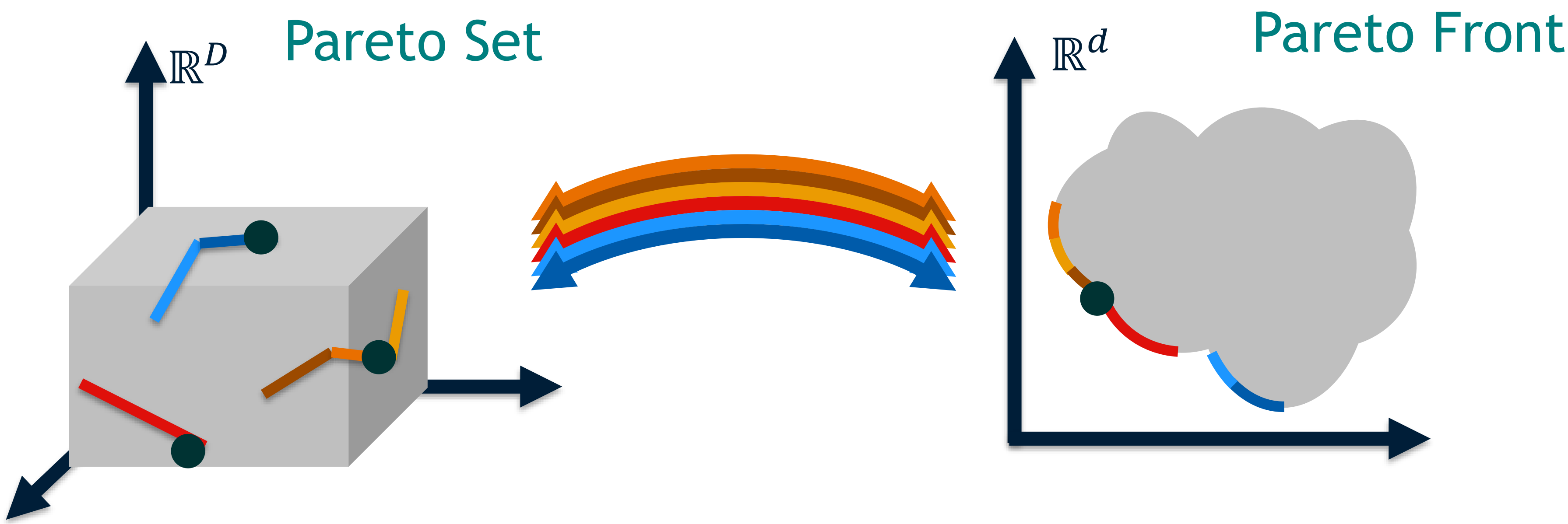
Source: Deb et al 2002

Finding the Full (Continuous) Front





Set of Manifolds



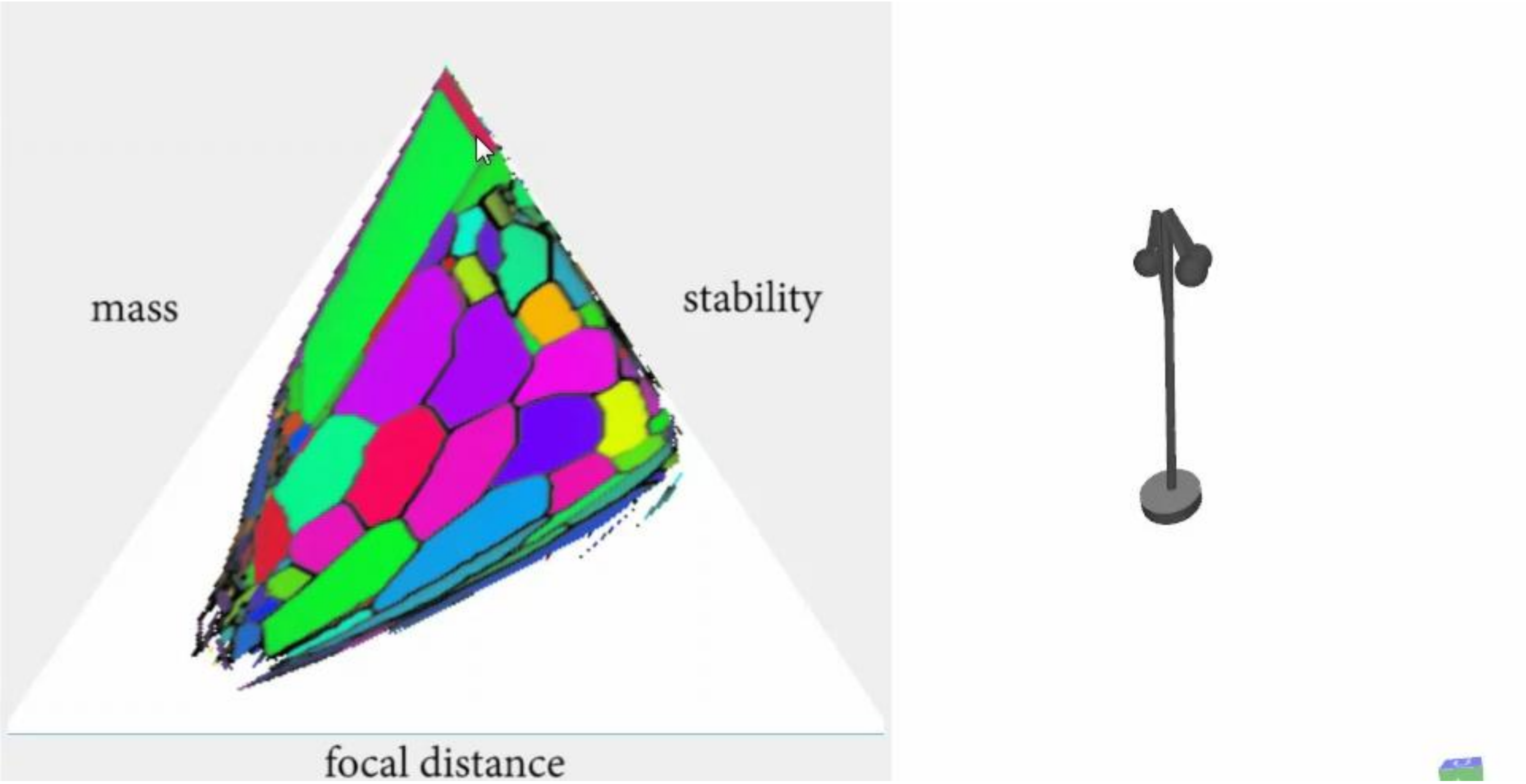
Design Space

Performance Space

Affine Subspaces
(Bounded, $d-1$ dimensional)

Manifolds
(Bounded, $d-1$ dimensional)

Example



Schulz et al 2018

Course Schedule

9:00 am – 9:10 am	Introduction
9:10 am – 9:25 am	Hardware Review
9:25 am – 9:50 am	From Design to Machine Code
9:50 am – 10:15 am	Design Space Representations
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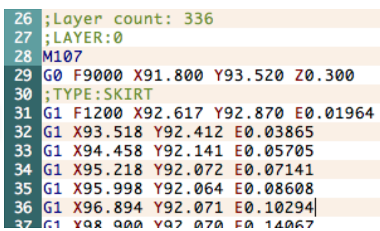
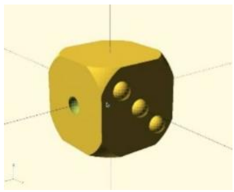
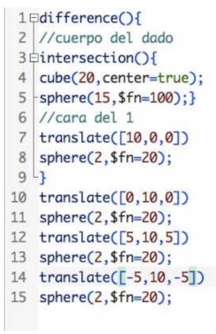
10:25 am - 10:40 am	Break
10:40 am – 10:55 am	Performance Space Representation
10:55 am - 11:15 am	Inverse Methods
11:15 am - 11:35 am	Multi-objective Inverse Methods
11:35 am – 12:00 pm	Advanced Performance-Driven Design
12:00 pm - 12:15 pm	Course Review

Advanced Performance-Driven Design

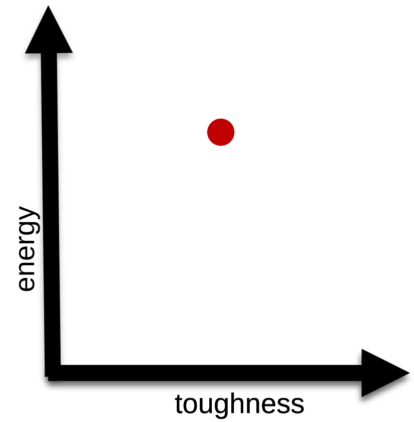


```
;Layer count: 336
;LAYER:0
M107
G0 F9000 X91.800 Y93.520 Z0.300
;TYPE:SKIRT
G1 F1200 X92.617 Y92.870 E0.01964
G1 X93.518 Y92.412 E0.03865
G1 X94.458 Y92.141 E0.05705
G1 X95.218 Y92.072 E0.07141
G1 X95.998 Y92.064 E0.08608
G1 X96.894 Y92.071 E0.10294
```





```
difference(){
//cuerpo del dado
intersection(){
cube(20,center=true);
sphere(15,$fn=100);}
//cara del 1
translate([10,0,0])
sphere(2,$fn=20);
}
translate([0,10,0])
sphere(2,$fn=20);
translate([5,10,5])
sphere(2,$fn=20);
translate([-5,10,-5])
sphere(2,$fn=20);
```



Hardware **Machine Code** **Design** **Performance**

Advanced Performance-Driven Design

- Performance Evaluation Speed-Up
  - Sensitivity Analysis
  - Precomputation + Interpolation
  - Replace Simulation with ML
- Design space exploration and Optimization
  - Expert Systems
  - Data-Driven Search
  - Incorporate Hardware Constraints
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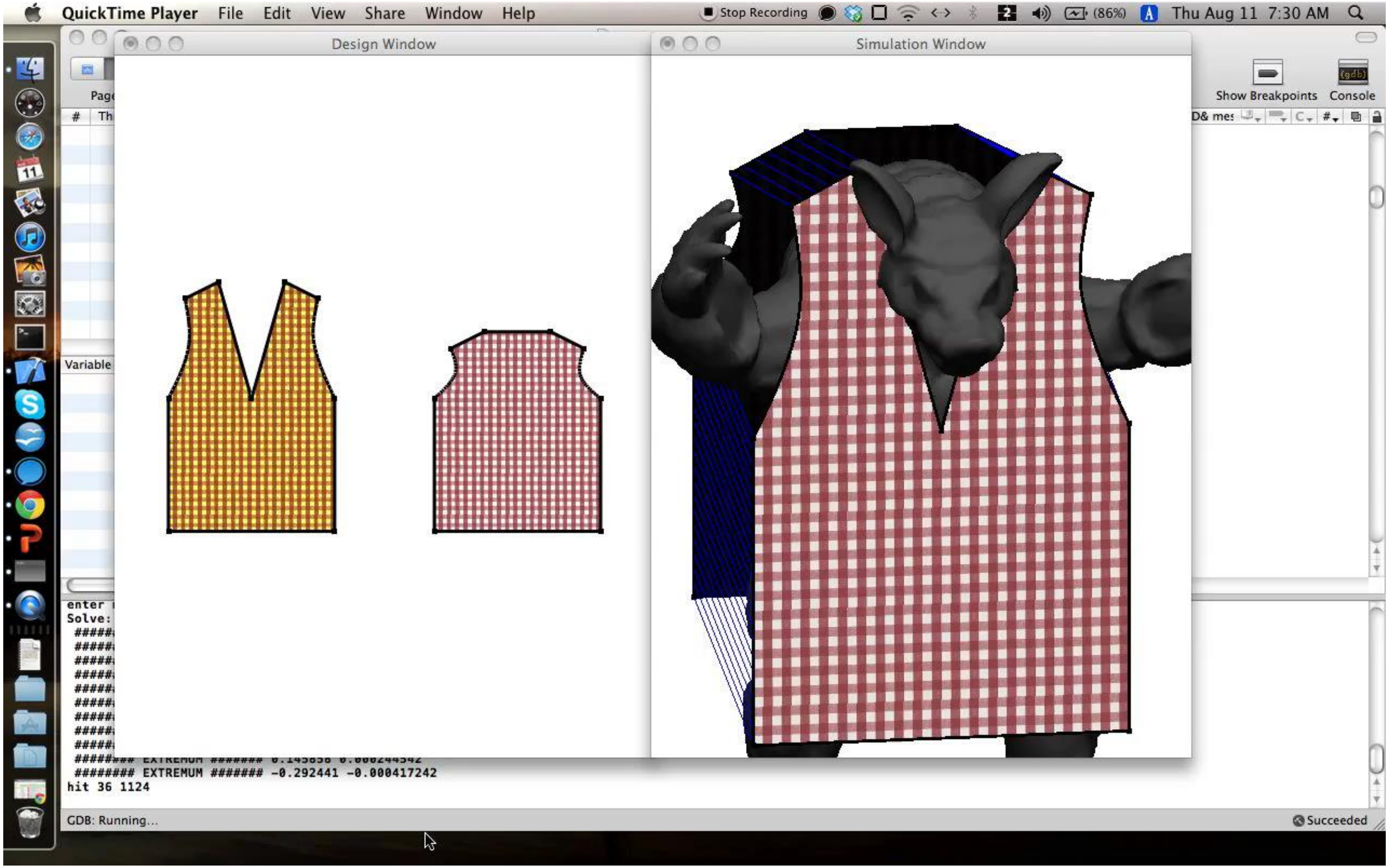
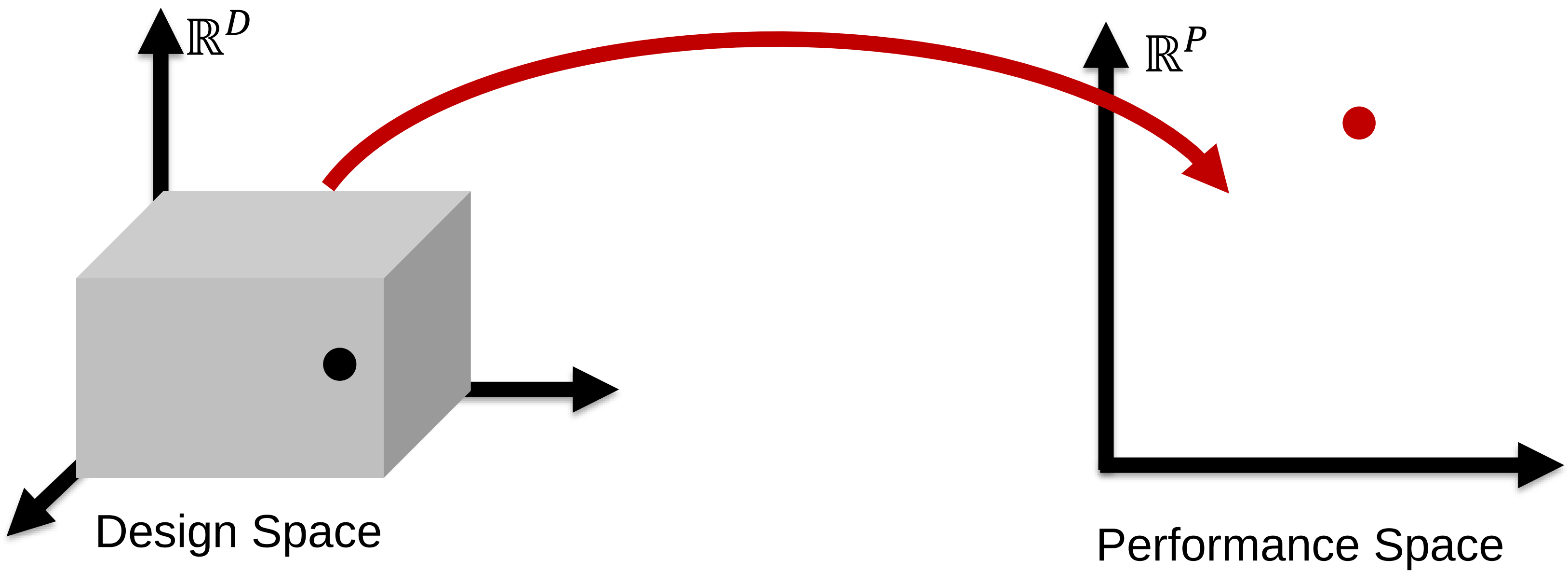
Application: Interactive Garment Design

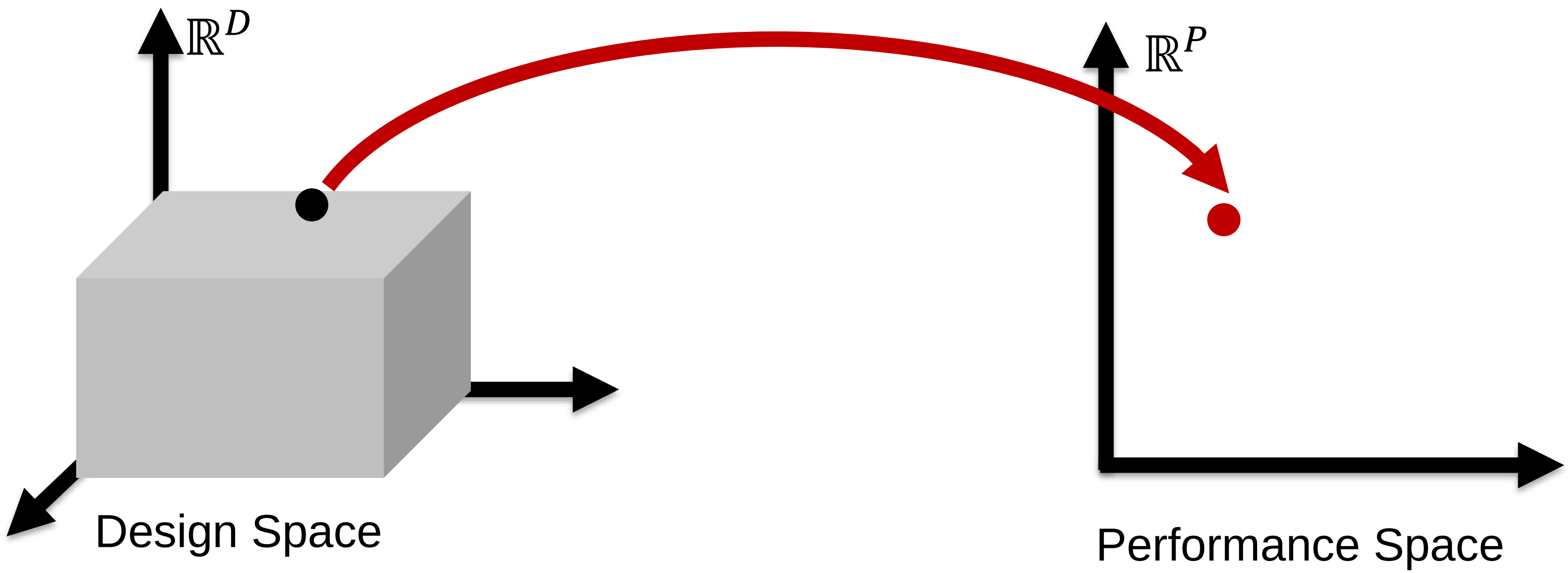


Source: Umetani et al 2011

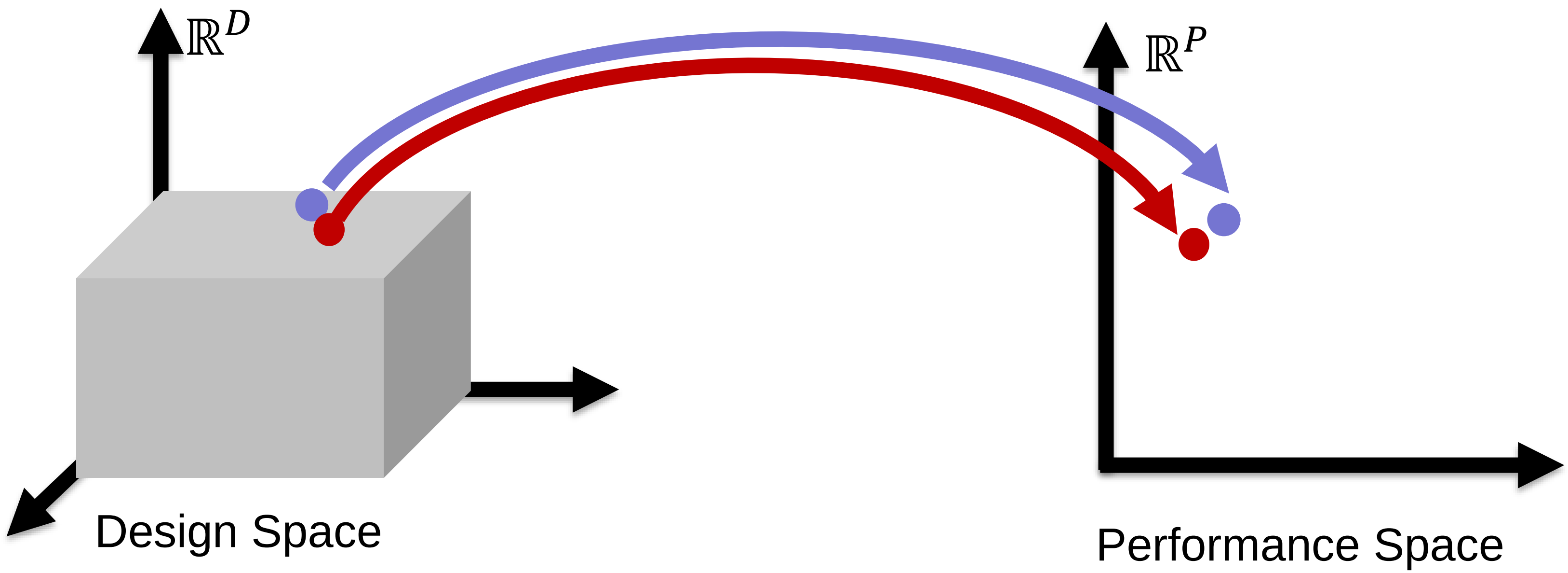
Design Space Exploration



Design Space Exploration



Design Space Exploration

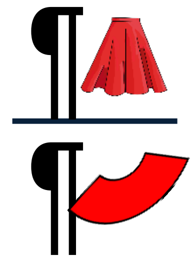


small change

fast update?

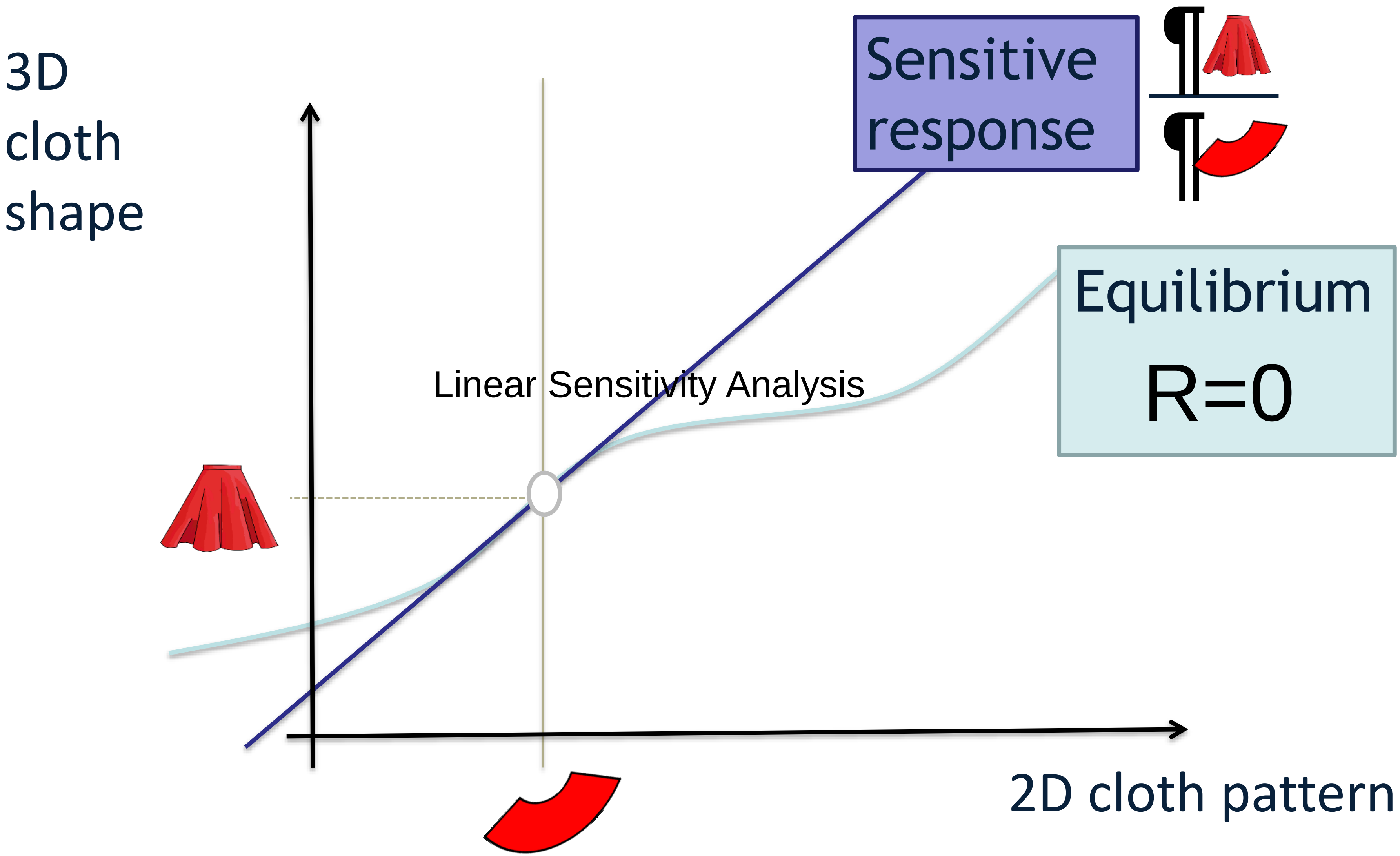
Linear Sensitivity Analysis

- What does this derivative tells us about our surface ?



Source: Umetani et al 2011

Linear Sensitivity Analysis



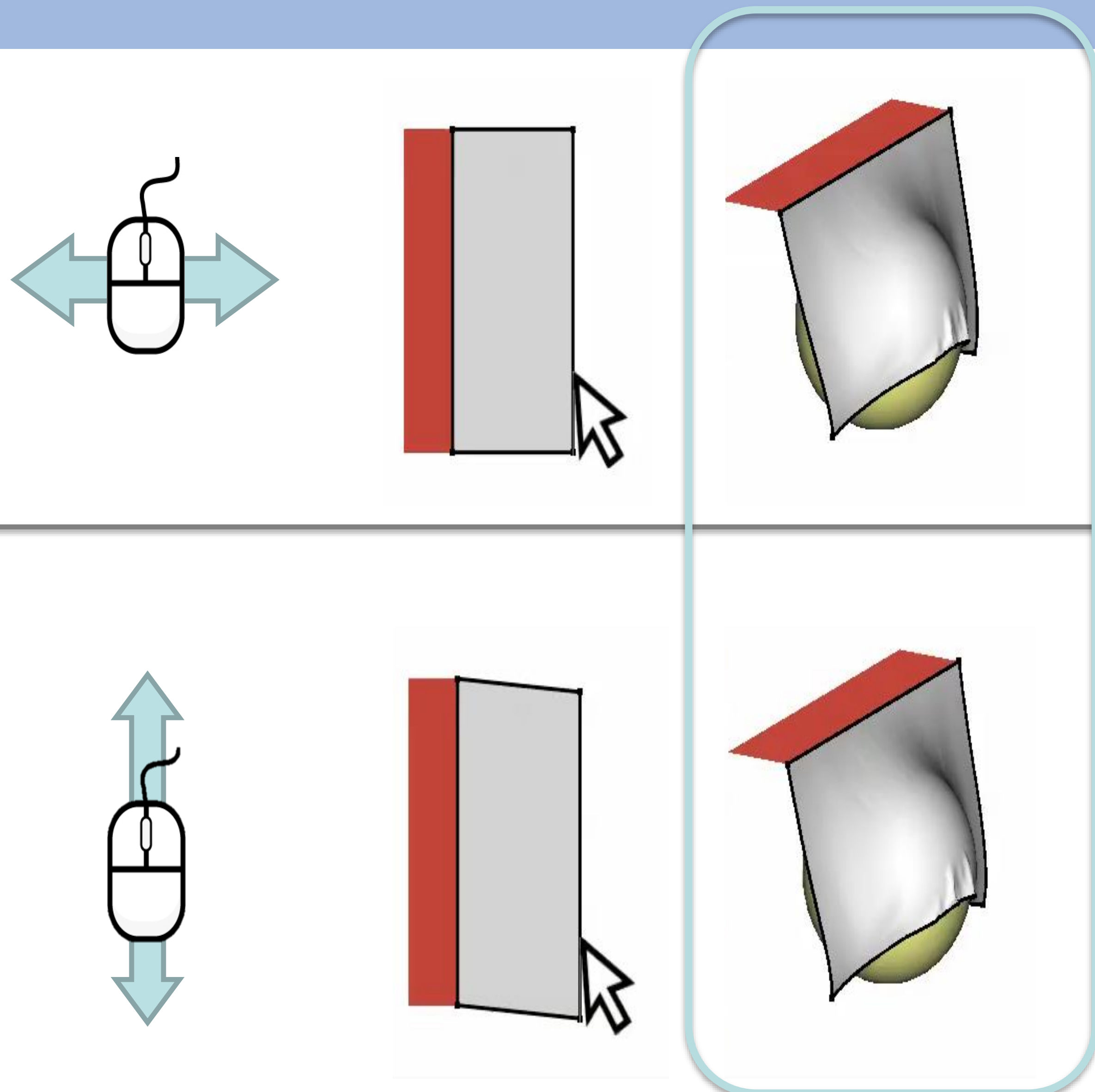
Source: Umetani et al 2011

Sensitivity Modes

Sensitivity Mode

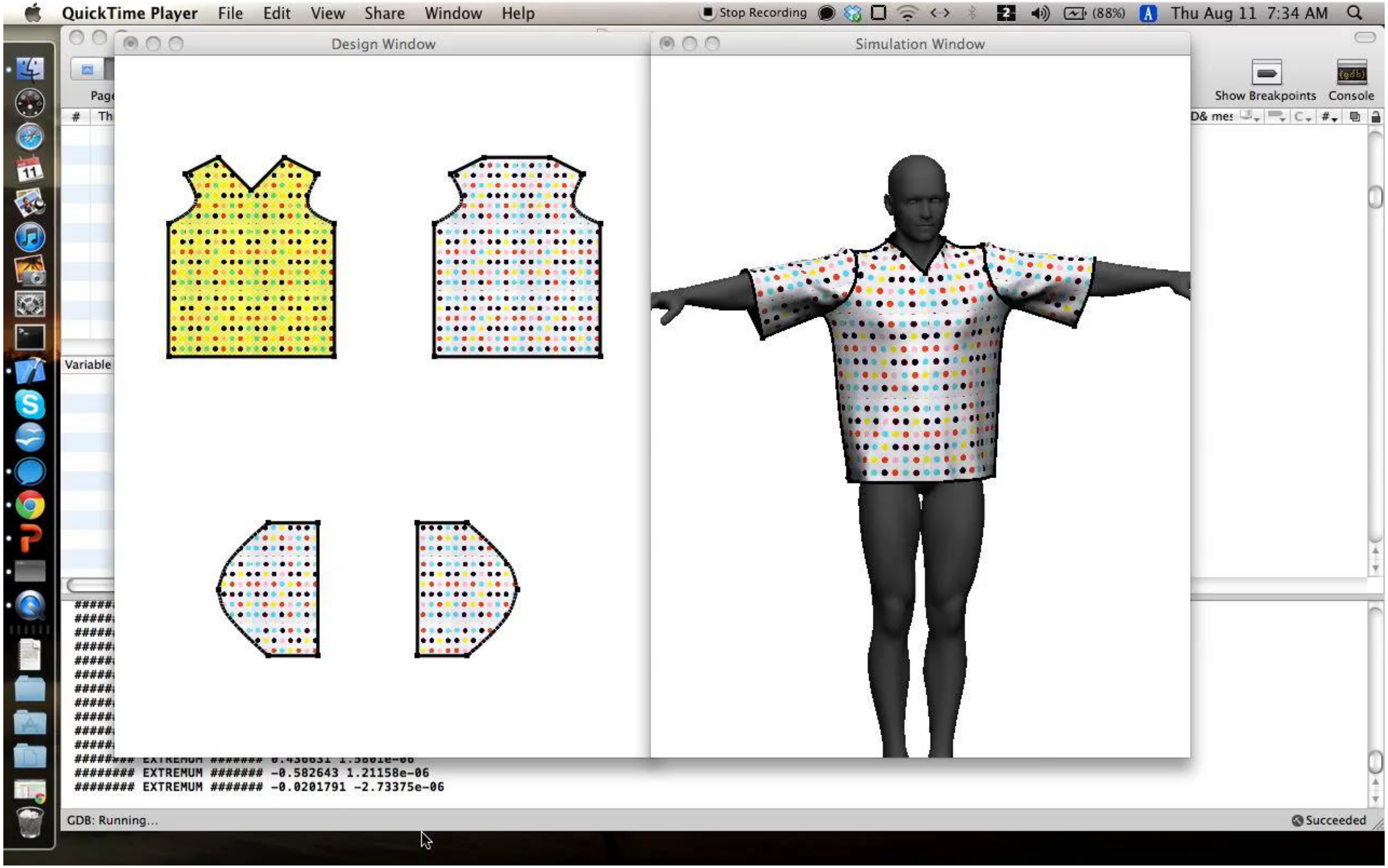
Horizontal

Vertical



Source: Umetani et al 2011

Result: Interactive Garment Design



Source: Umetani et al 2011

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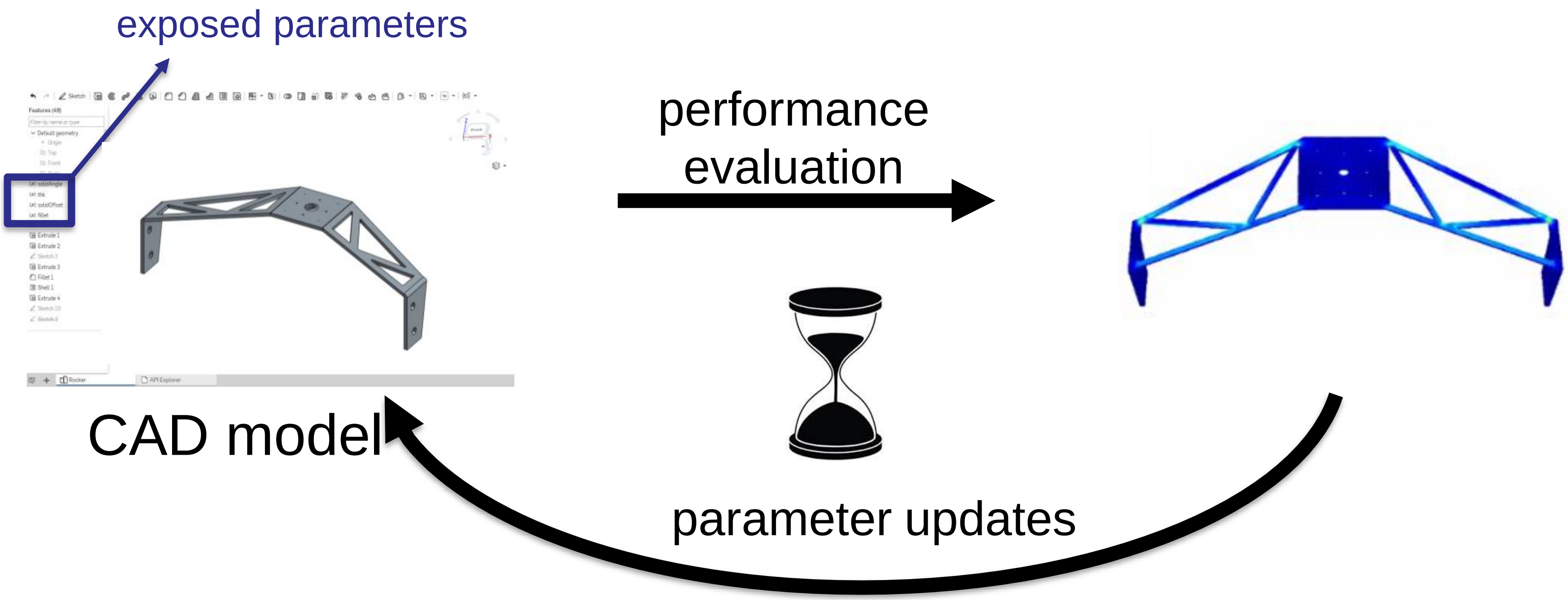
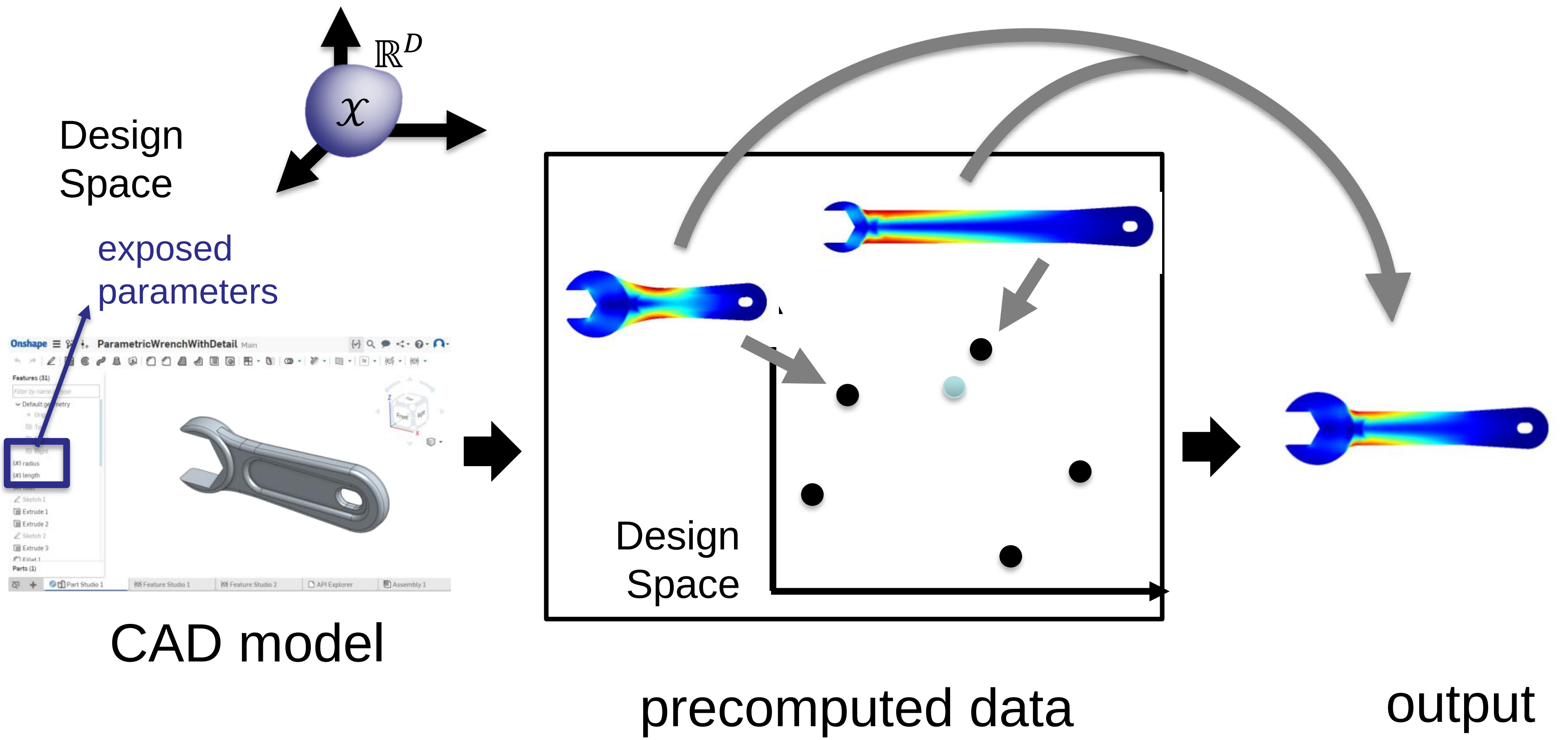
Application: Performance-Driven Design in CAD Systems

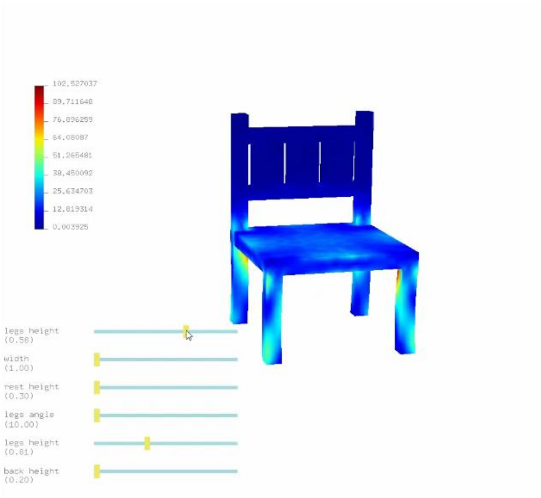


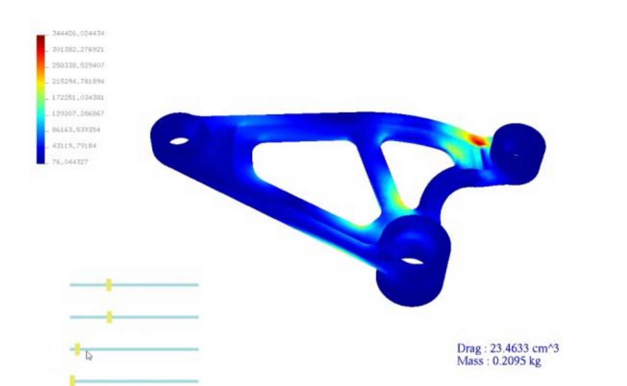
Precomputation and Interpolation

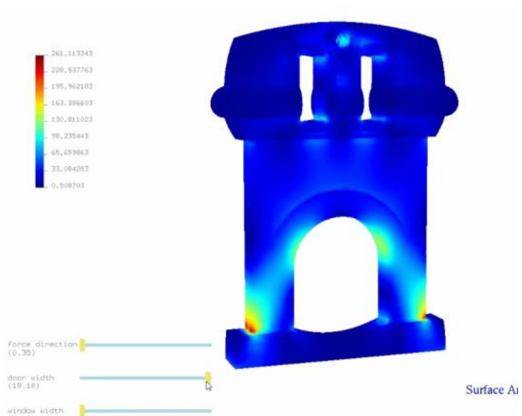


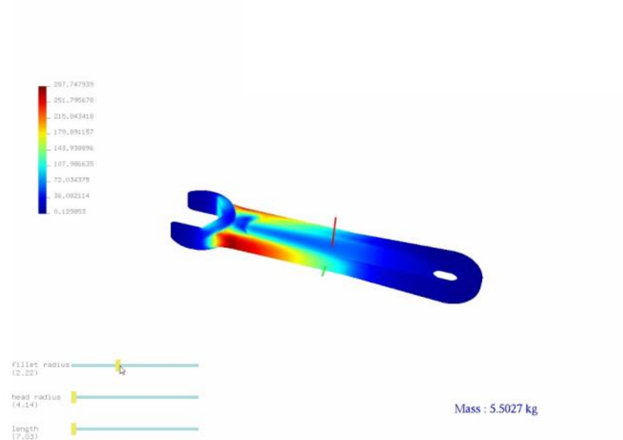
Results

Stress Distribution

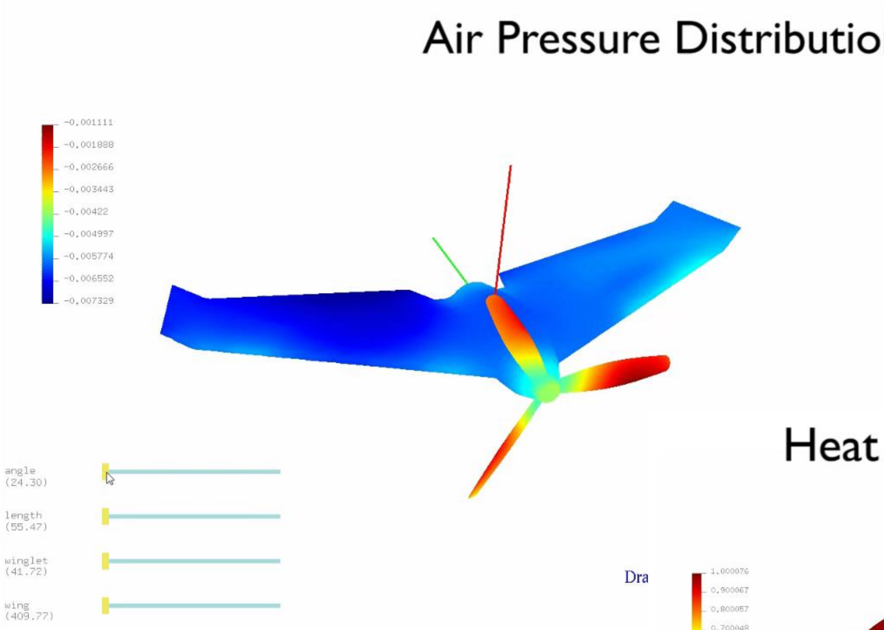


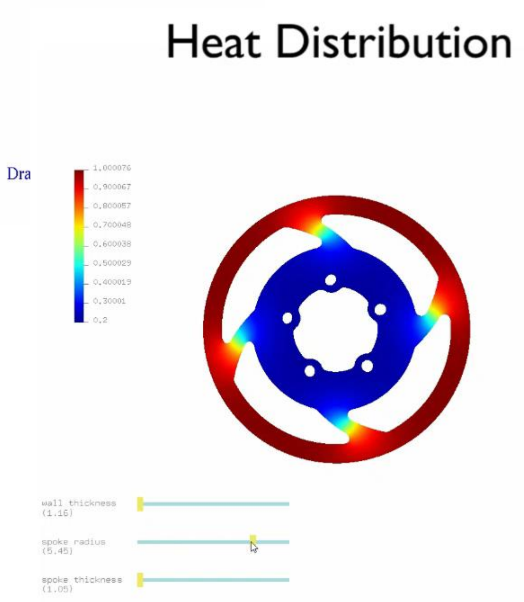


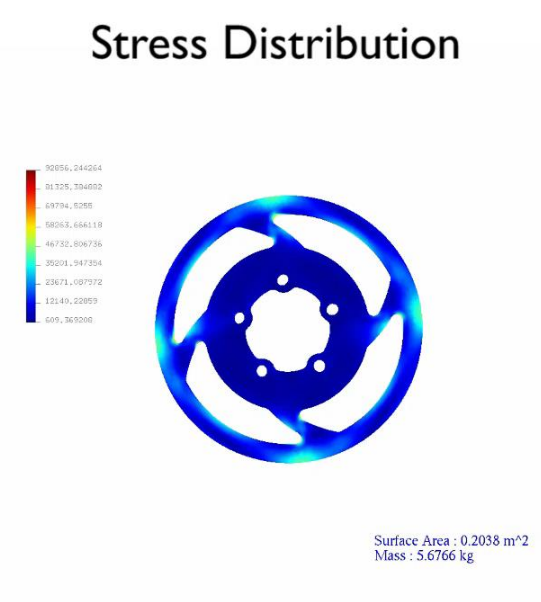




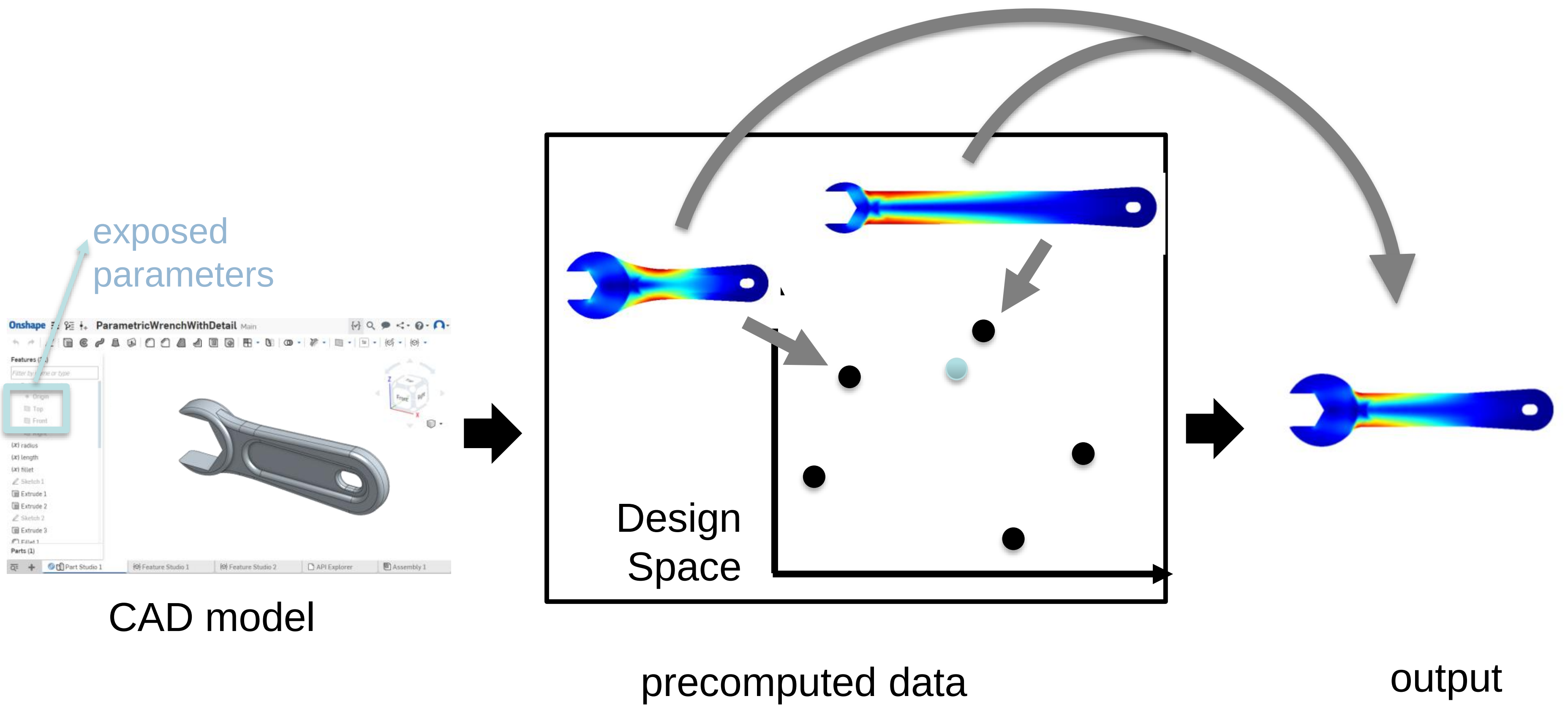
Results


Air Pressure Distribution
-0,001111
-0,001888
-0,002666
-0,003443
-0,00422
-0,004997
-0,005774
-0,006552
-0,007329
angle (24.30)
length (55.47)
winglet (41.72)
wing (409.77)


Heat Distribution
Dra
1,000076
0,900067
0,800057
0,700048
0,600038
0,500029
0,400019
0,30001
0,2
wall thickness (1.16)
spoke radius (5.45)
spoke thickness (1.05)


Stress Distribution
92856,244264
81325,384882
69794,5255
58263,666118
46732,806736
35201,947354
23671,087972
12140,22859
609,369208
Surface Area : 0.2038 m^2
Mass : 5.6766 kg

InstantCAD


exposed
parameters
Onshape
ParametricWrenchWithDetail
CAD model
Design
Space
precomputed data
output

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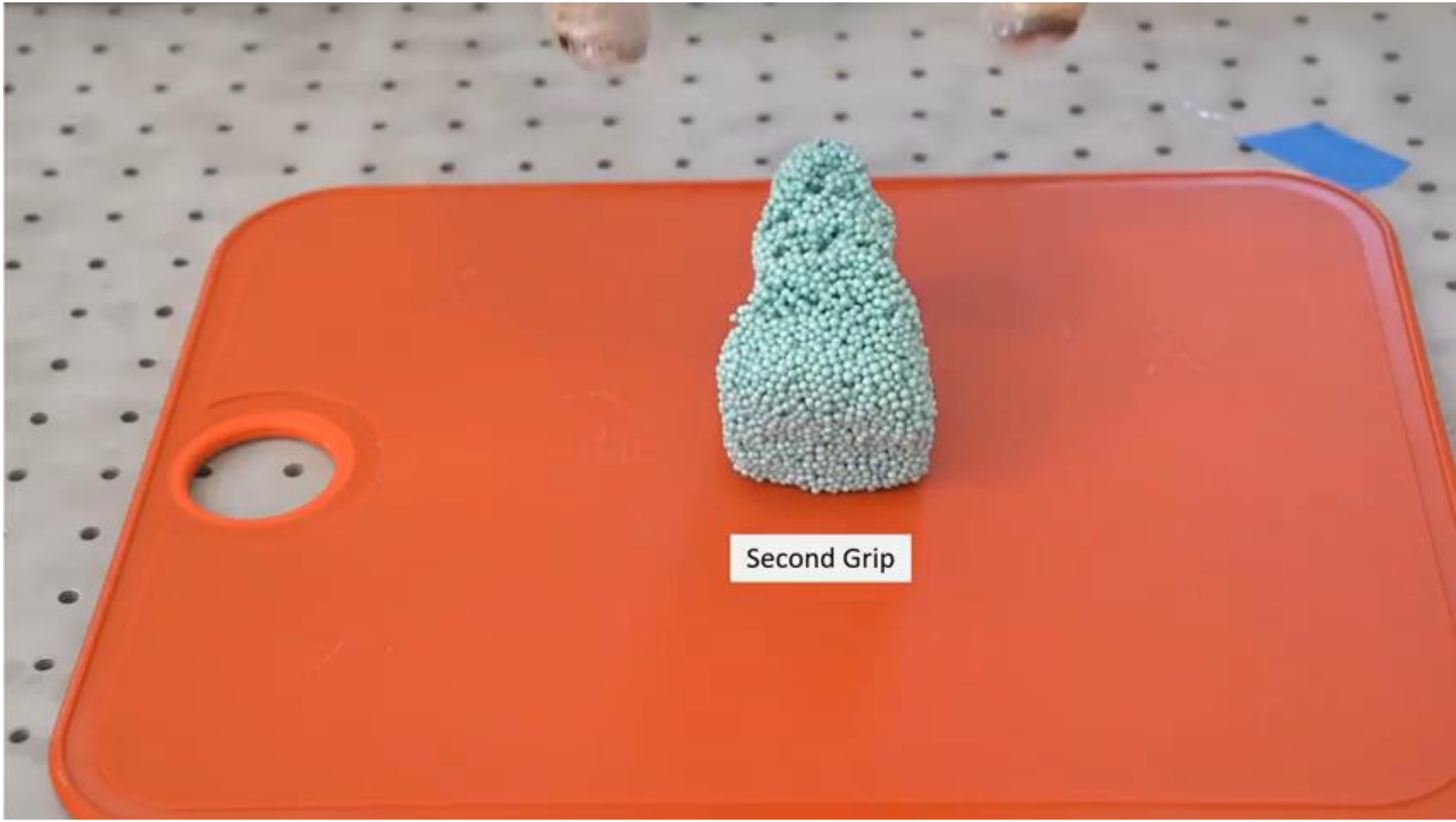
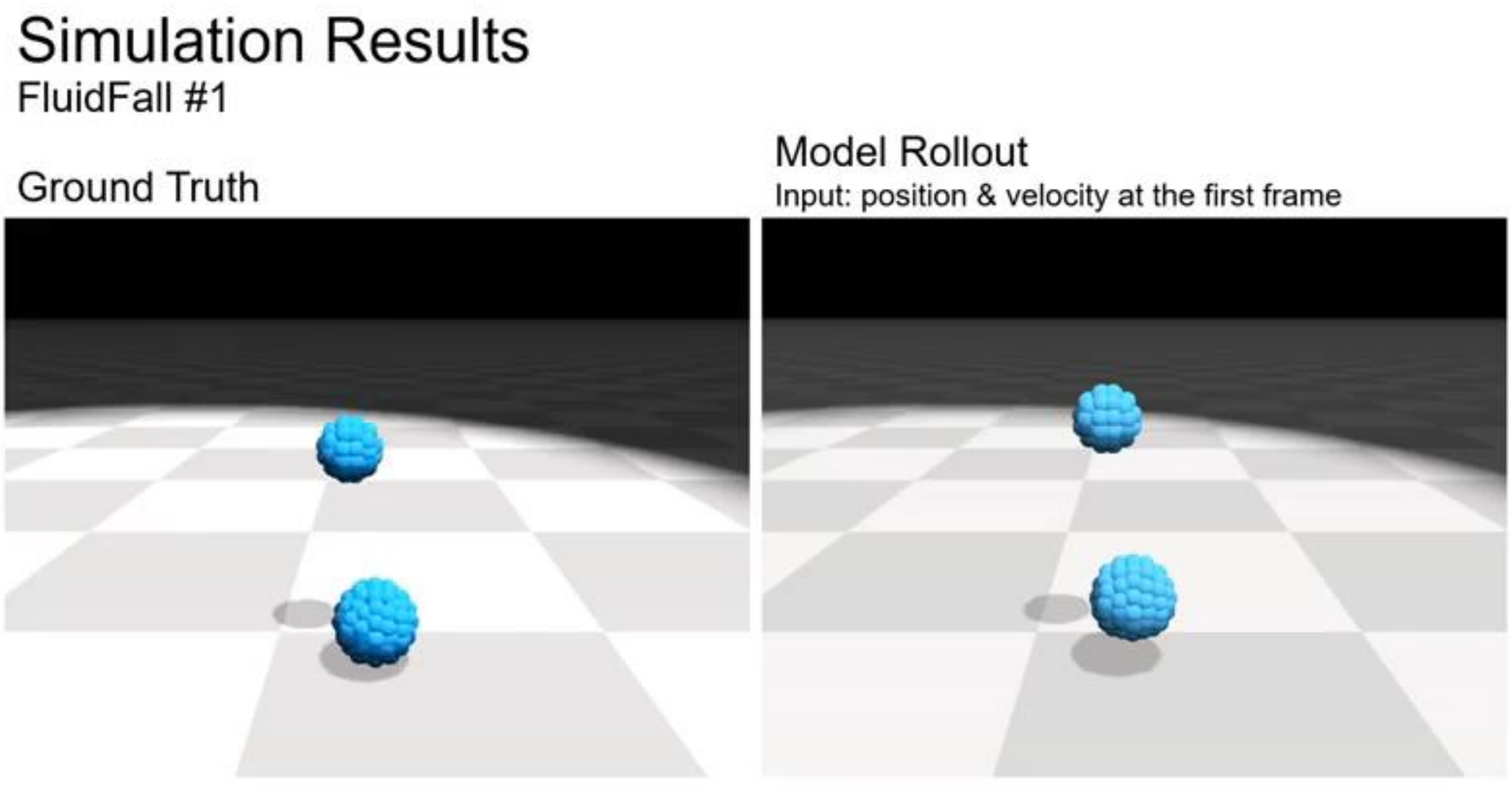
Application: Fast Simulation for Control



Source: Li et al 2019

Replacing Simulation with Machine Learning



Source: Li et al 2019

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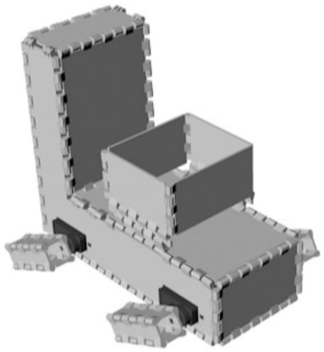
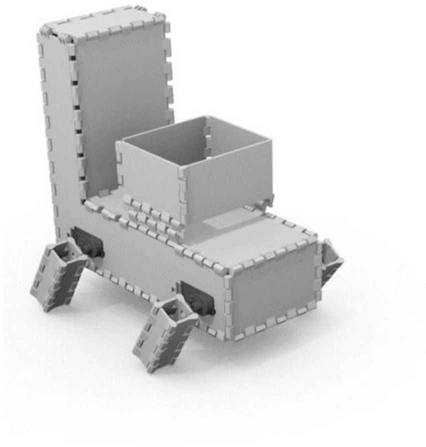
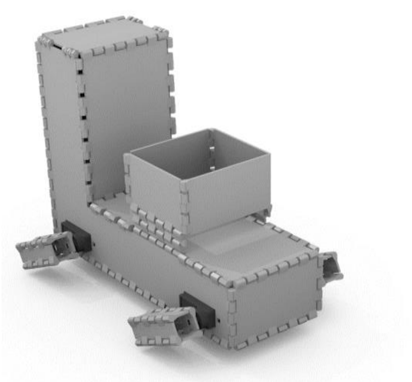
Application: Design of Robots with Ground Locomotion



Fast Gait

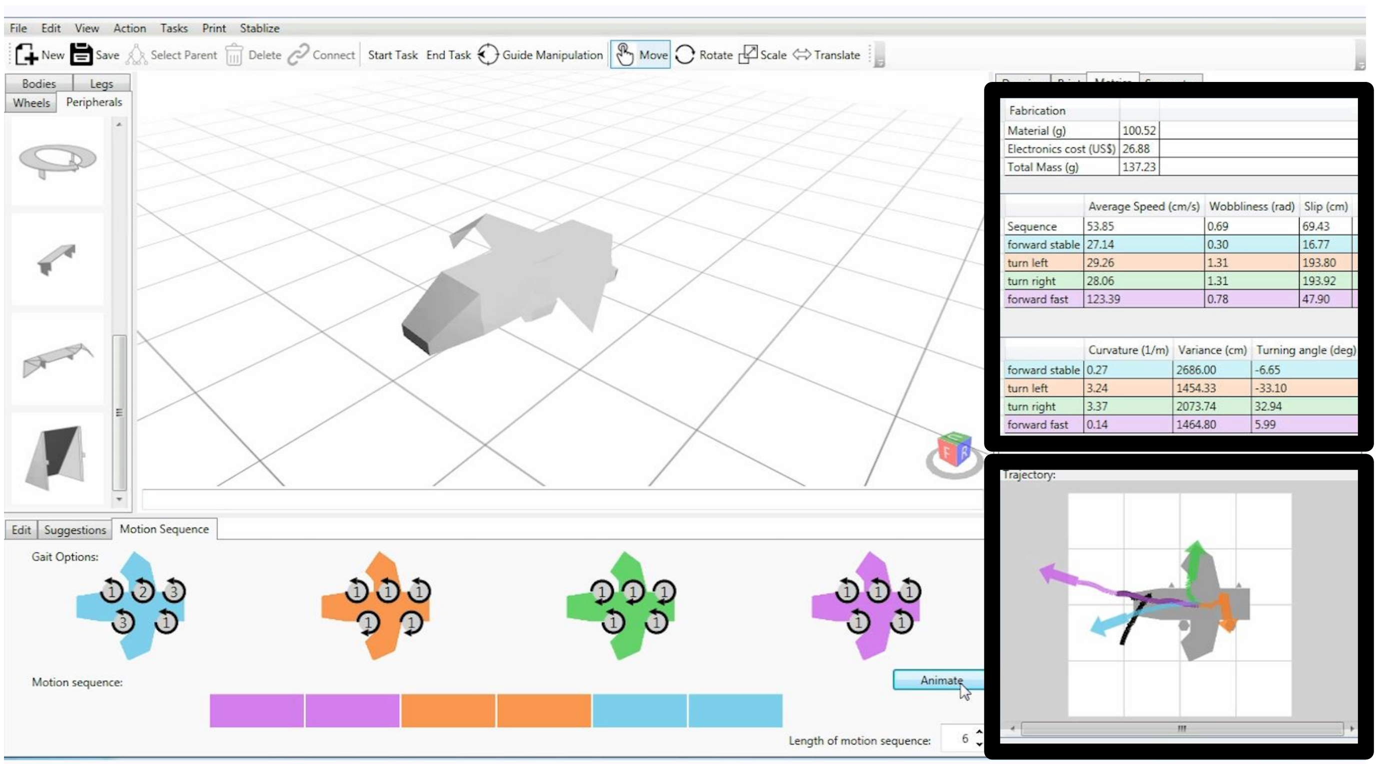


Slower Gait



Geometry Change

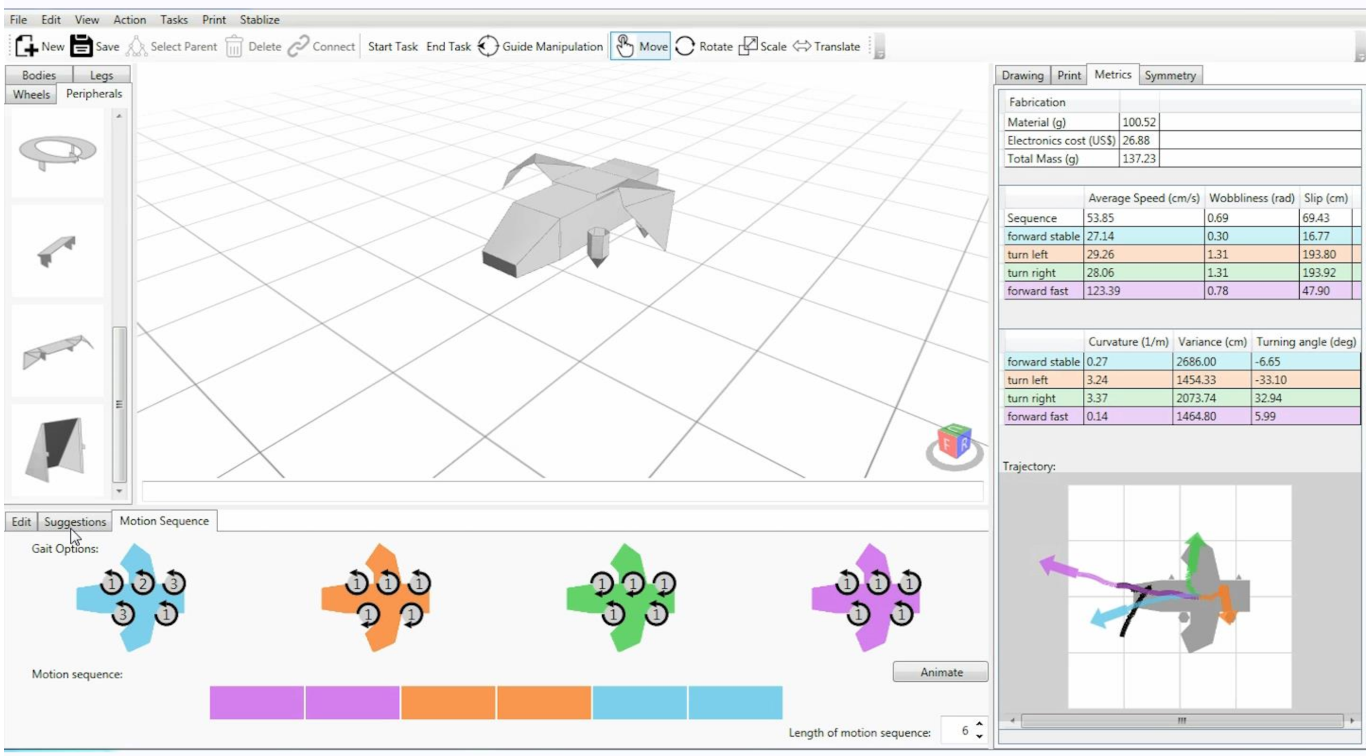
Application: Design of Robots with Ground Locomotion



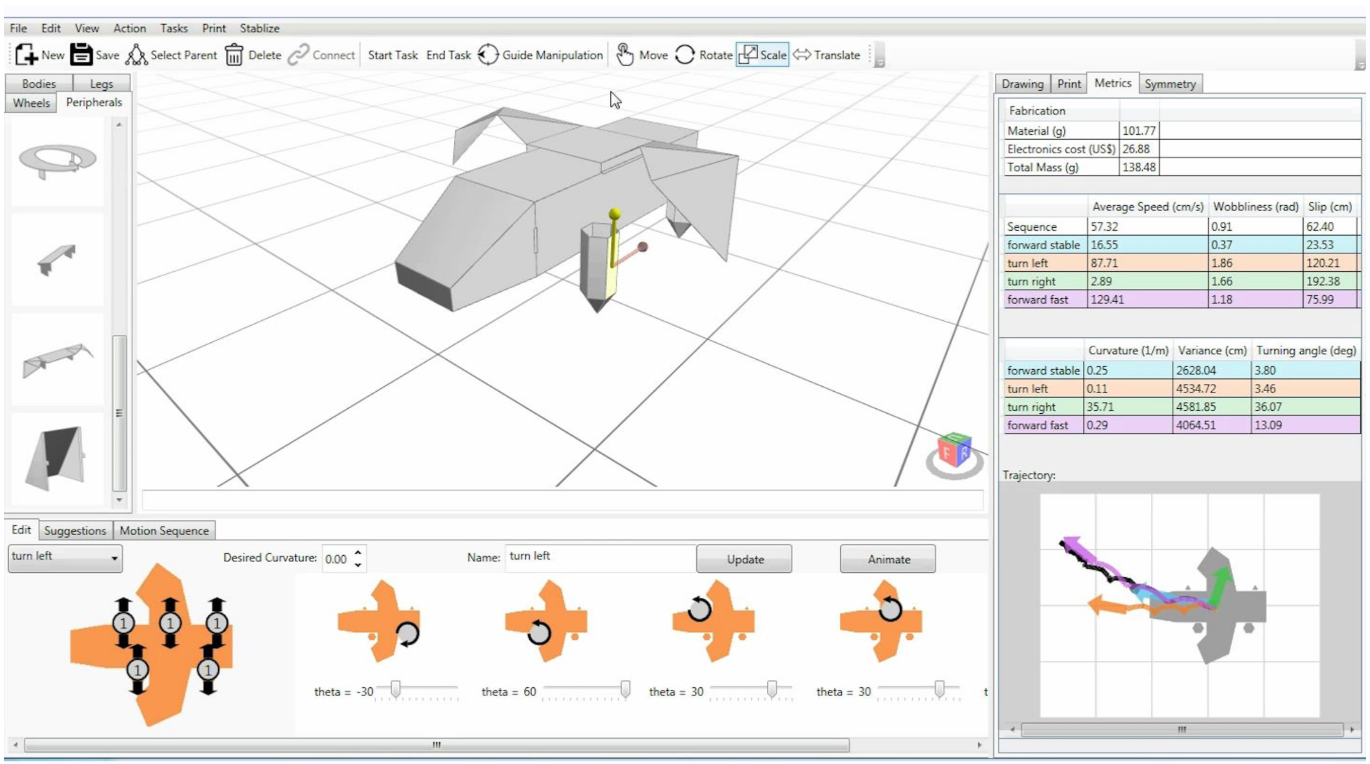
Metrics

Trajectory

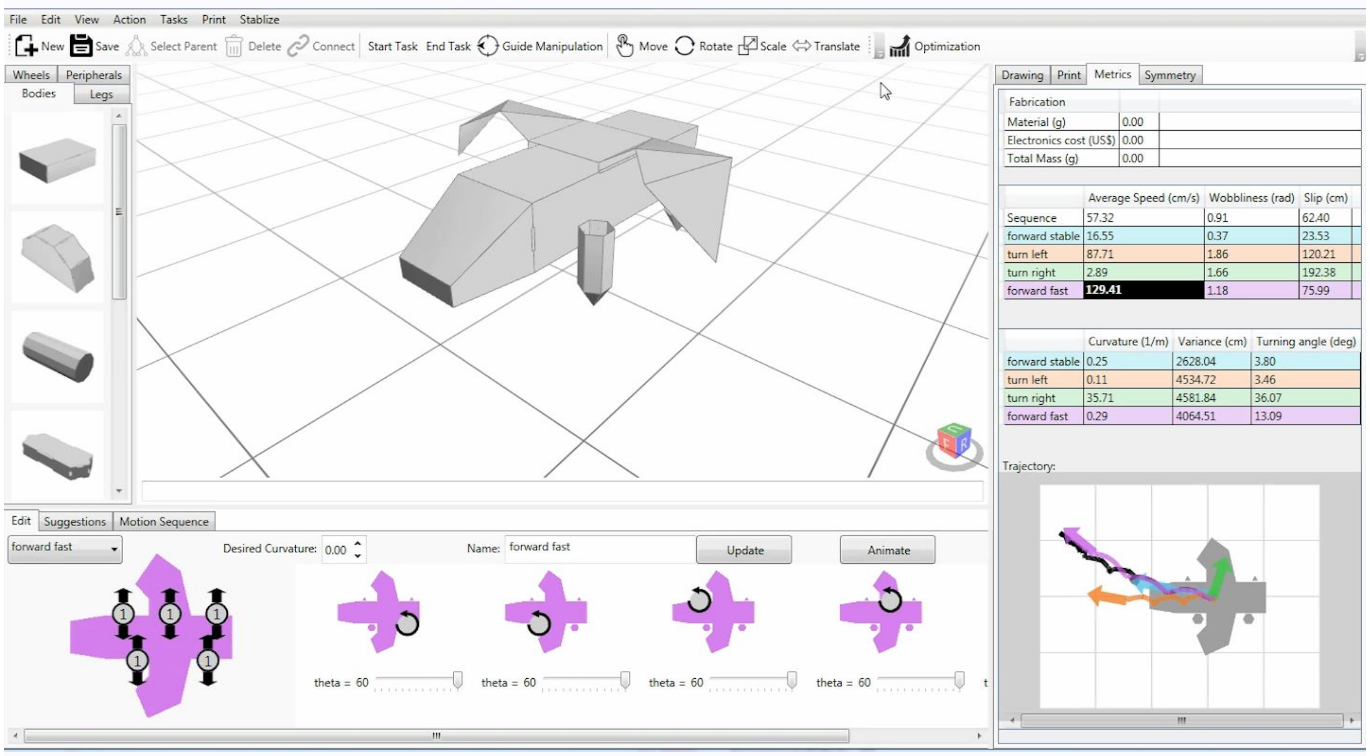
Real Time Feedback



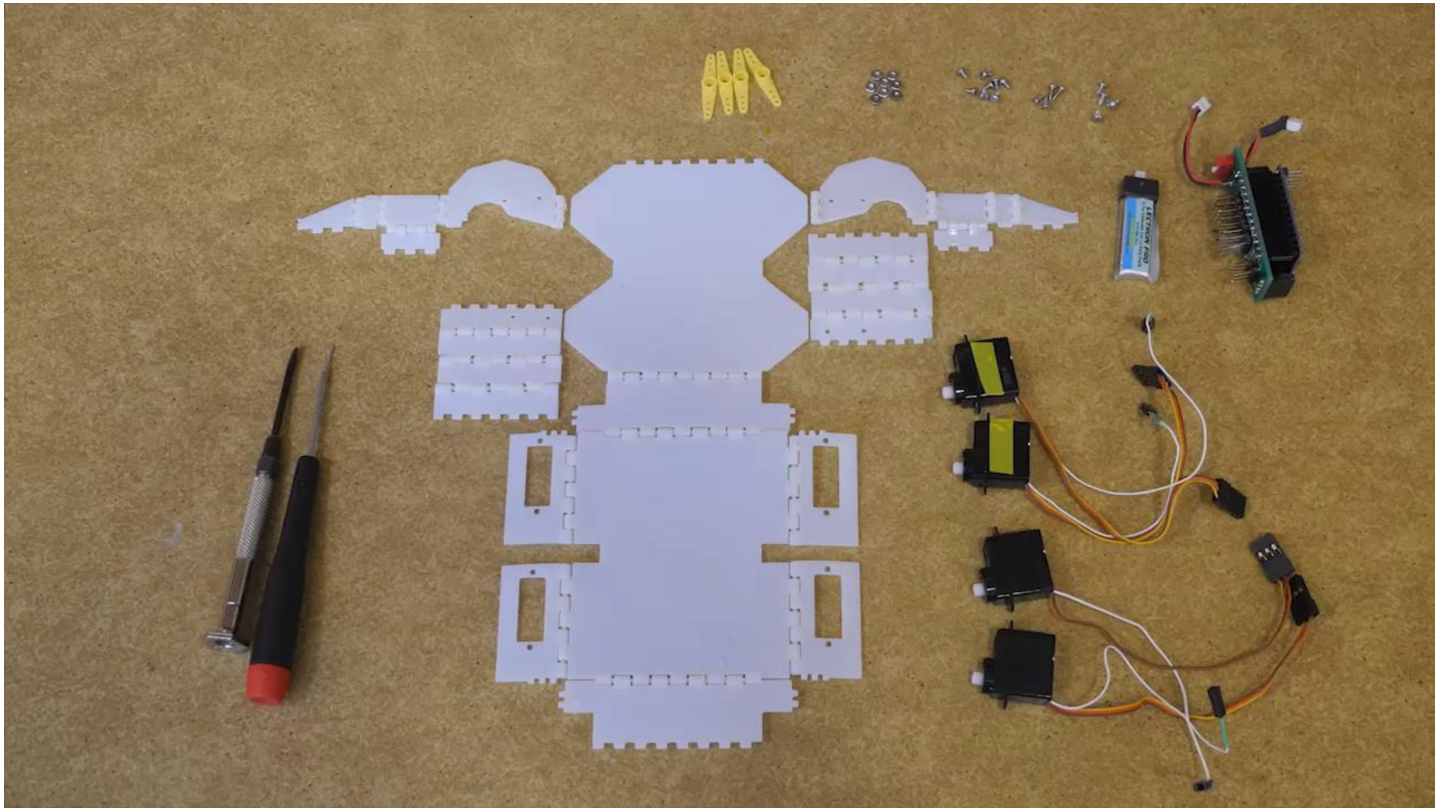
Design Space Exploration



Optimization



Assembly



Physical Robots Created

Source: Schulz et al 2017

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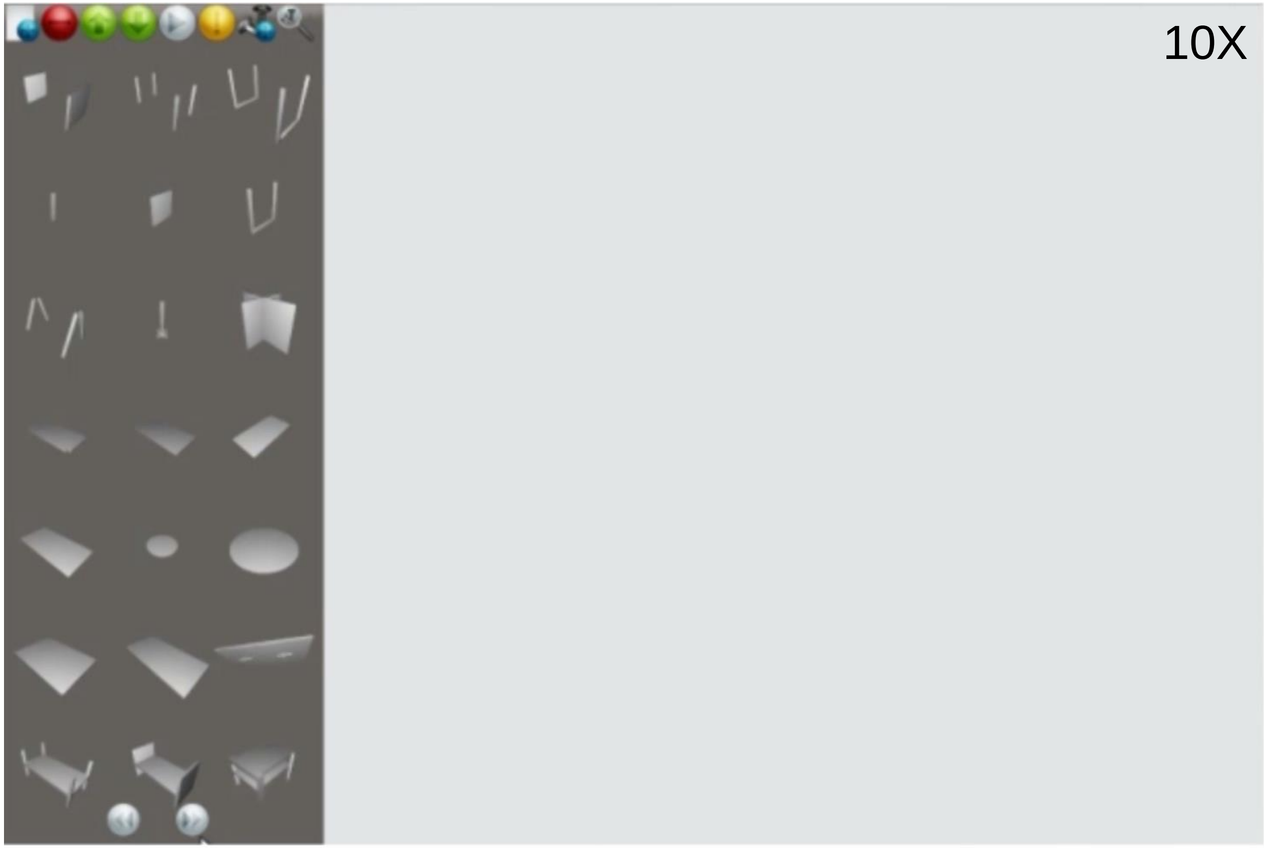
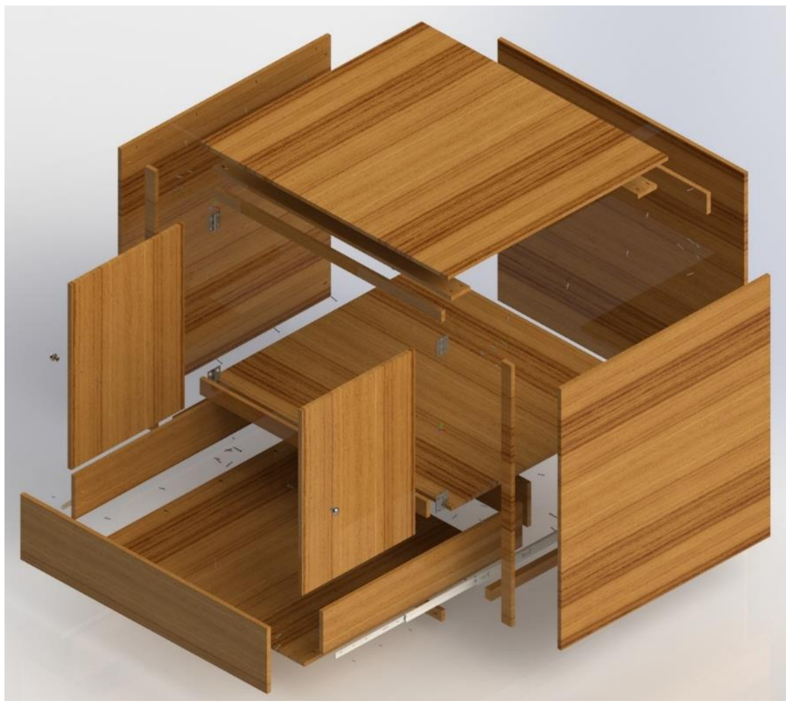
Application: Design by Composition

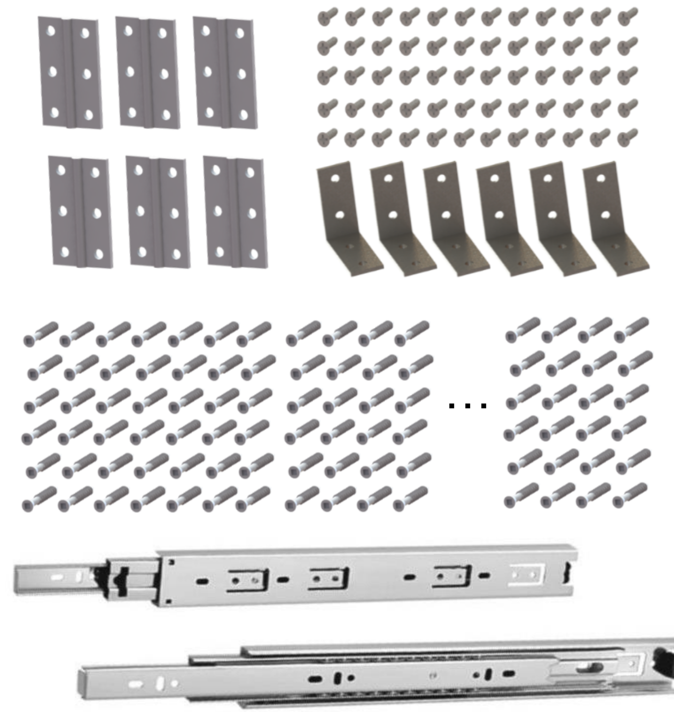


Source: Schulz et al 2014

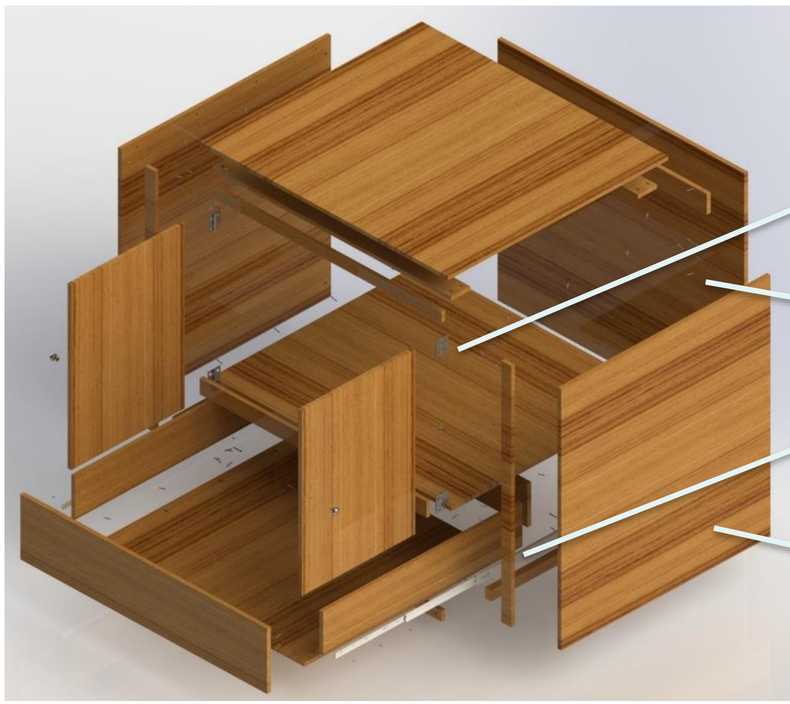
Design and Fabrication by Example

Dataset





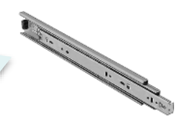
Dataset



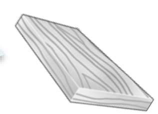
Items Catalog

Ref# 1789A25
$5.69

Ref# 90198A105
$7.38/100



Ref# 1057A51
$25.61

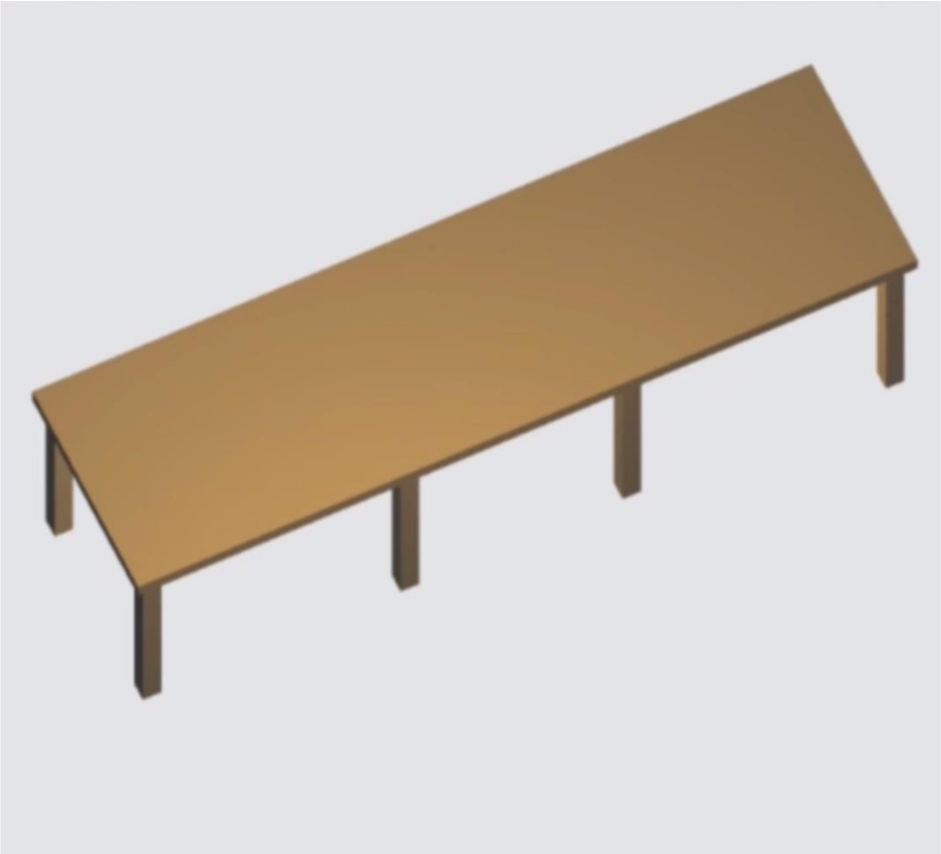


Ref# 90198A105
12”X12”: $7.38
12”X24”: $13:54
24”x24”: $24.62

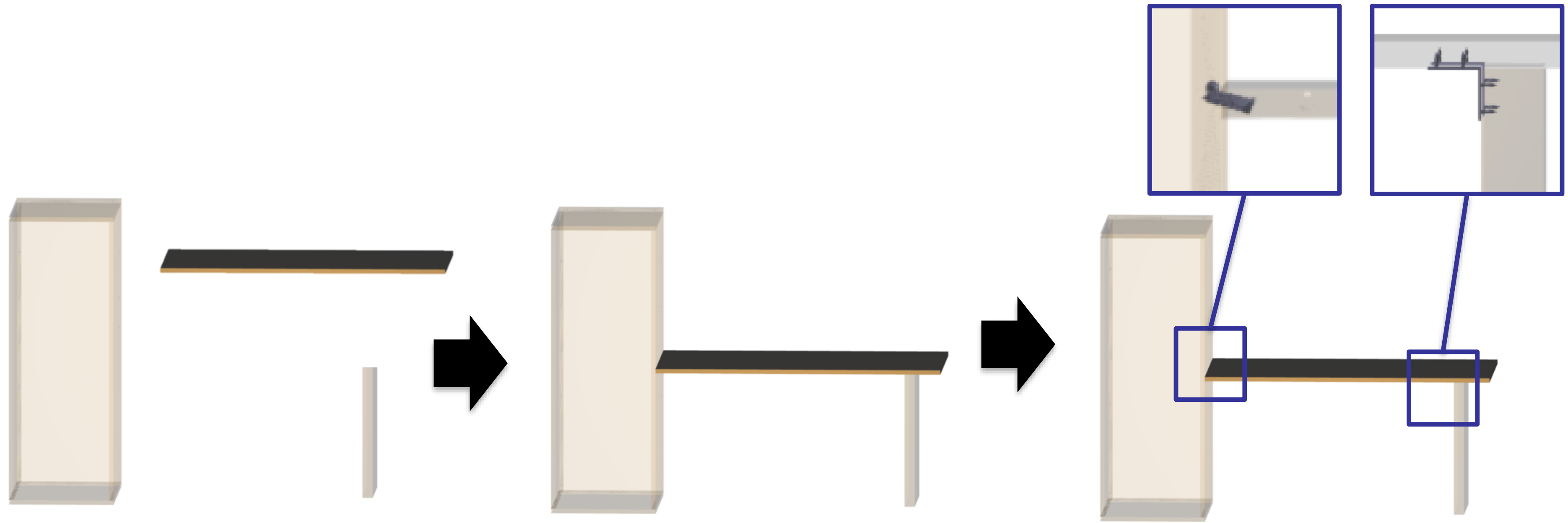
Snapping

- Constraints:
  - Data driven: similar connections

- Optimization:
  - user interaction

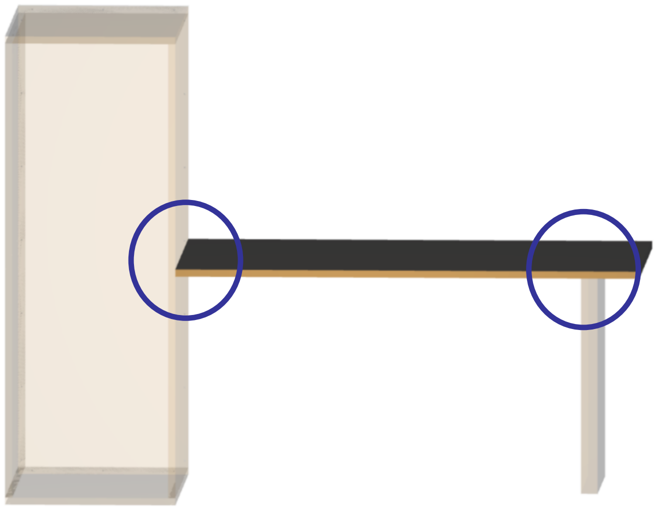


Adding Physical Connectors

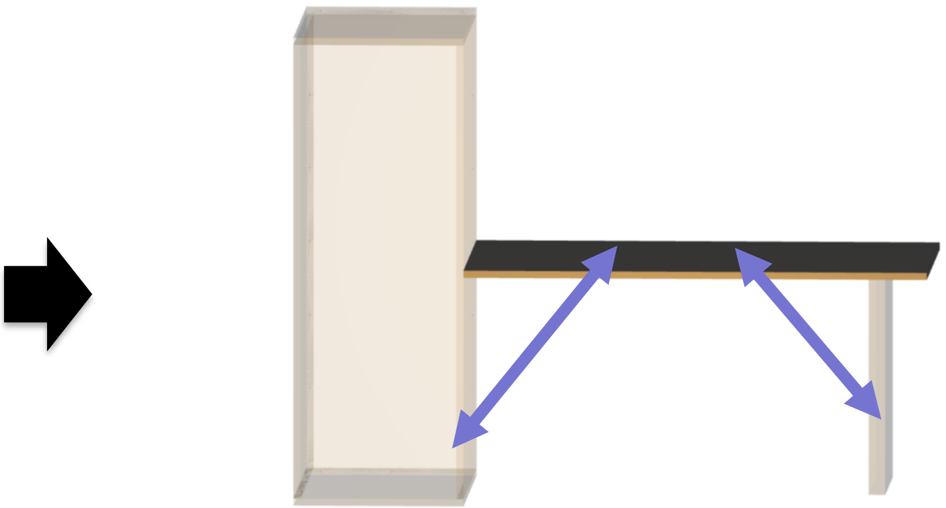


Working Model **Snapped Configuration** **Connected Configuration**

Searching for Connections

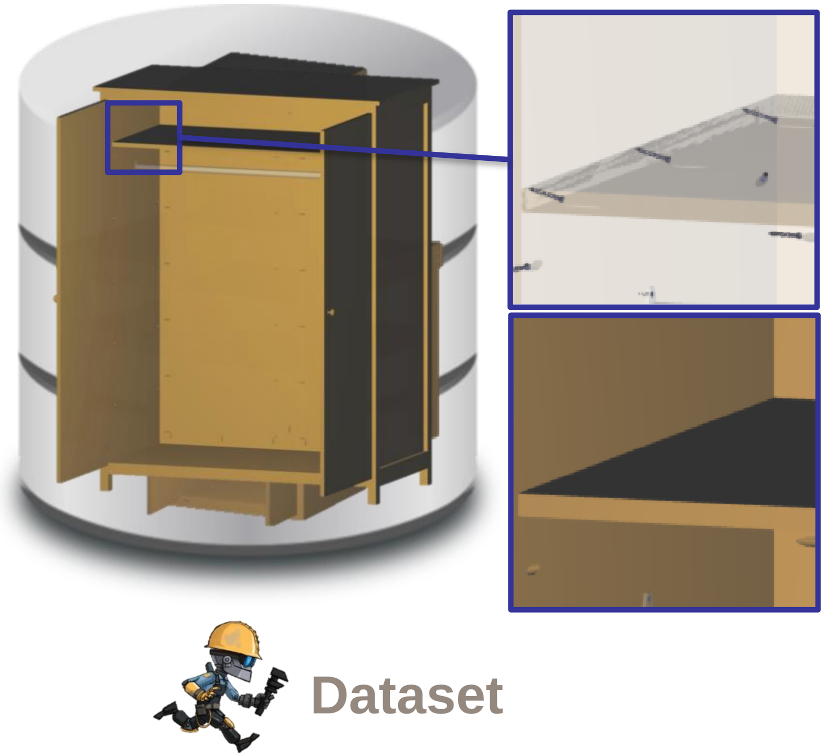


Snapped configuration

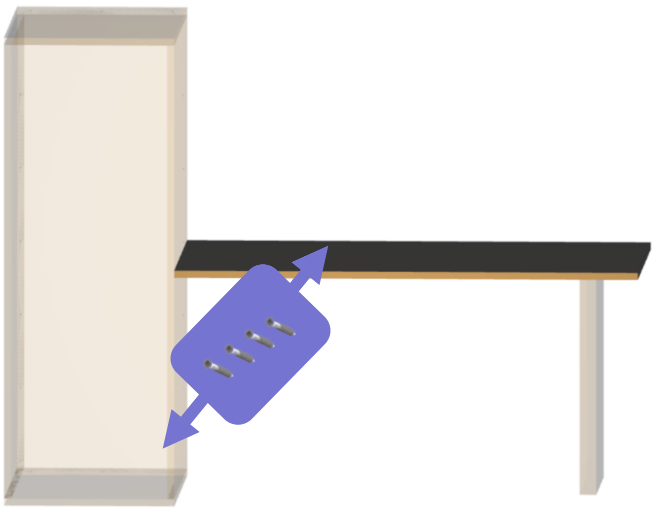


Linked Elements

Searching for Connections

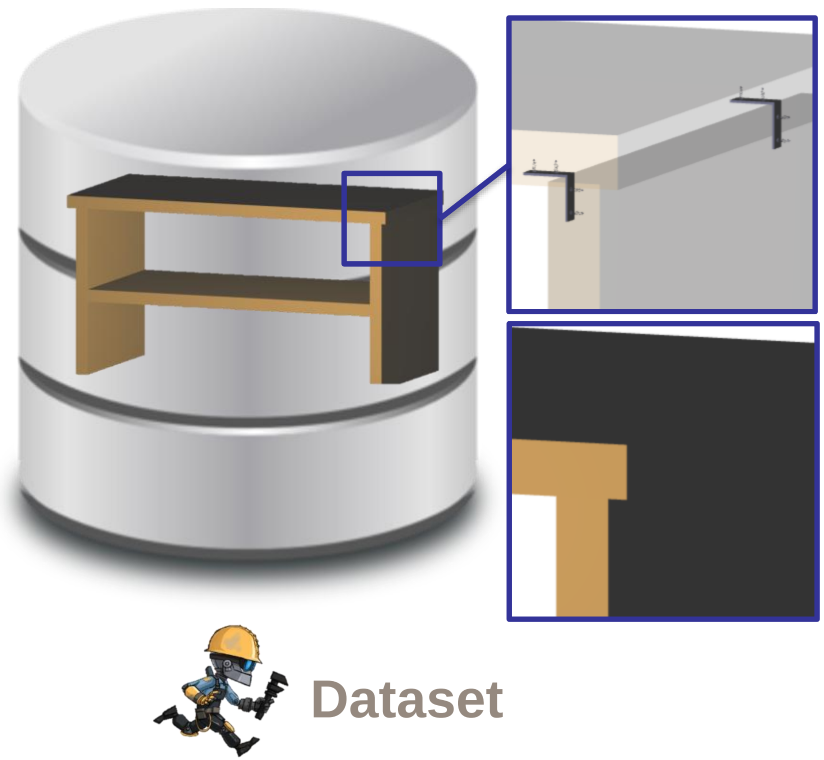


Dataset

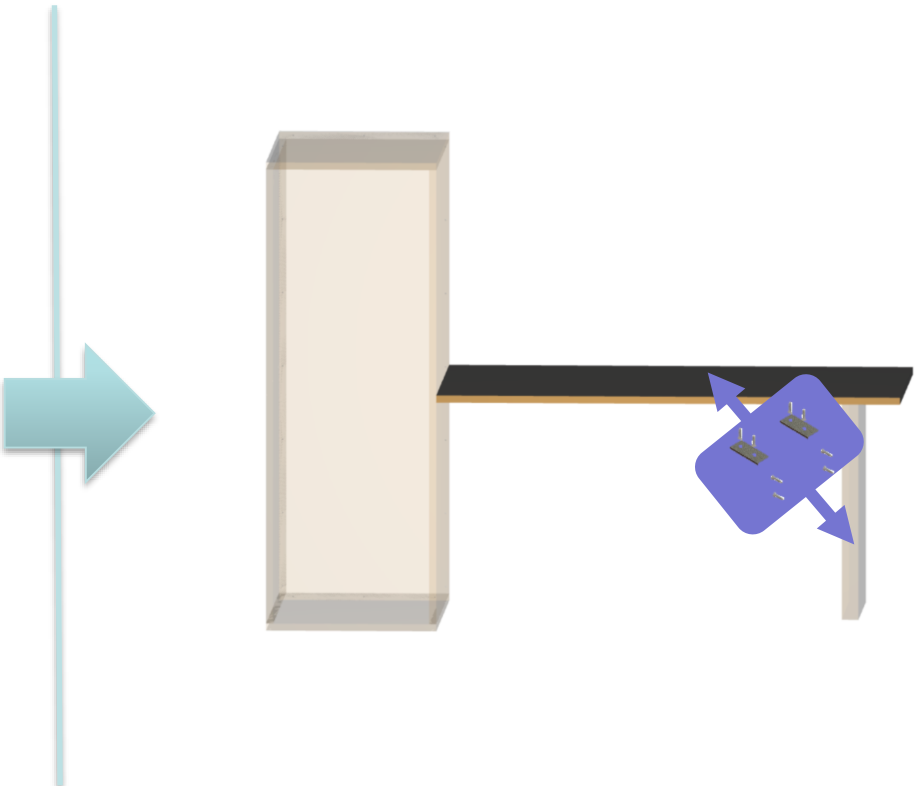


Working Model

Searching for Connections

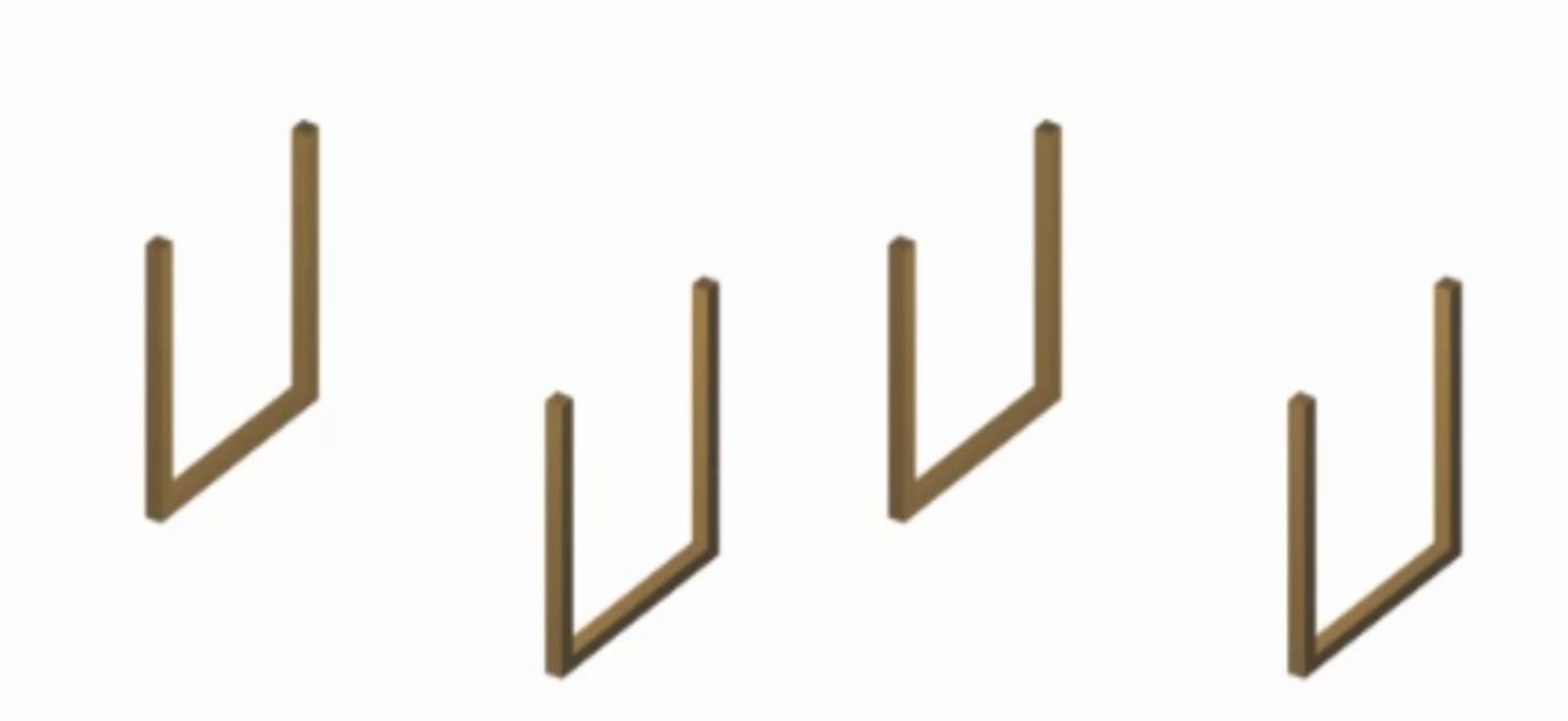


Dataset



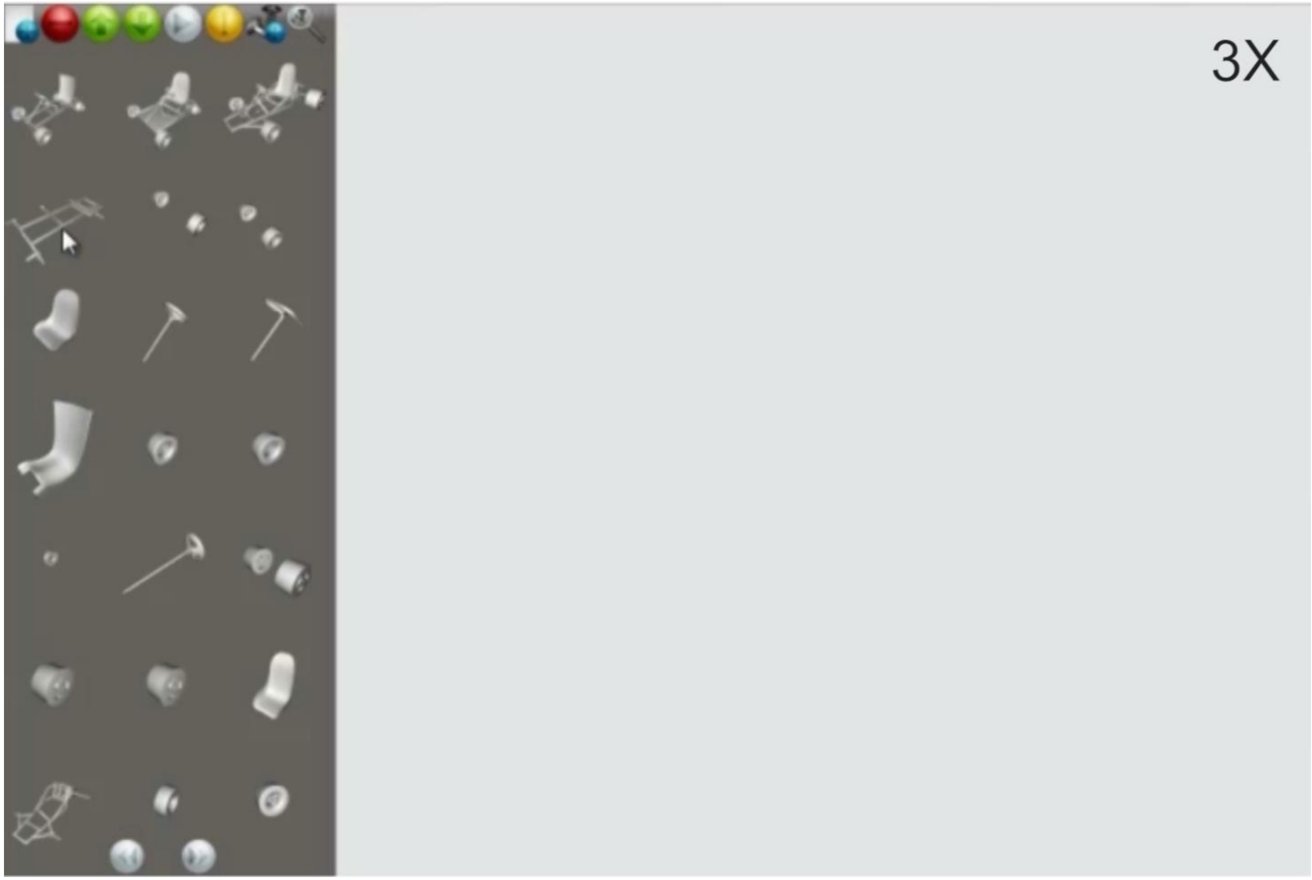
Working Model

Physical Connectors: An Example



Extracted Directly From Data!

Designing a Go-Kart



Source: Schulz et al 2014

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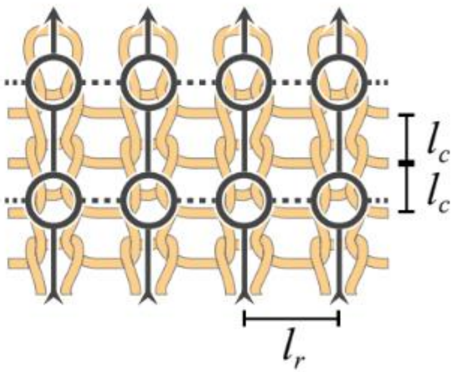
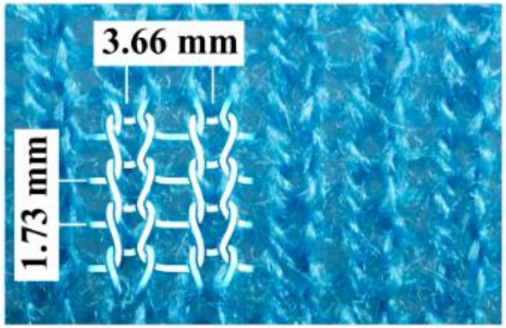
Application: Machine Knitting

Source: Ministry of Supply

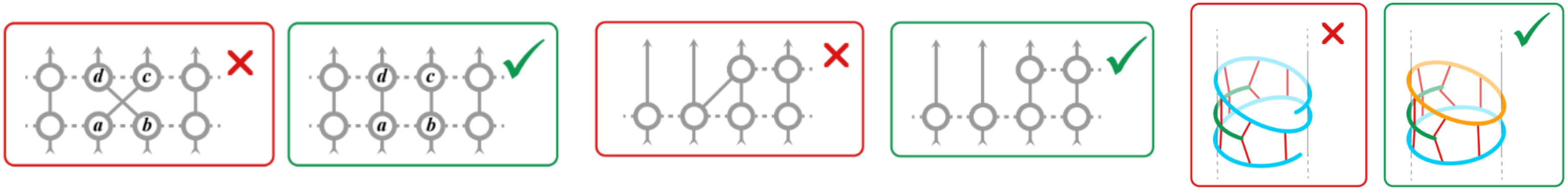
Solution: Knit Graph Representation

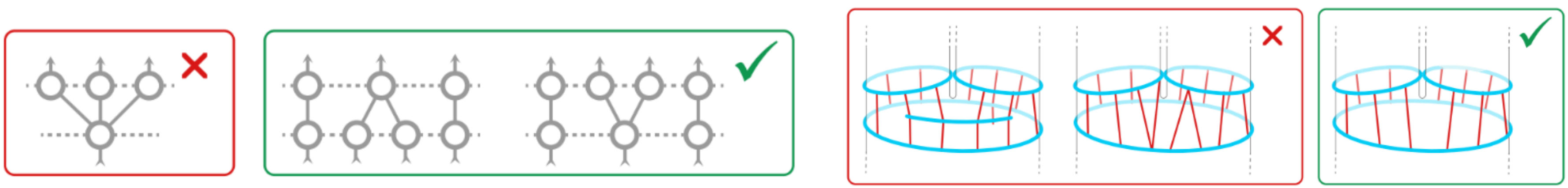
$$\mathcal{N} \equiv \{n, \ldots\}$$
$$\mathcal{R} \equiv \{(n_i, n_j), \ldots\}$$
$$\mathcal{C} \equiv \{(n_i, n_j), \ldots\}$$





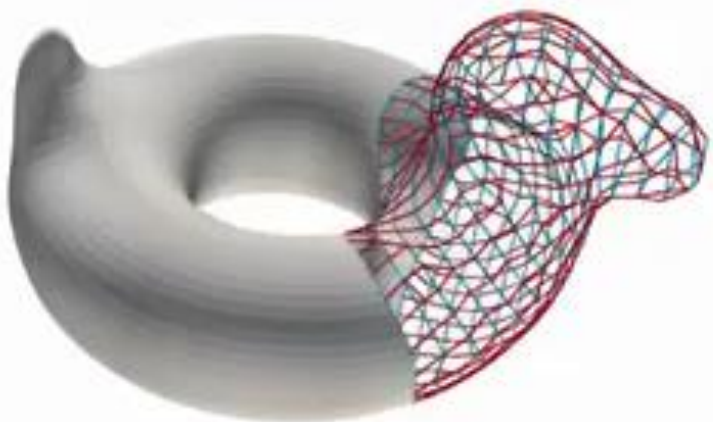
Graph Properties:





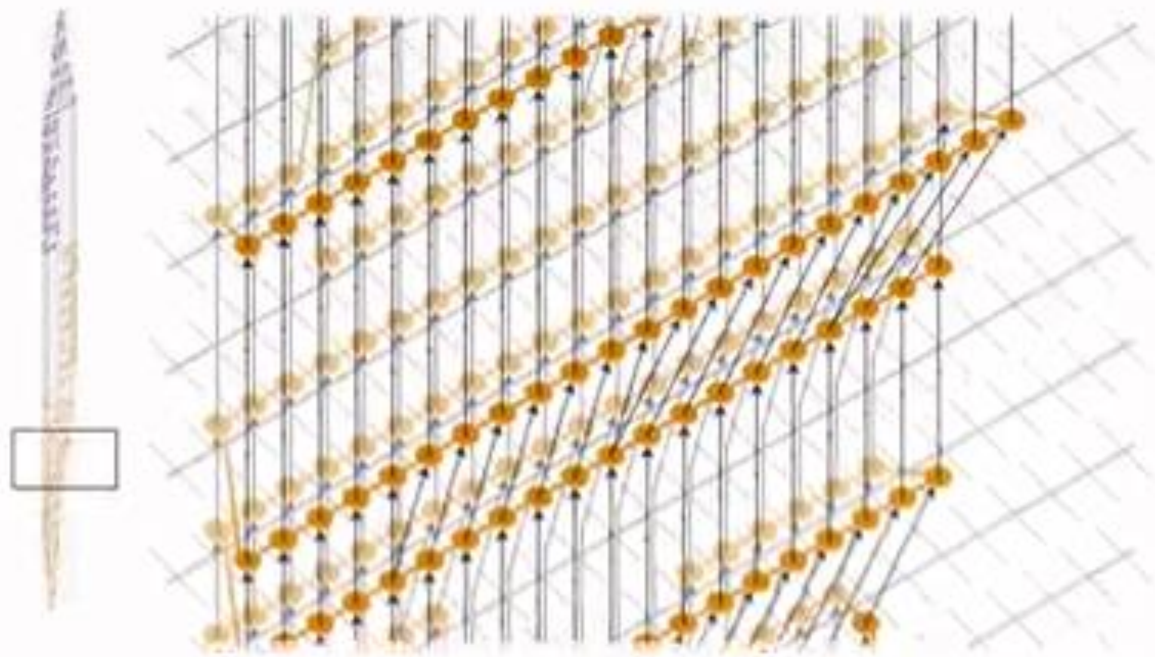
Source: Narayanan et al 2018

From Geometry to Knitting Instructions



Source: Narayanan et al 2018

From Geometry to Knitting Instructions



Source: Narayanan et al 2018

Results

Source: Narayanan et al 2018

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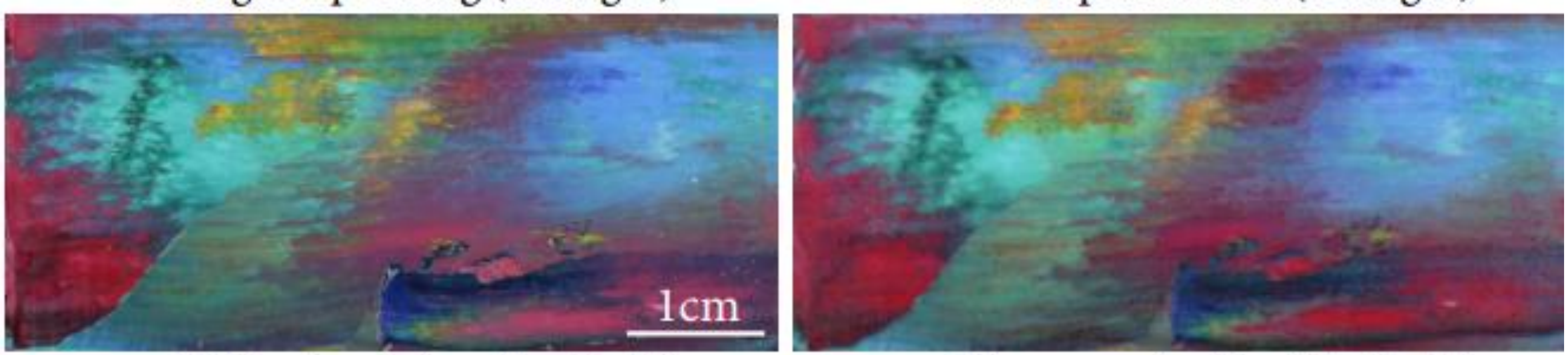
Application: Color Reproduction via Multi-Layer Printing

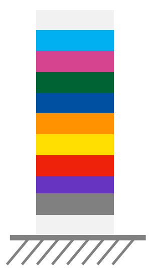
Original painting (Sunlight) Our reproduction (Sunlight)



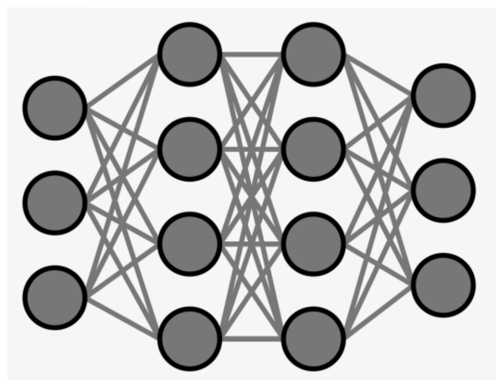
Original painting (Sunlight) Our reproduction (Sunlight)

Source: Shi et al 2018

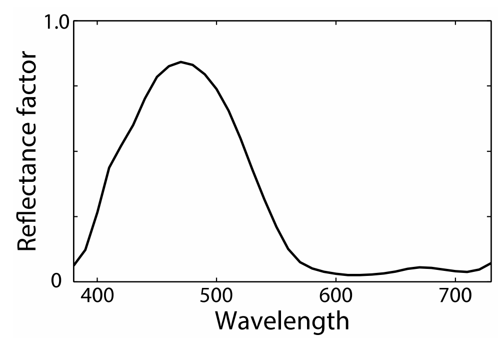
Bidirectional Layout–Spectrum Mapping



Layout
(11-D vector)



Neural Networks

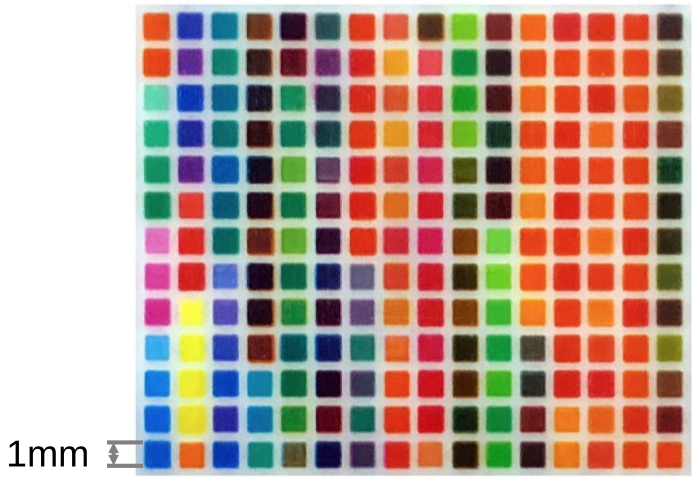


Spectrum
(31-D vector)

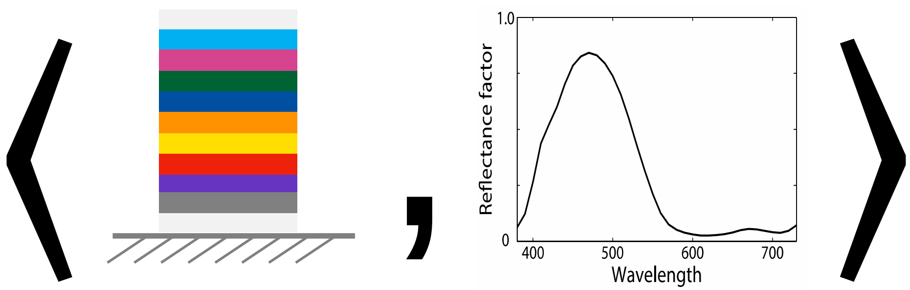
Requires more than
tens of thousands paired training data

Source: Shi et al 2018

Contoning Dataset



A Calibration Patch
(101 patches in total)



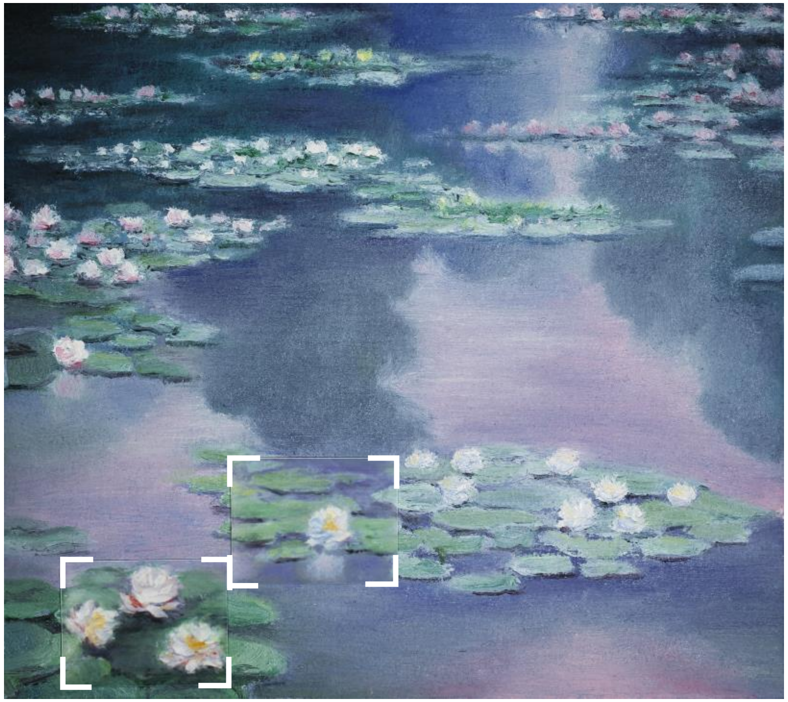
Layout

Spectrum

Samples reduced from 0.8 billion to 21k

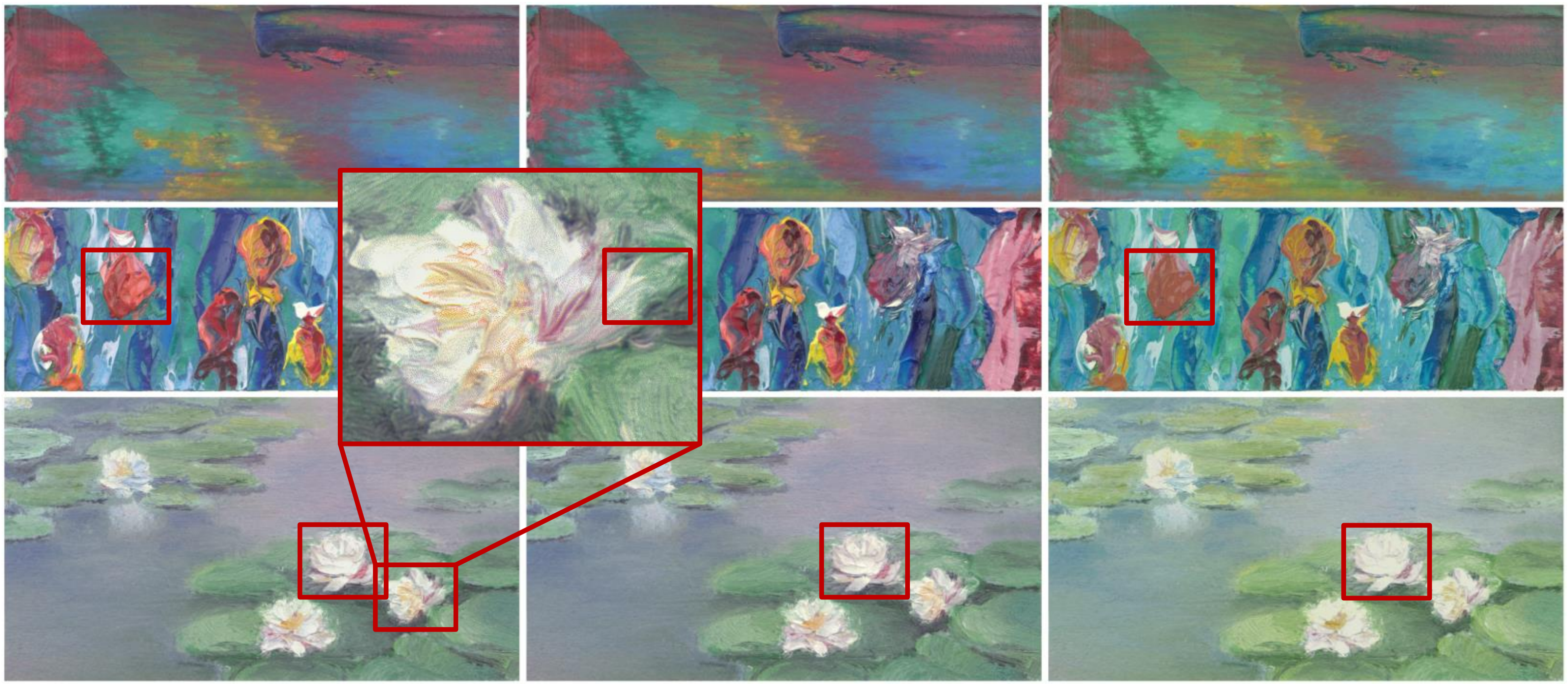
Source: Shi et al 2018

Physical Reproductions



Source: Shi et al 2018

Comparison with Color Contoning



Ours

Original

Color Contoning
[Babaei et al. 2017]

Source: Shi et al 2018

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  - Data-Driven Models
  - Learning Models

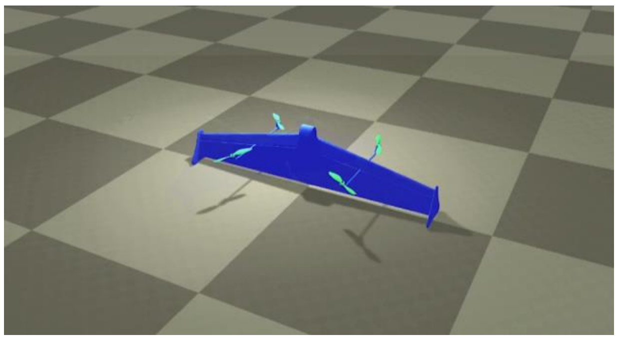
Application: Hybrid Copter Design

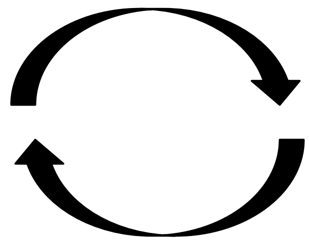
Hybrid UAVs

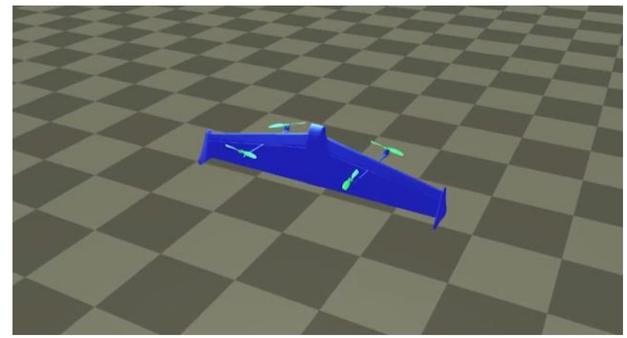
Multicopter

Fixed-wing
Plane

Advantages of Hybrid Copters







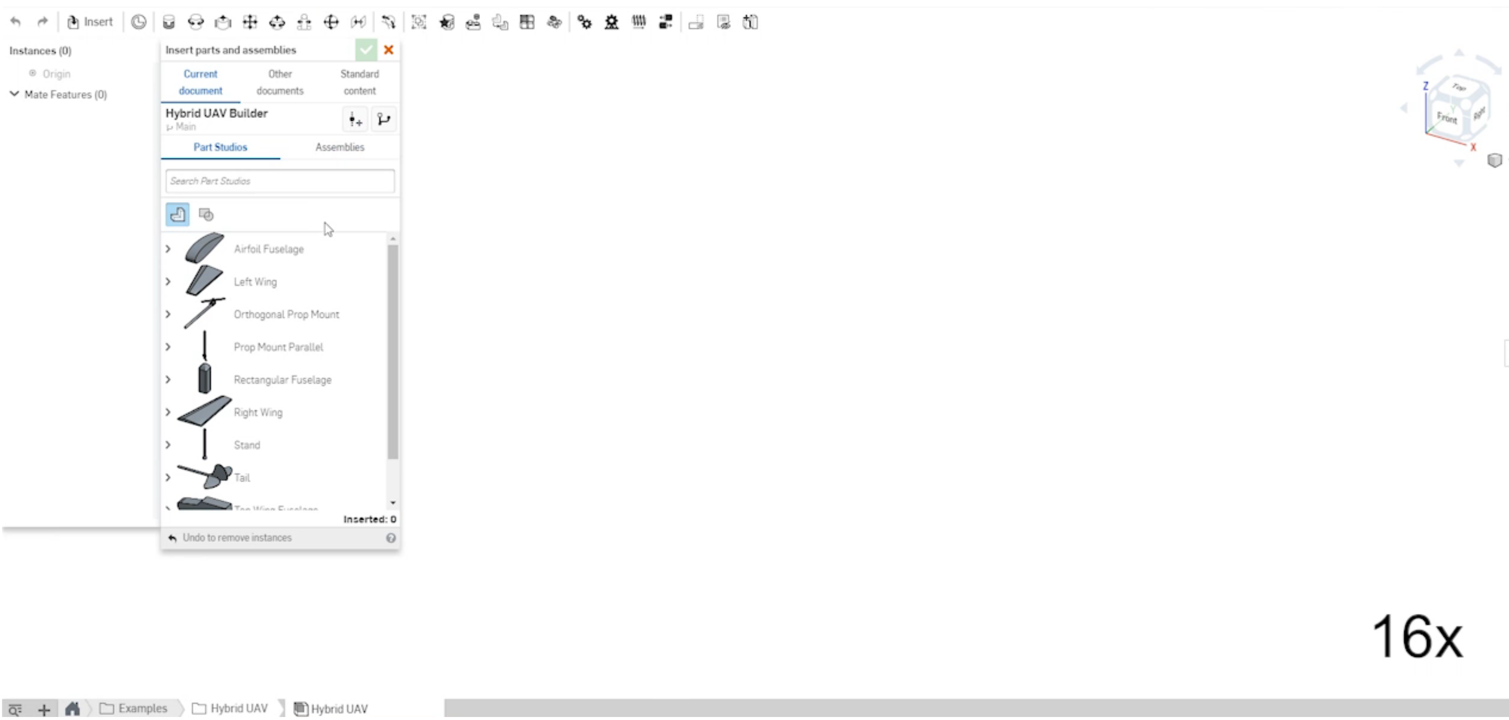
Copter mode

- ✔ Stability
- ✔ Flexibility

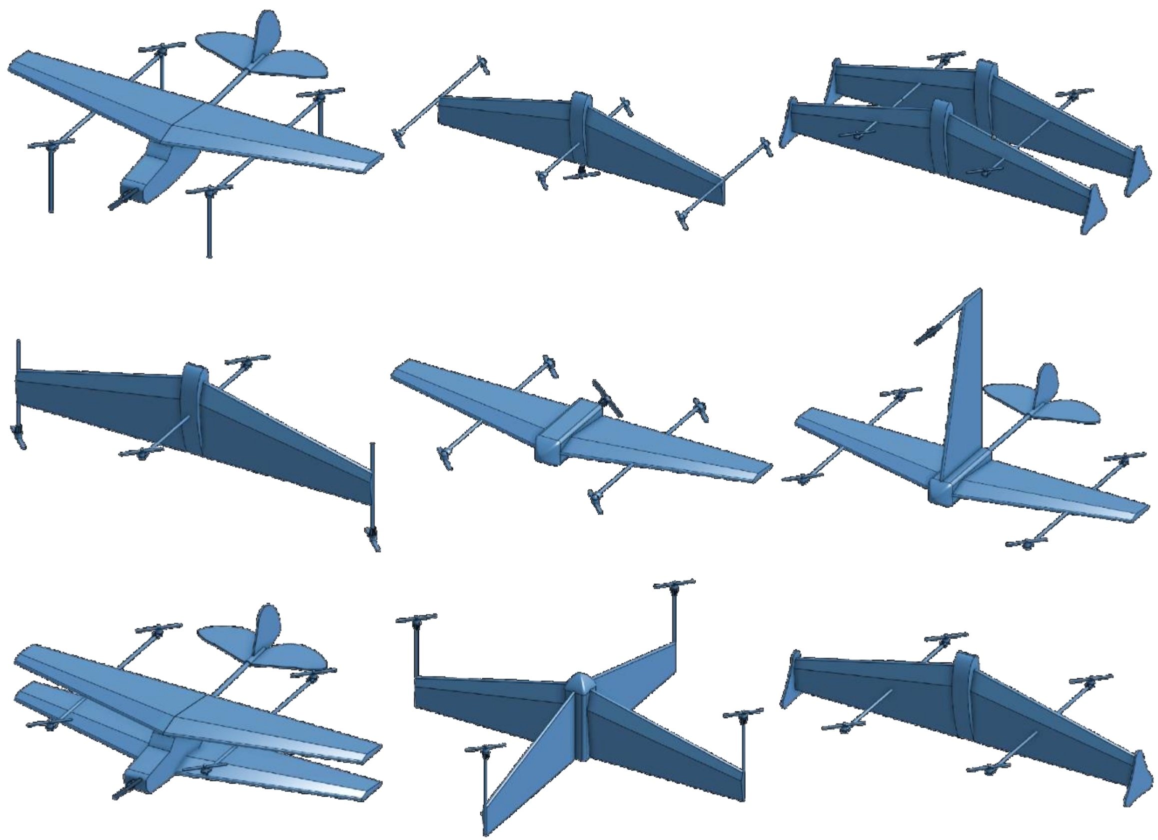
Plane mode

- ✔ High speed
- ✔ Energy efficiency

Interactive Hybrid-Copter Design

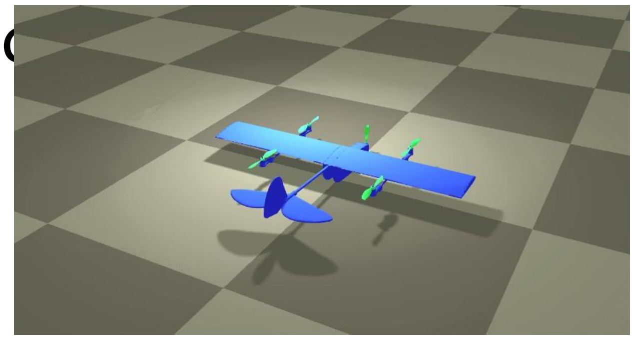


Interactive Hybrid-Copter Design



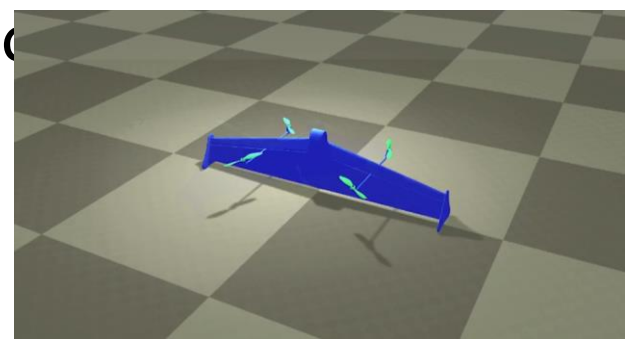
Traditional Controller Design

Quad-plane controller



Copter mode controlle r ↔ Transition mode: front rotor controller ↔ Plane mode controlle r

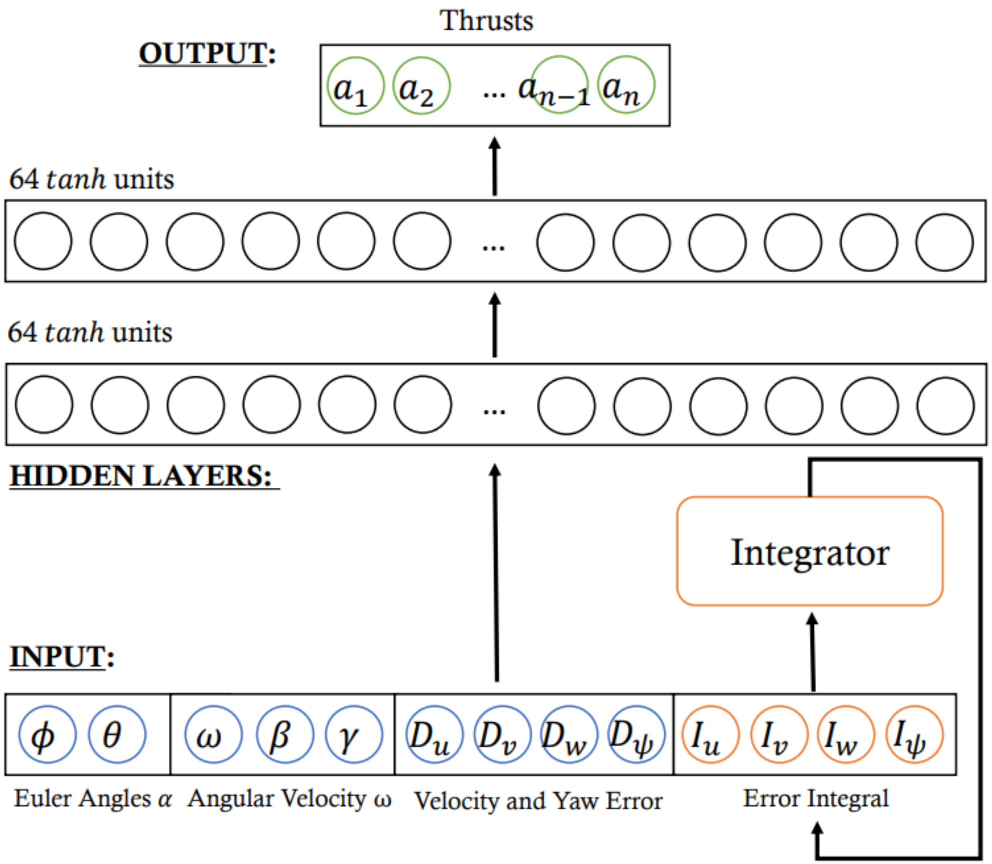
Tail-sitter controller



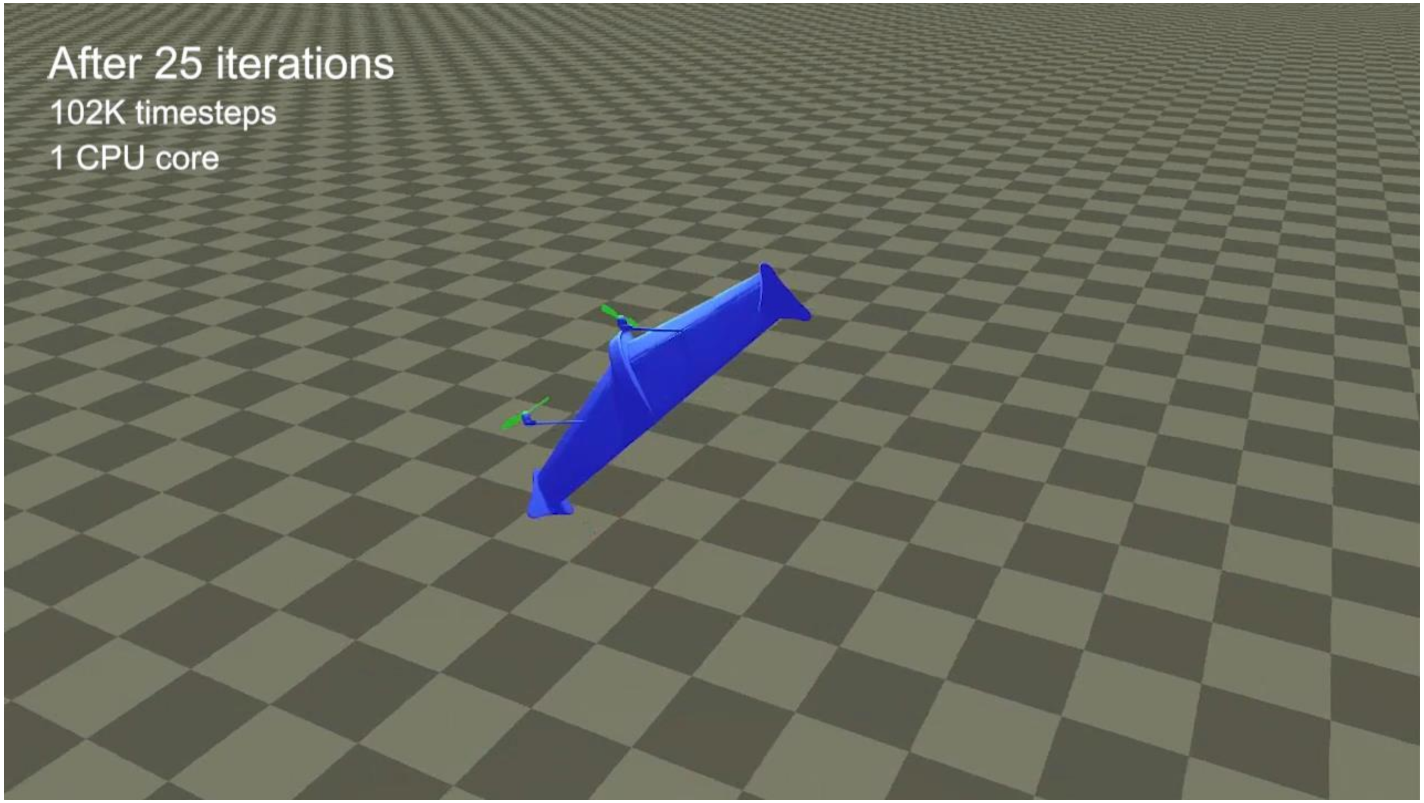
Copter mode controlle r ↔ Transition mode: pitch controller ↔ Plane mode controlle r

Our Approach: NN Controller

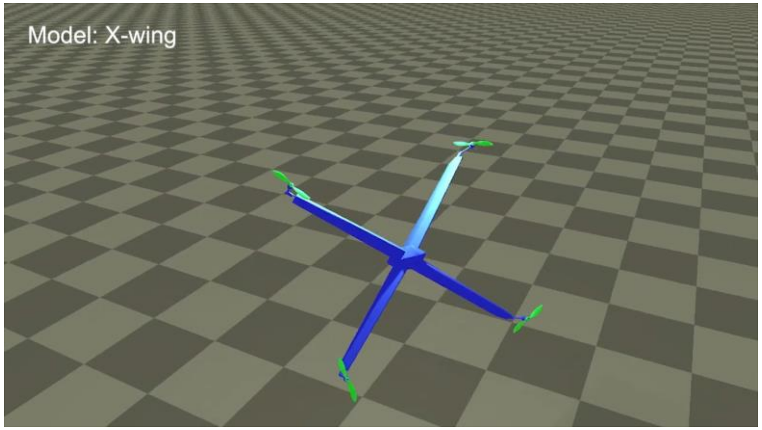
- ☺ general

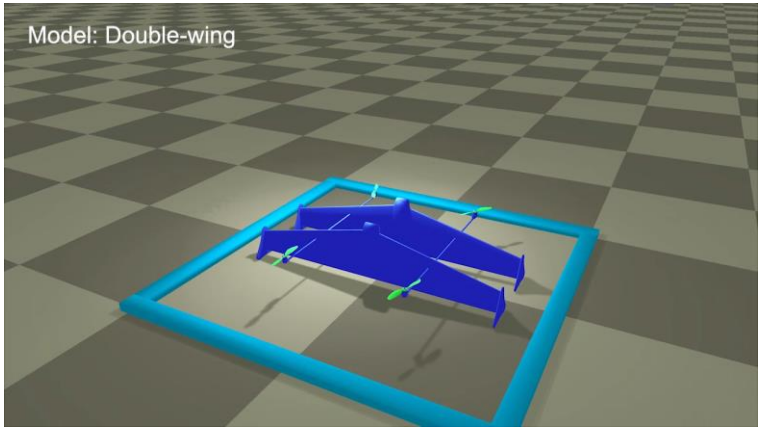


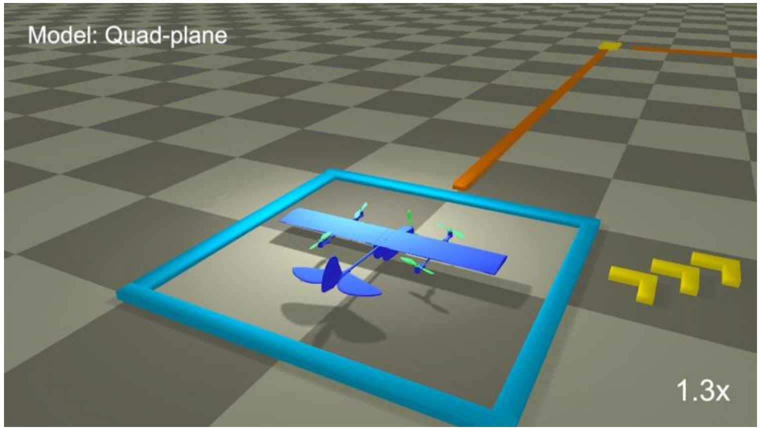
Reinforcement Learning

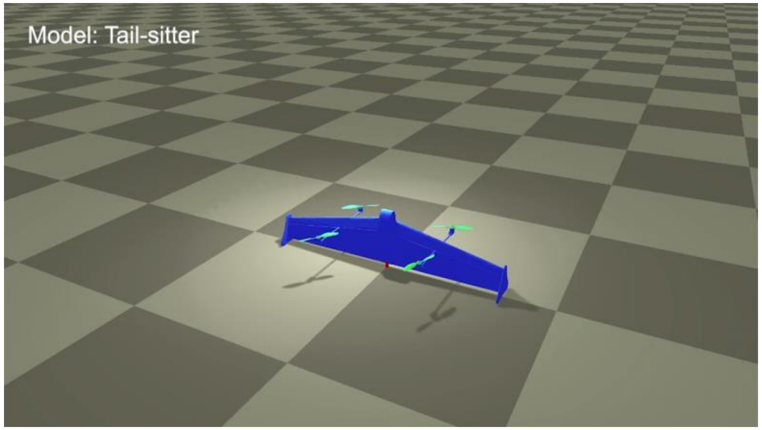


Reinforcement Learning

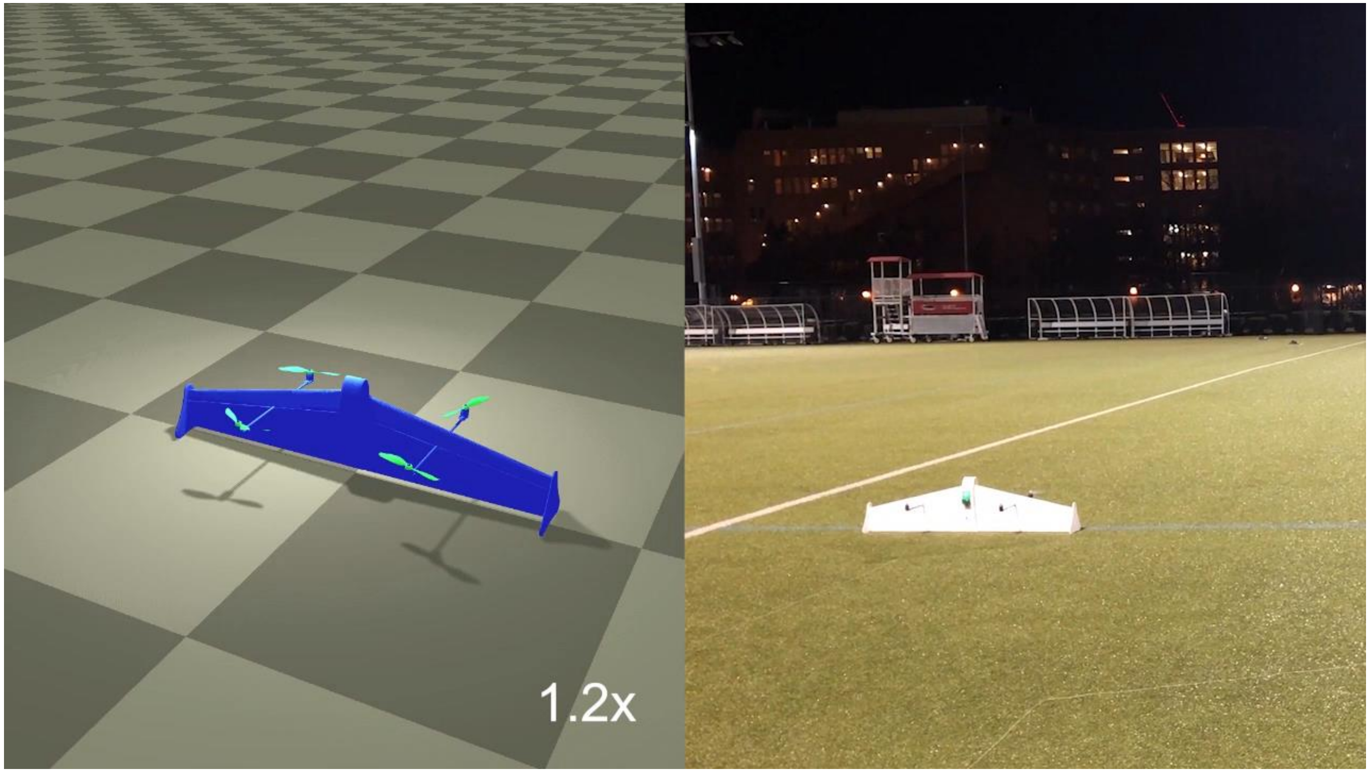






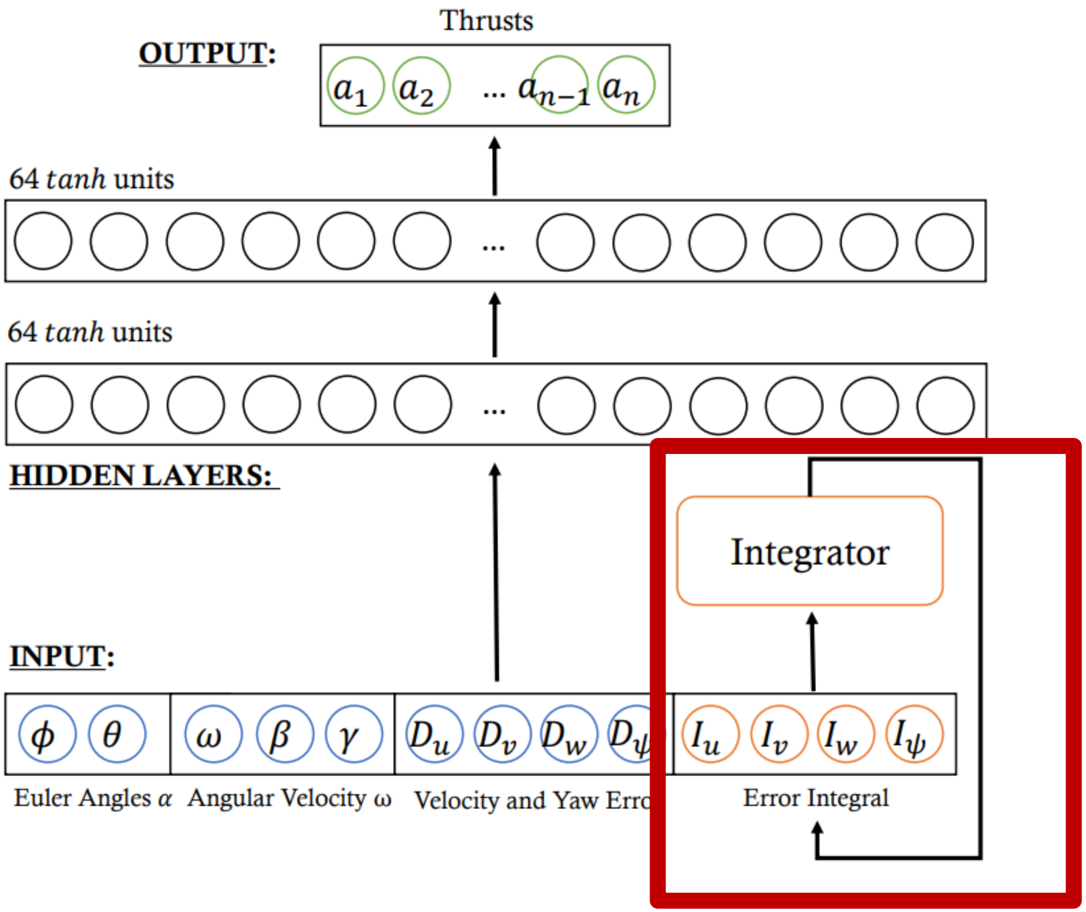


Real Flight Tests



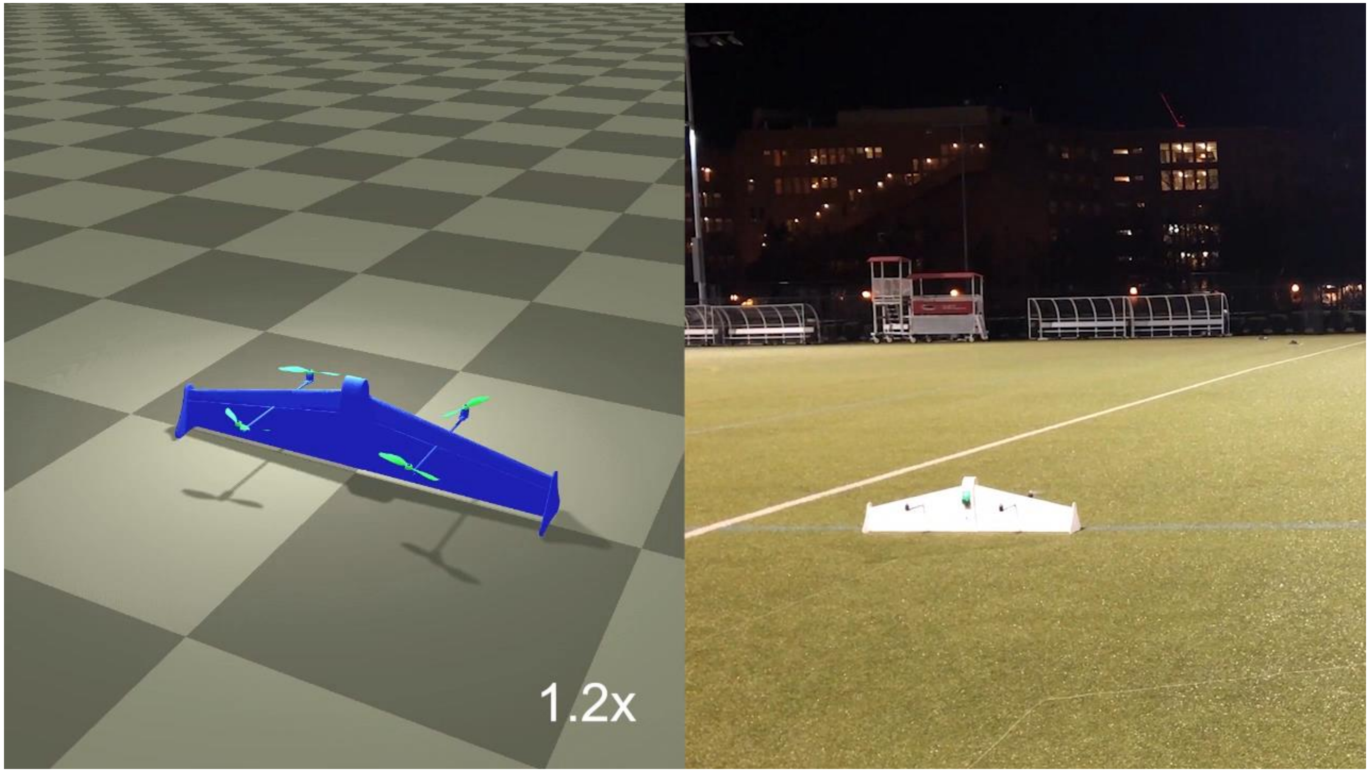
Our Approach: NN Controller

☺ general
☹ reality-gap



Integral Block

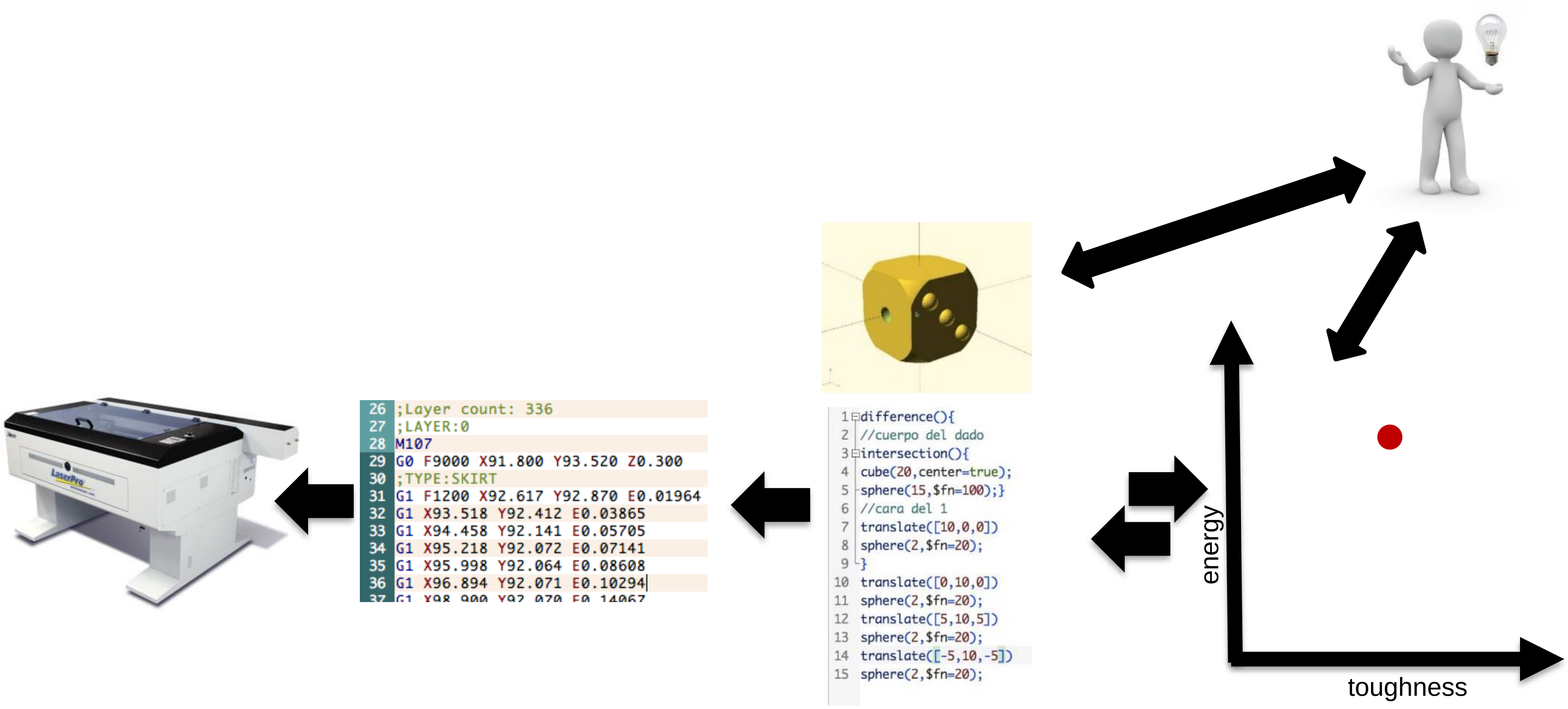
Real Flight Tests



Course Schedule

9:00 am – 9:10 am	Introduction
9:10 am – 9:25 am	Hardware Review
9:25 am – 9:50 am	From Design to Machine Code
9:50 am – 10:20 am	Design Space Representations
10:20 am – 10:25 am	Performance-Driven Design
10:25 am - 10:40 am	Break
10:40 am – 10:55 am	Performance Space Representation
10:55 am – 11:15 am	Inverse Methods
11:15 am – 11:35 am	Multi-objective Inverse Methods
11:35 am – 12:00 pm	Advanced Performance-Driven Design
12:00 pm – 12:15 pm	Course Review

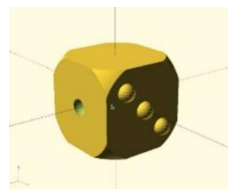
Computational Design Stack



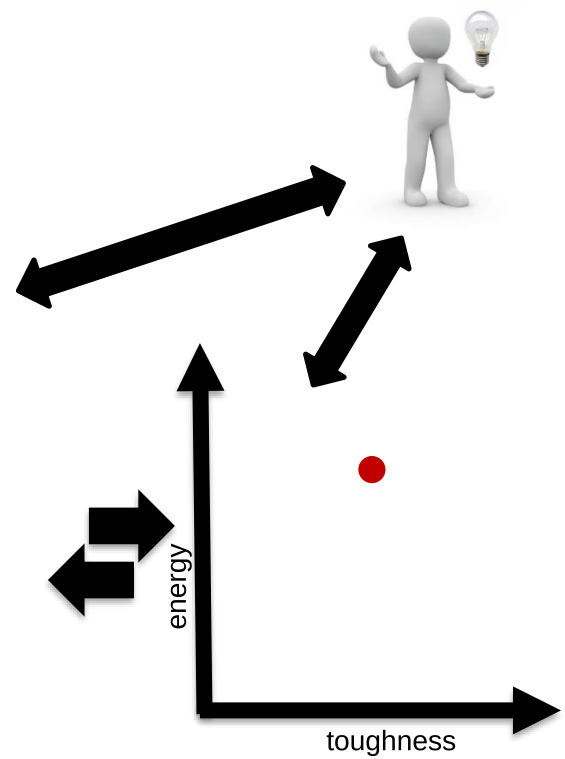
Hardware | **Machine Code** | **Design** | **Performance**

Computational Design Stack

```
;Layer count: 336
;LAYER:0
M107
G0 F9000 X91.800 Y93.520 Z0.300
;TYPE:SKIRT
G1 F1200 X92.617 Y92.870 E0.01964
G1 X93.518 Y92.412 E0.03865
G1 X94.458 Y92.141 E0.05705
G1 X95.218 Y92.072 E0.07141
G1 X95.998 Y92.064 E0.08608
G1 X96.894 Y92.071 E0.10294
G1 X98.900 Y92.070 E0.14067
```



```
difference(){
//cuerpo del dado
intersection(){
cube(20,center=true);
sphere(15,$fn=100);}
//cara del 1
translate([10,0,0])
sphere(2,$fn=20);
}
translate([0,10,0])
sphere(2,$fn=20);
translate([5,10,5])
sphere(2,$fn=20);
translate([-5,10,-5])
sphere(2,$fn=20);
```



Hardware

Machine Code

Design

Performance

Additive Manufacturing Processes

- Thermoplastic Extrusion
  - Fused deposition modeling (FDM)
- UV Curable Resins/thermosets
  - Stereolithography (SLA) & DLP Printing
  - Photopolymer Inkjet Printing
- Powders
  - Selective laser sintering (SLS)
  - Binder jetting/3D Printing
- Sheets
  - Laminated object manufacturing (LOM)

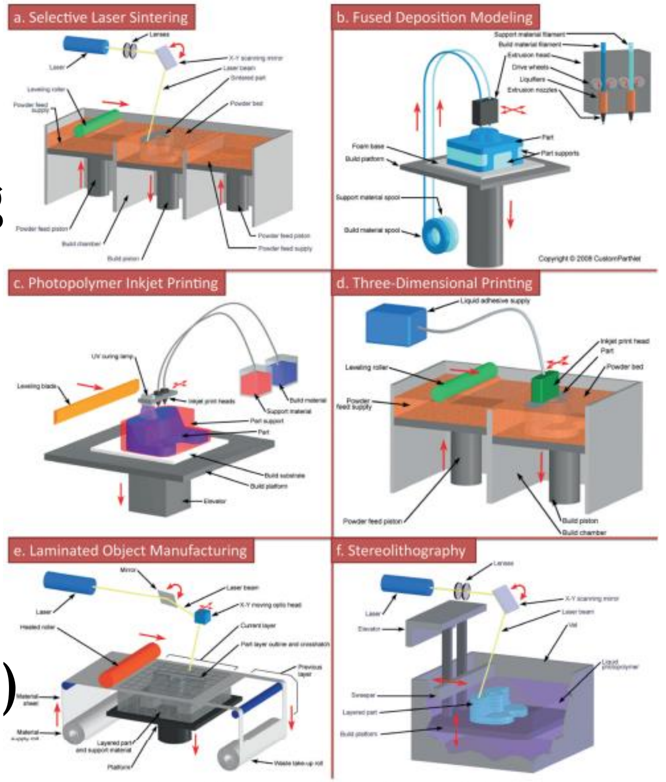
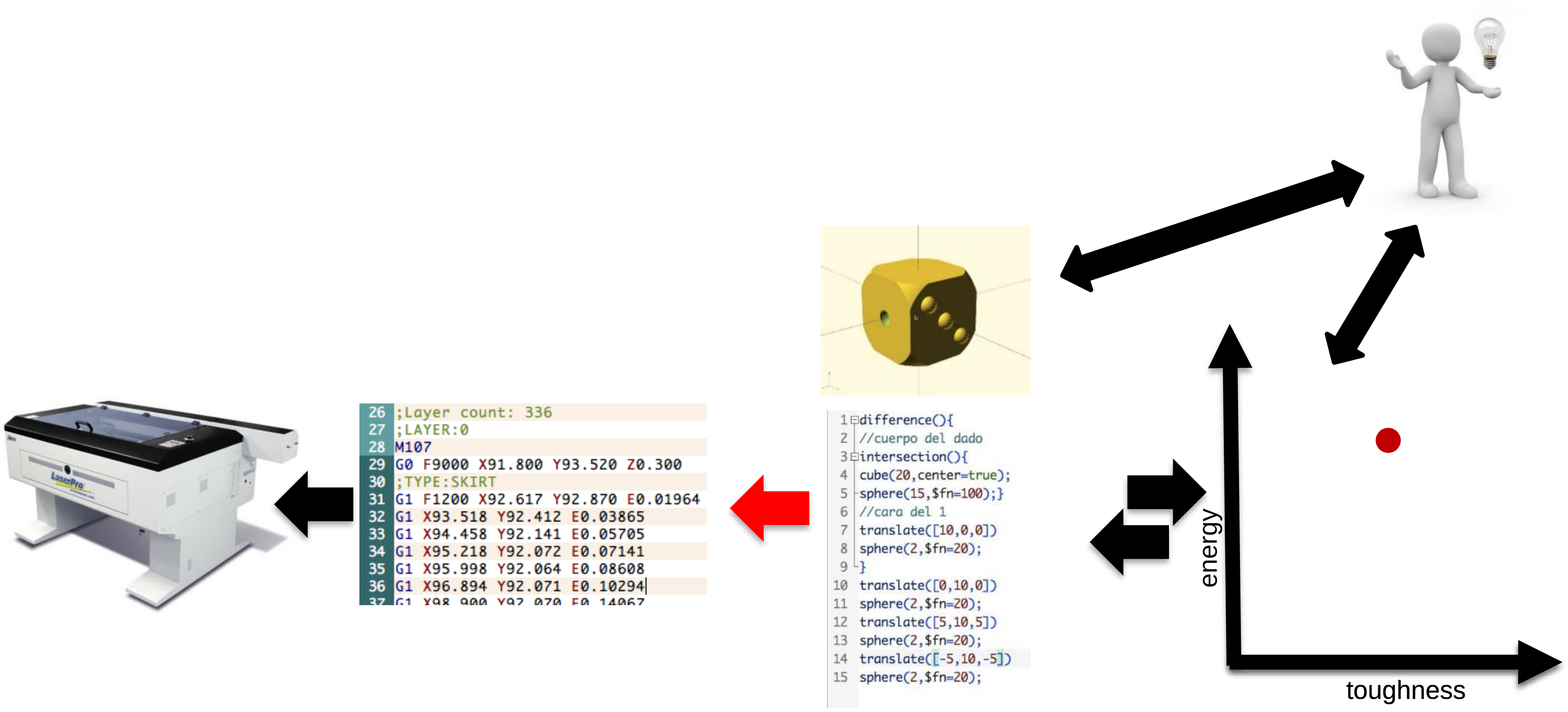


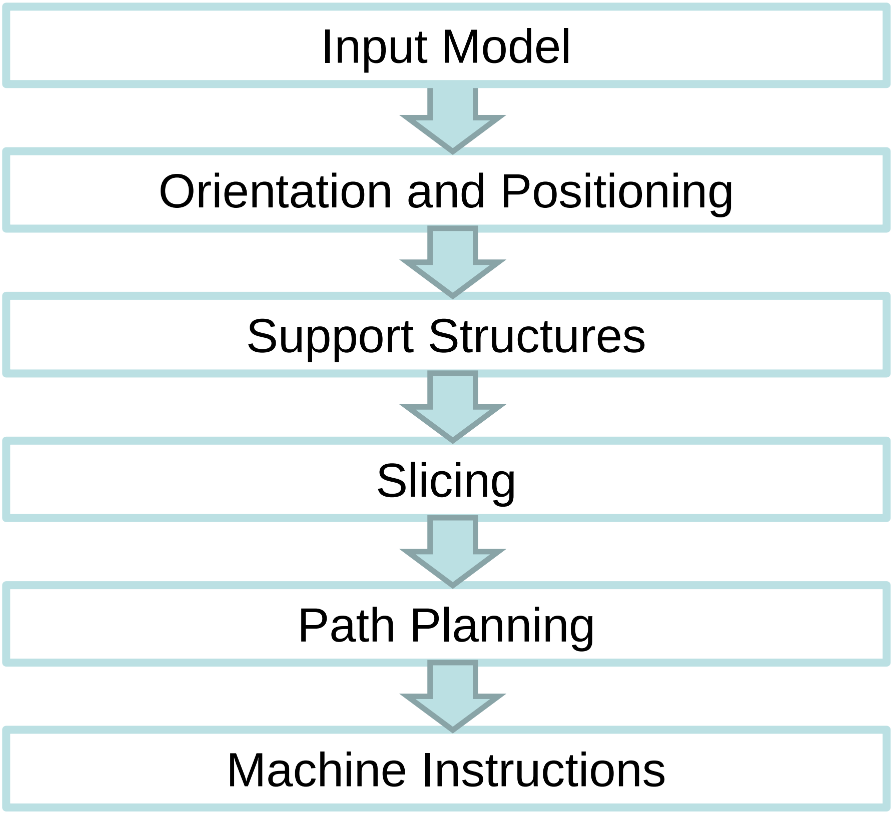
Figure 2. Various 3D printing techniques. a) Selective laser sintering (SLS). b) Fused deposition modeling (FDM, also termed "thermoplastic extrusion"). c) Photopolymer inkjet printing. d) Binder ketting, also trademarked as 3DP. e) Laminated object manufacturing (LOM). f) Stereo-lithography (SL). Images courtesy of CustomPartNet.com.

Computational Design and Fabrication Pipeline



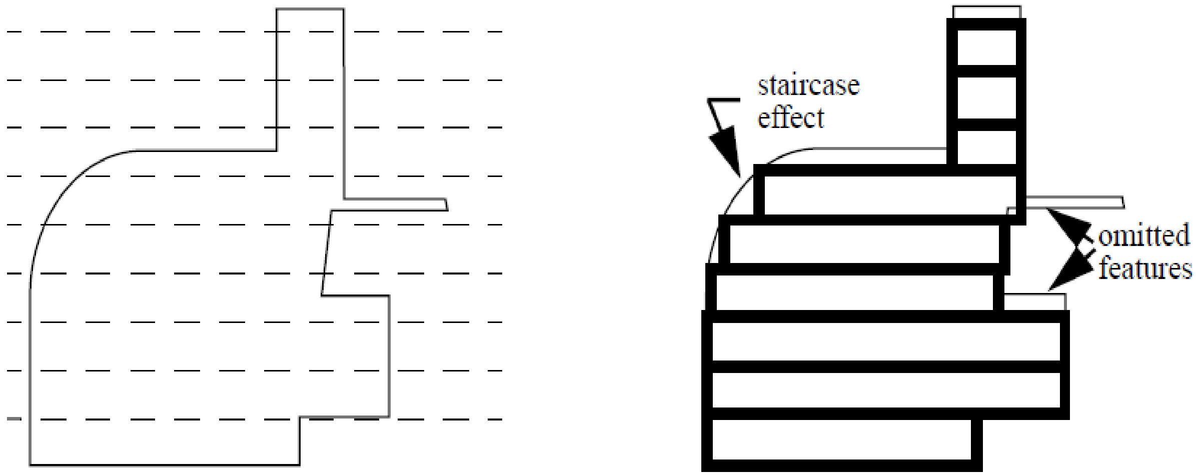
Hardware **Machine Code** **Design** **Performance**

3D Printing Software Pipeline

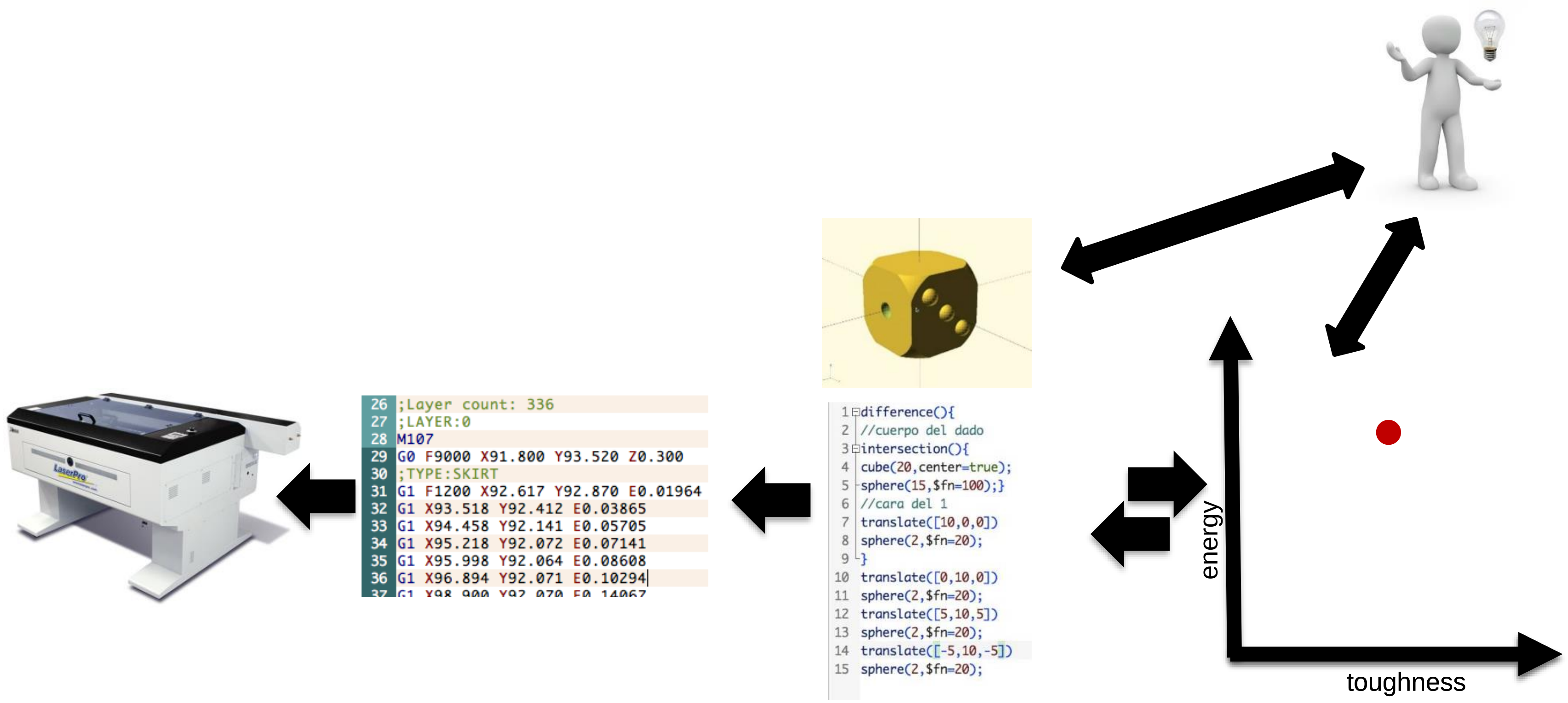


Slicing

- For a discrete z value, compute an intersection of a plane with a model



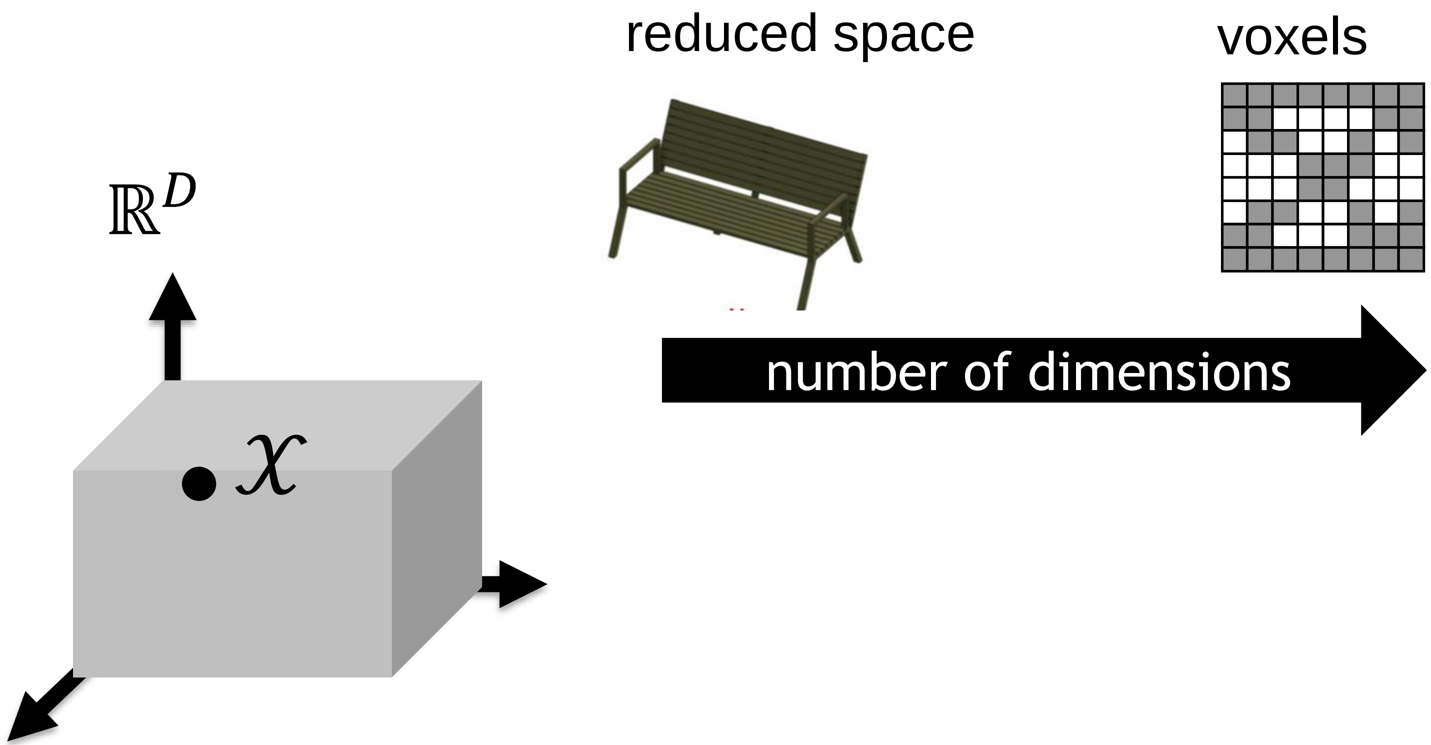
Computational Design Stack



Hardware **Machine Code** **Design** **Performance**

Design Space

- Each design can be mathematically represented as a point in $\mathbb{R}^D$



Design Space

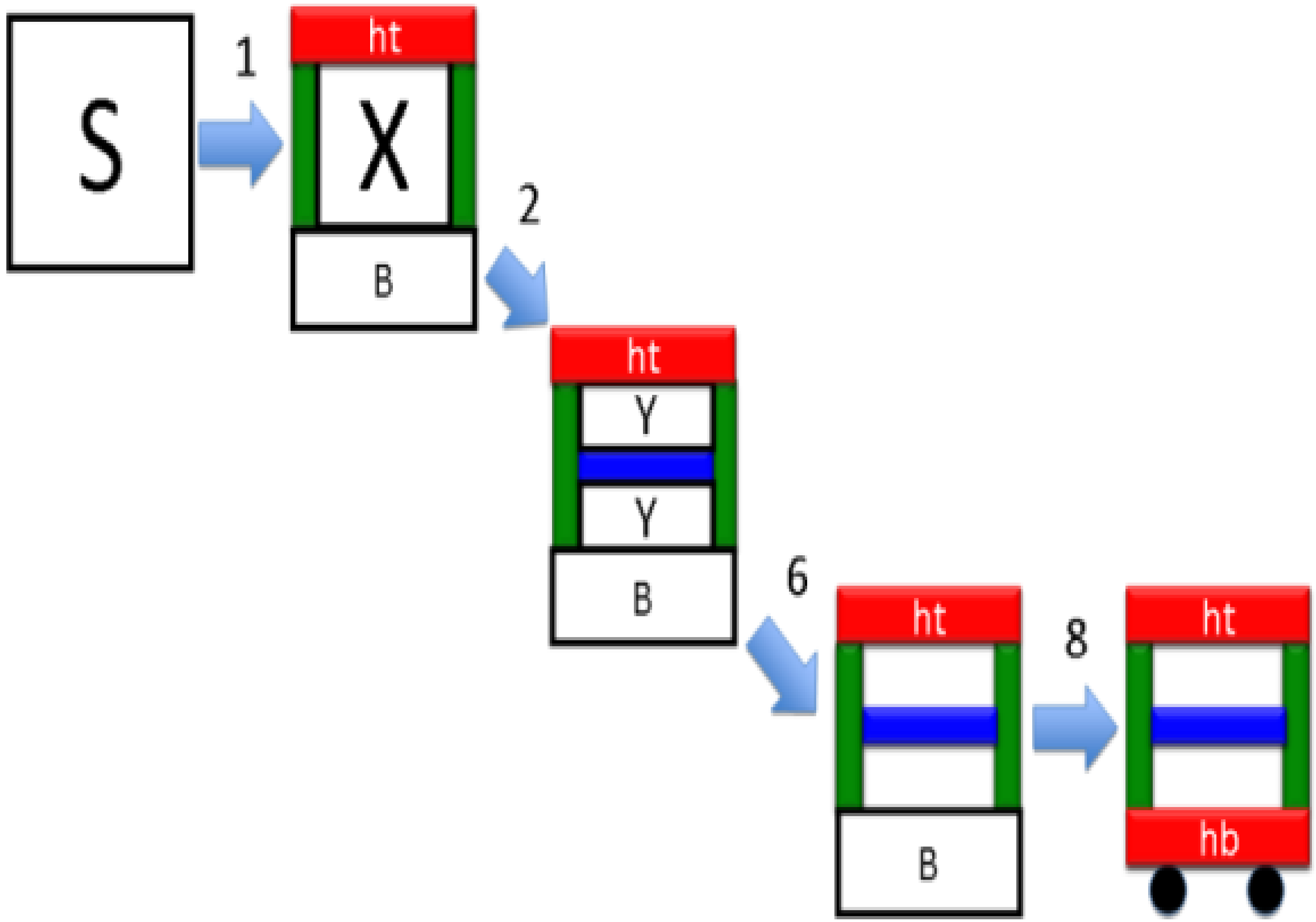
Parametric Design and CAD

$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{bmatrix}$$

parameters

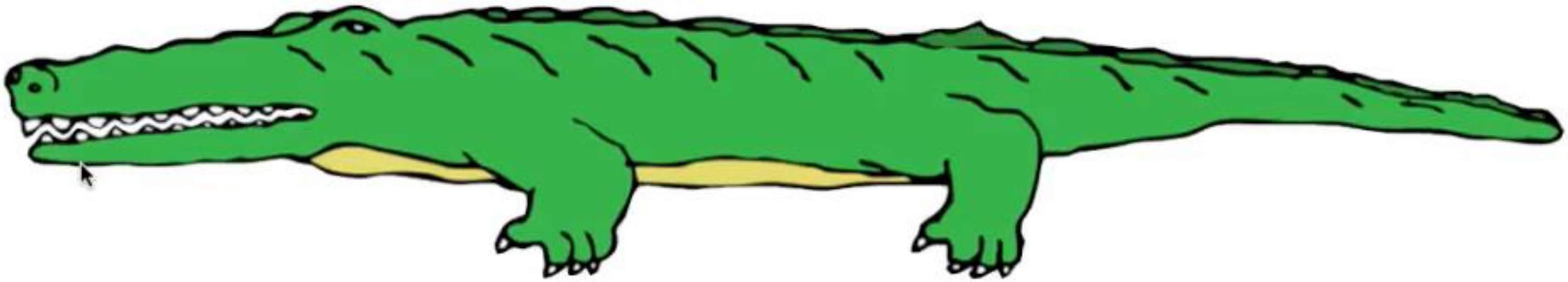
➡ **Parametric Design** ➡

Procedural Modeling

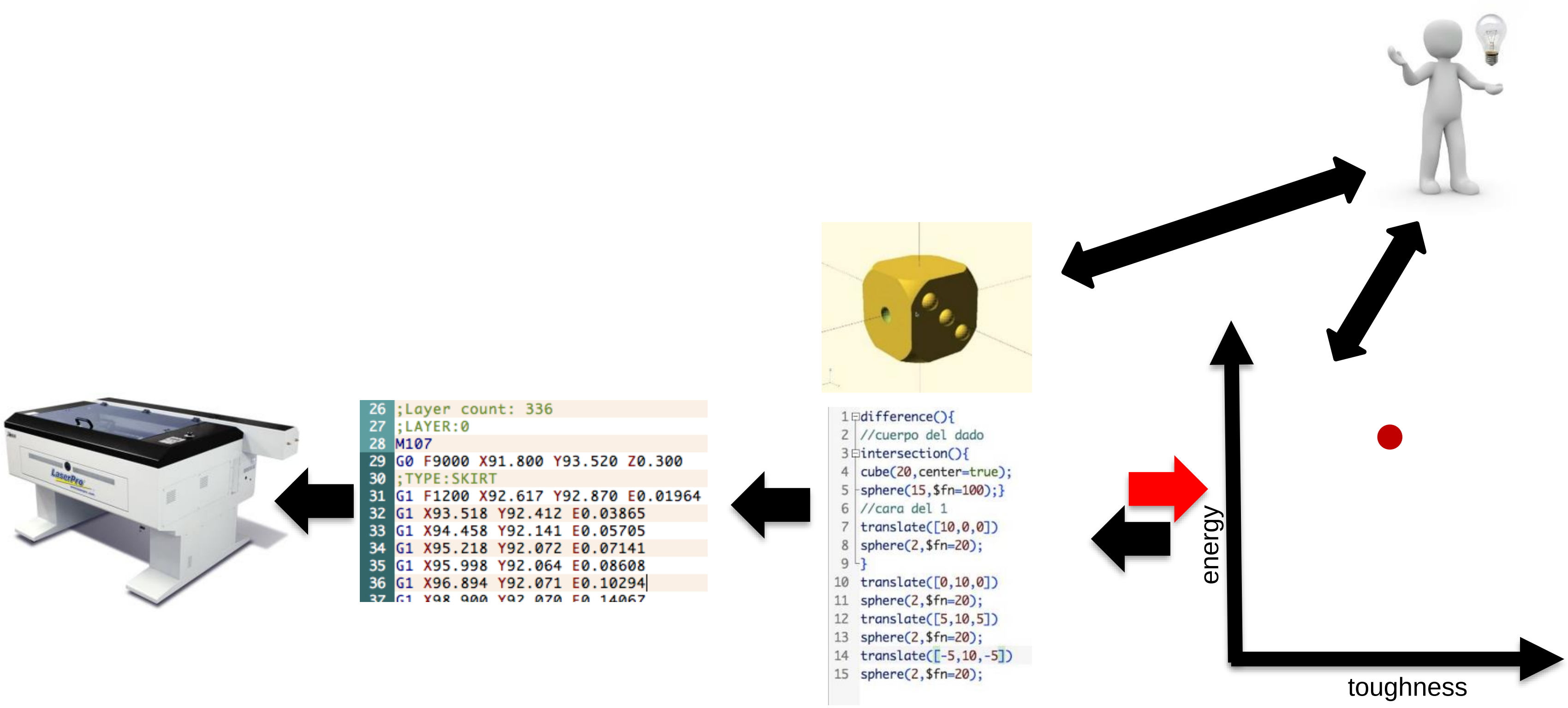


Source: Converting 3D Furniture Models to Fabricable Parts and Connectors, Lau et al., Siggraph 2011

Deformation Methods

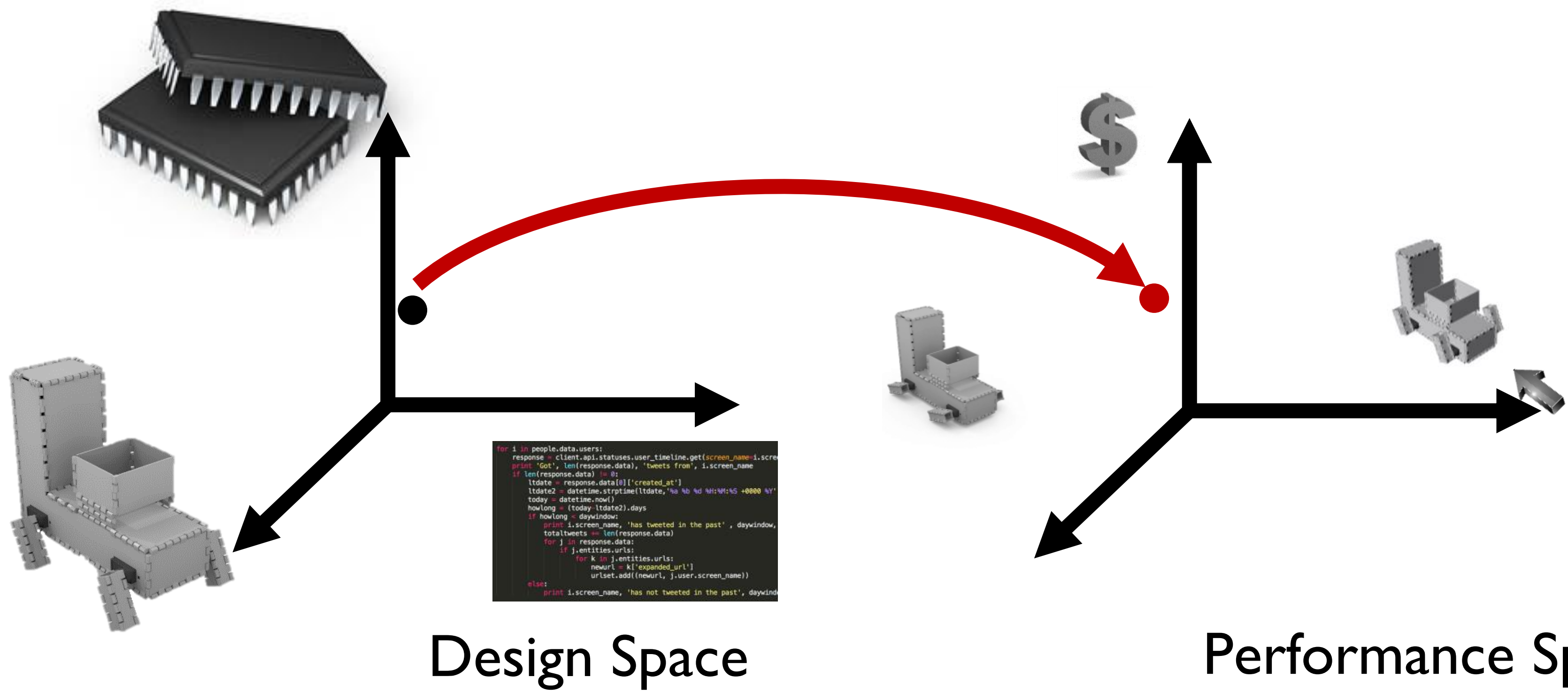


Computational Design Stack



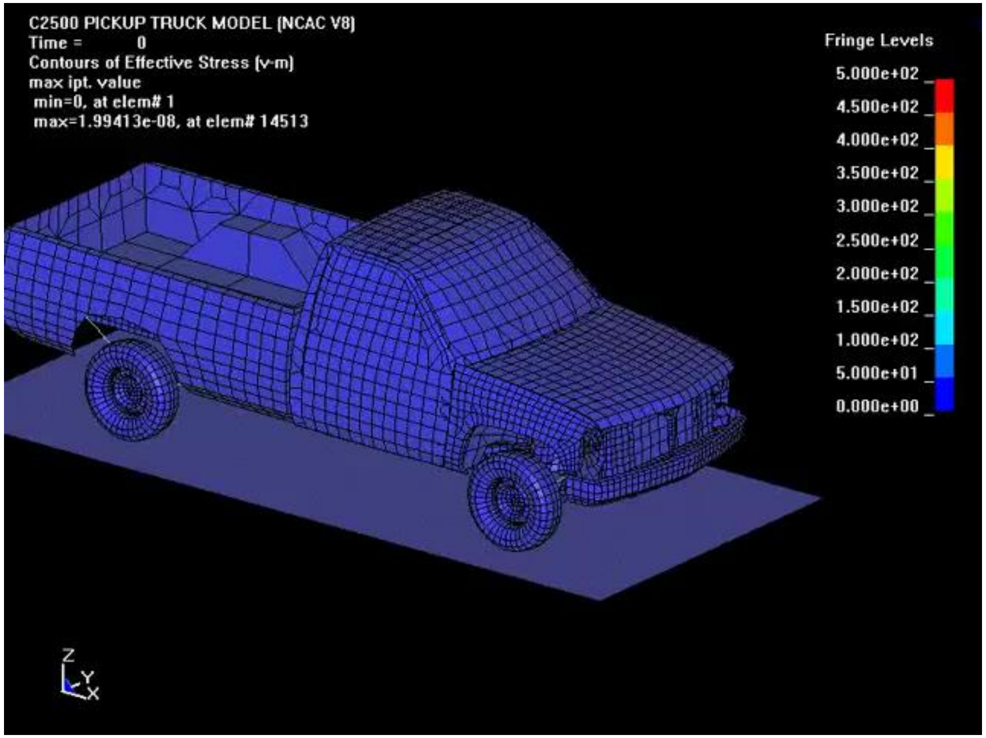
Hardware **Machine Code** **Design** **Performance**

Design Driven By Performance



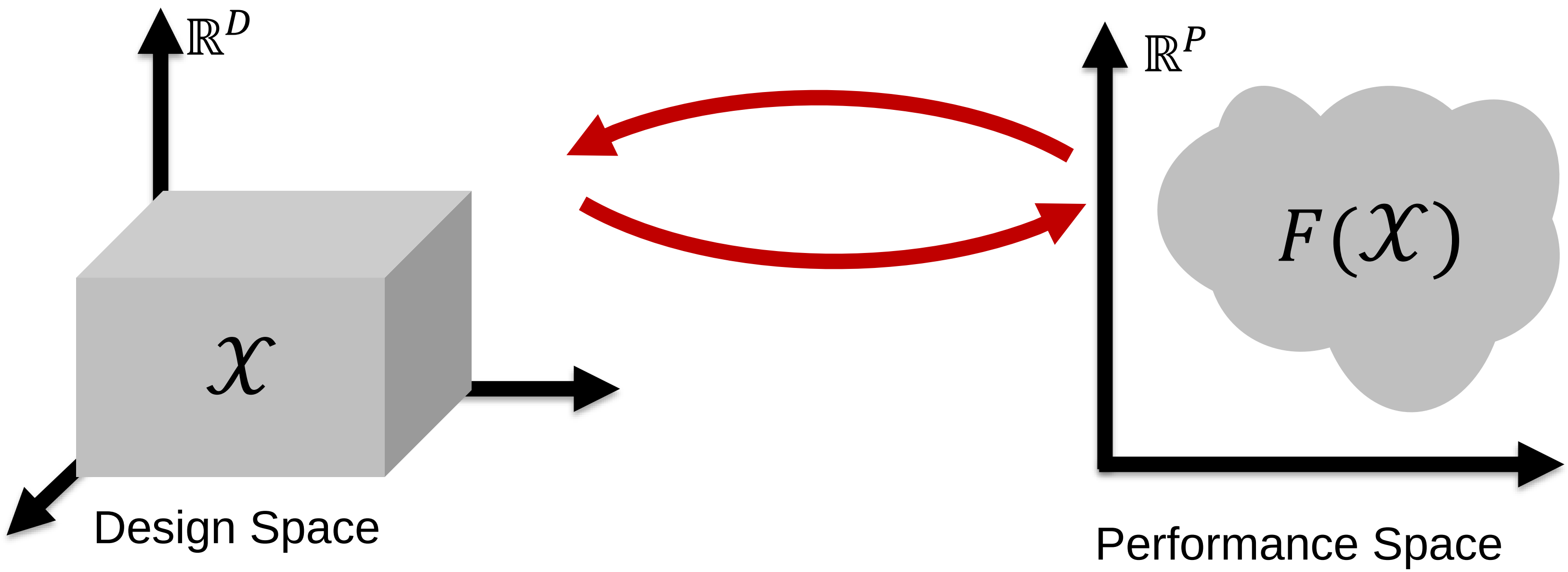
Simulation

- Mechanical
  - dynamic
  - static
- Acoustic
- Thermal
- Electromagnetic
- etc.



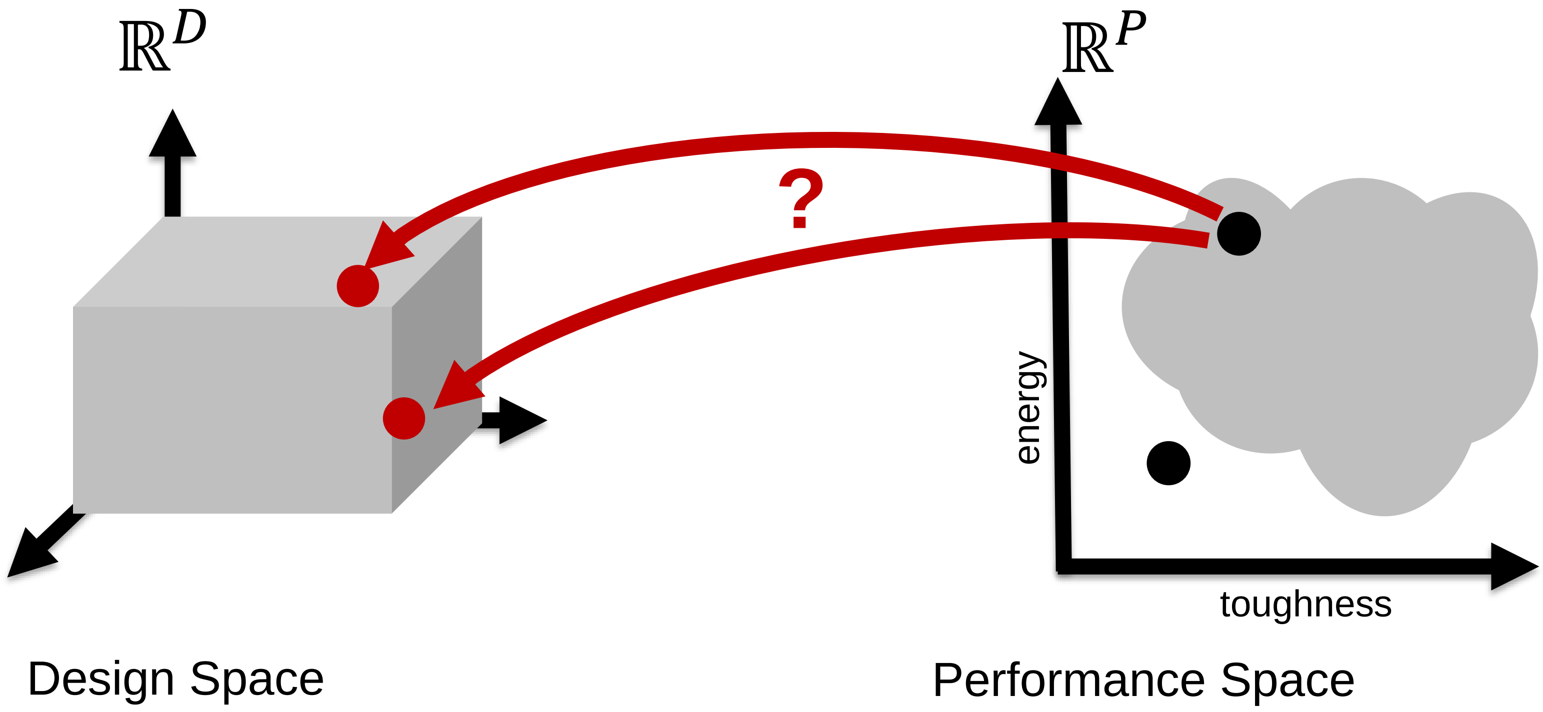
Performance Space Representations: Gamut

$F(\mathcal{X})$ = Gamut

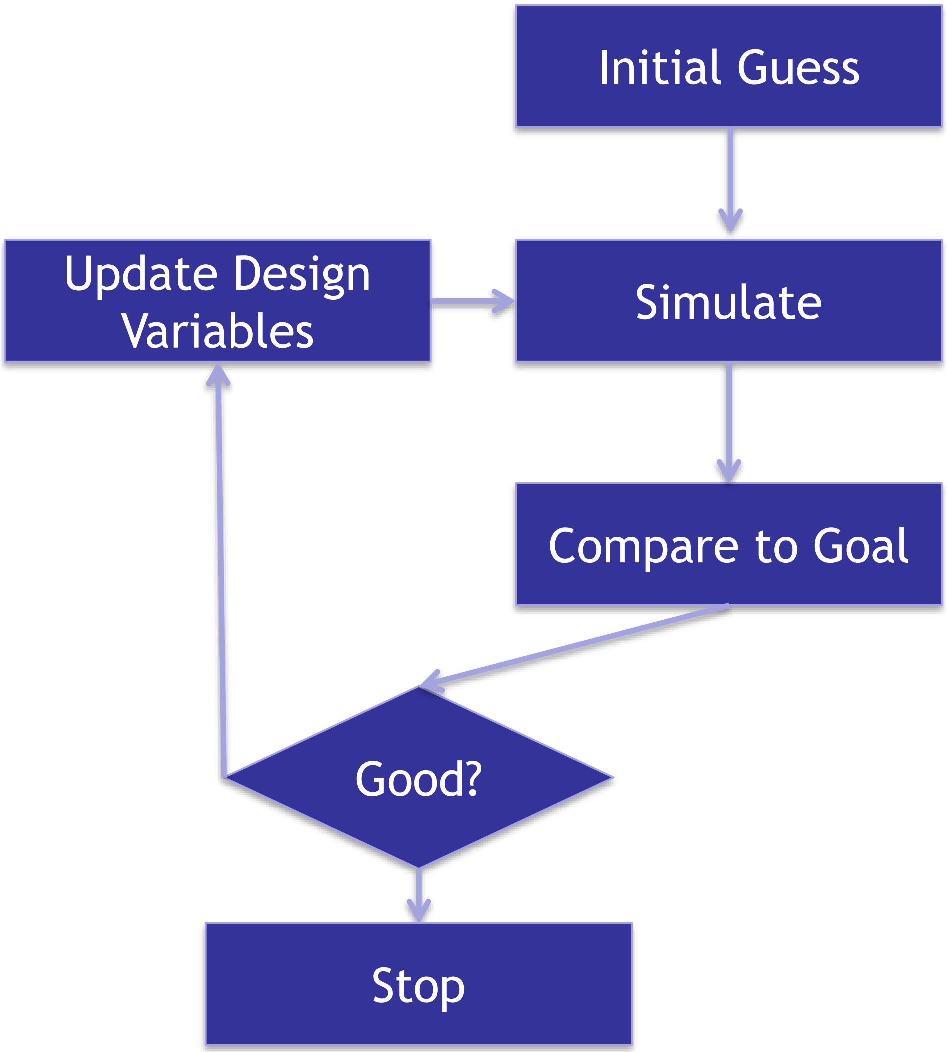


Inverse: From Performance Space to Design Space

- Inverse problem is much more difficult



From Performance Space to Design Space



Optimization in Reduced Space

Design target

fabrication

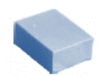
Rest shape

fabrication

Topology Optimization

Goals

base material



Initial layout

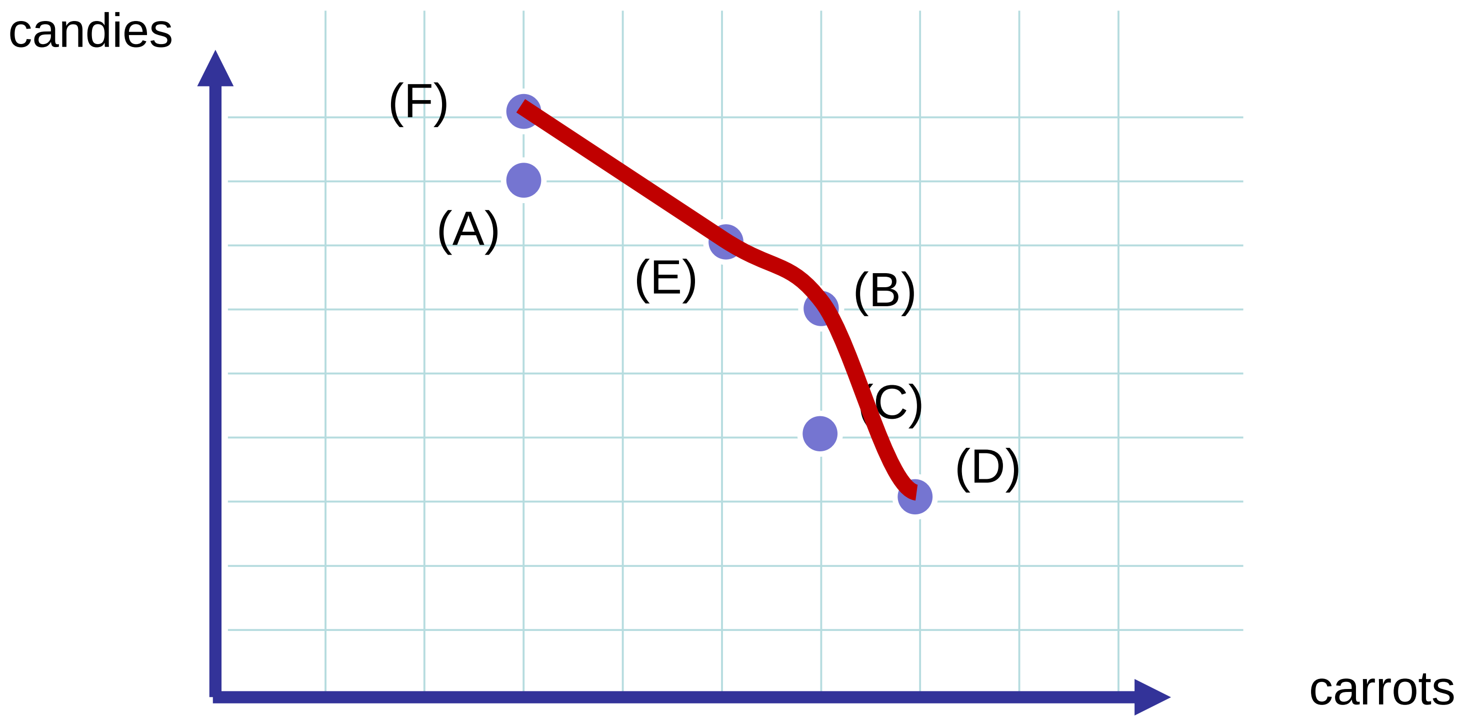
Boundary conditions

Load

Optimization

Structure that
meets the goals

Multi-Objective Optimization: Pareto Front



(A)

3 carrots
8 candies

(B)

6 carrots
6 candies

(C)

6 carrots
4 candies

(D)

7 carrots
3 candies

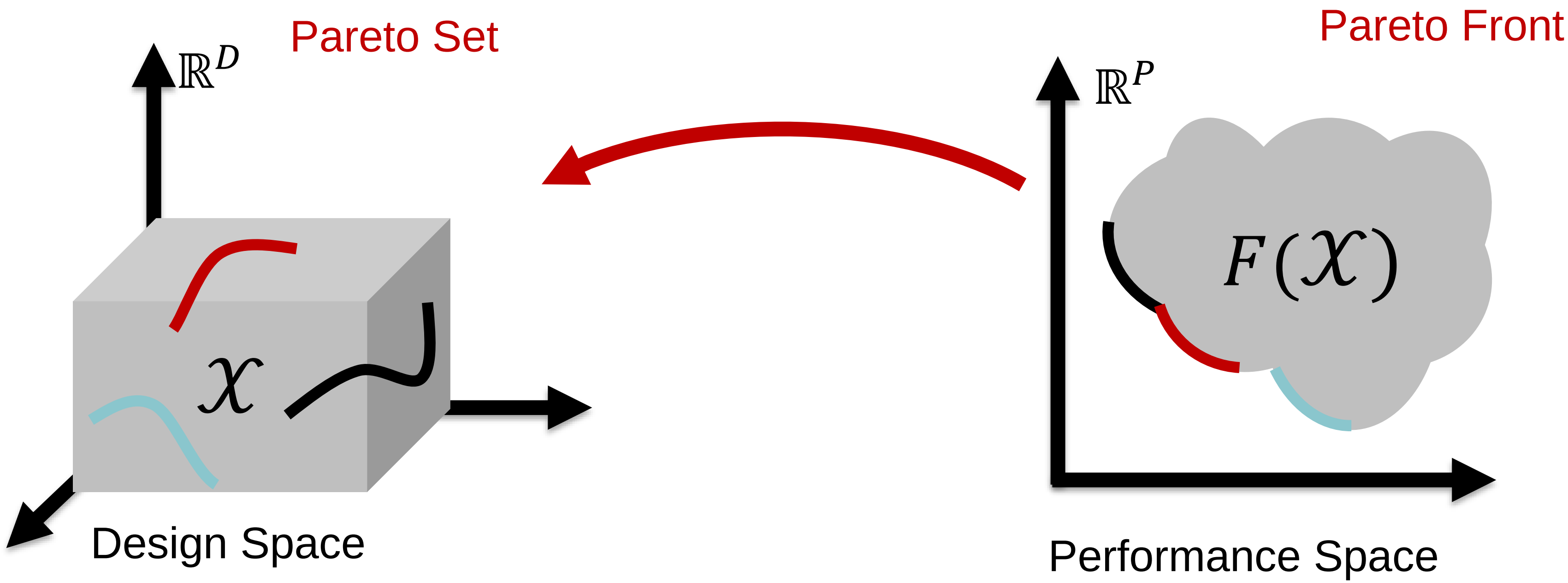
(E)

5 carrots
7 candies

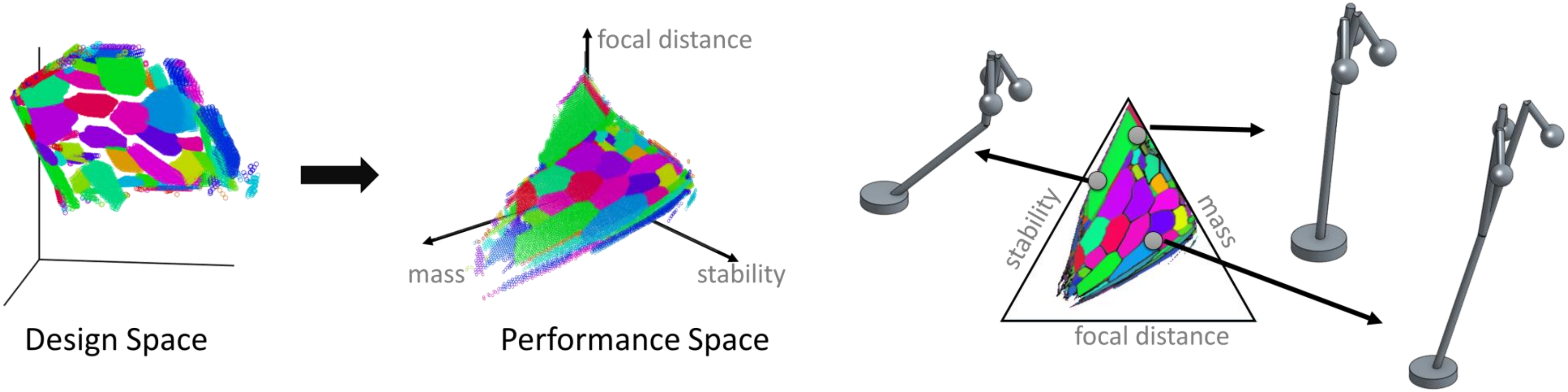
(F)

3 carrots
9 candies

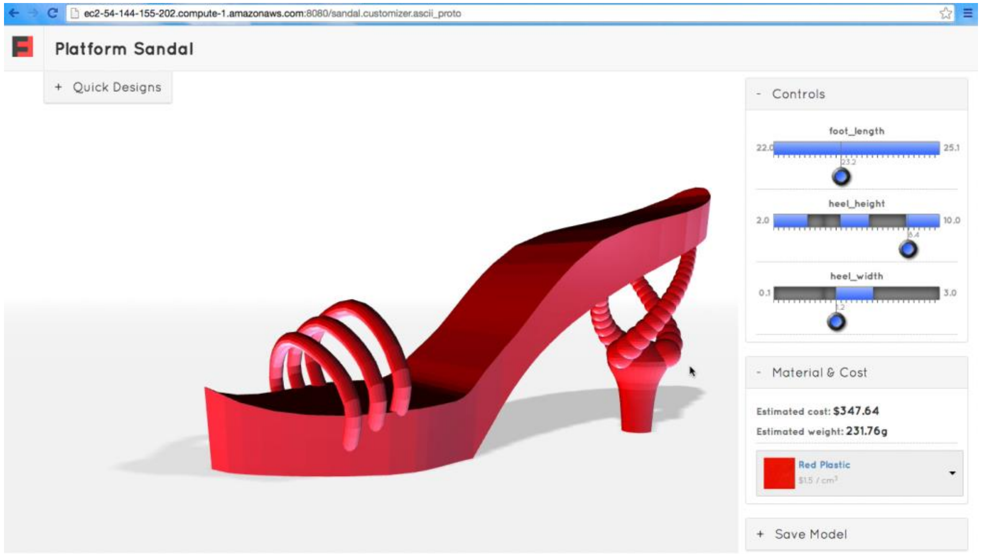
Multi-Objective Optimization: Pareto Front

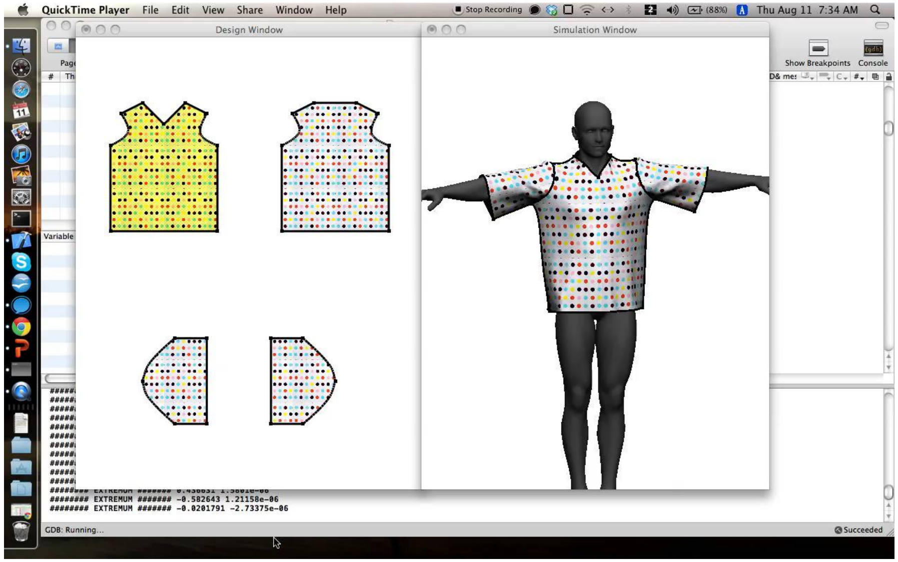


Pareto Front

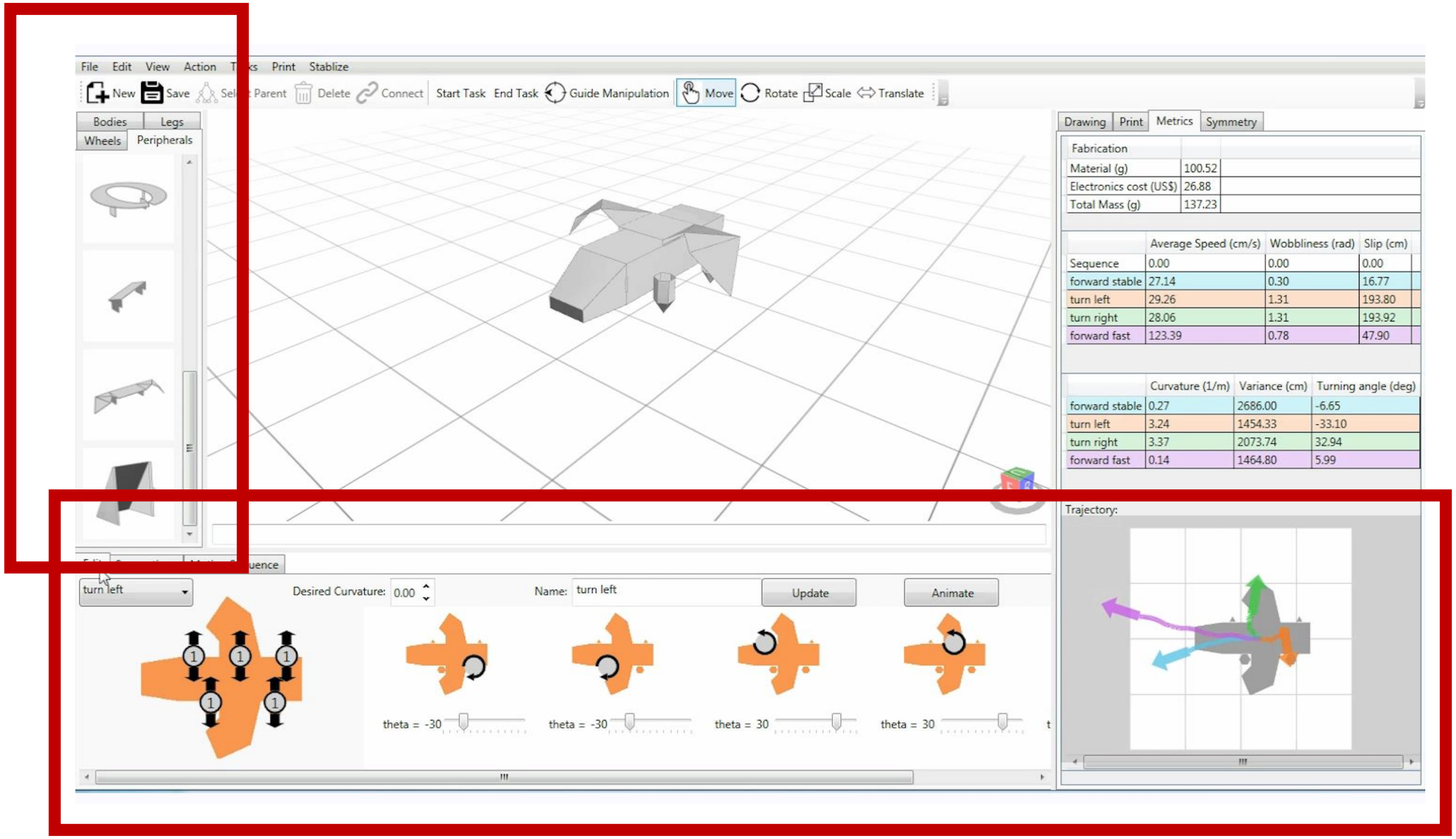


Speeding up Simulation

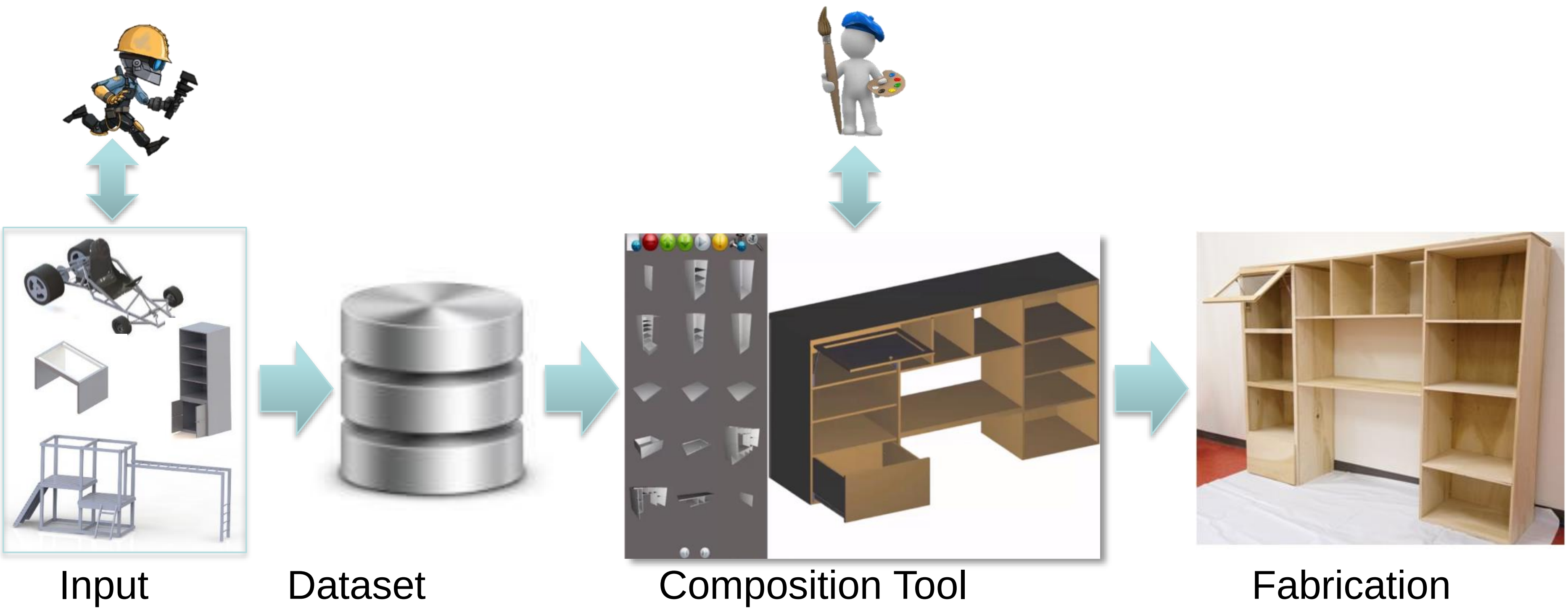




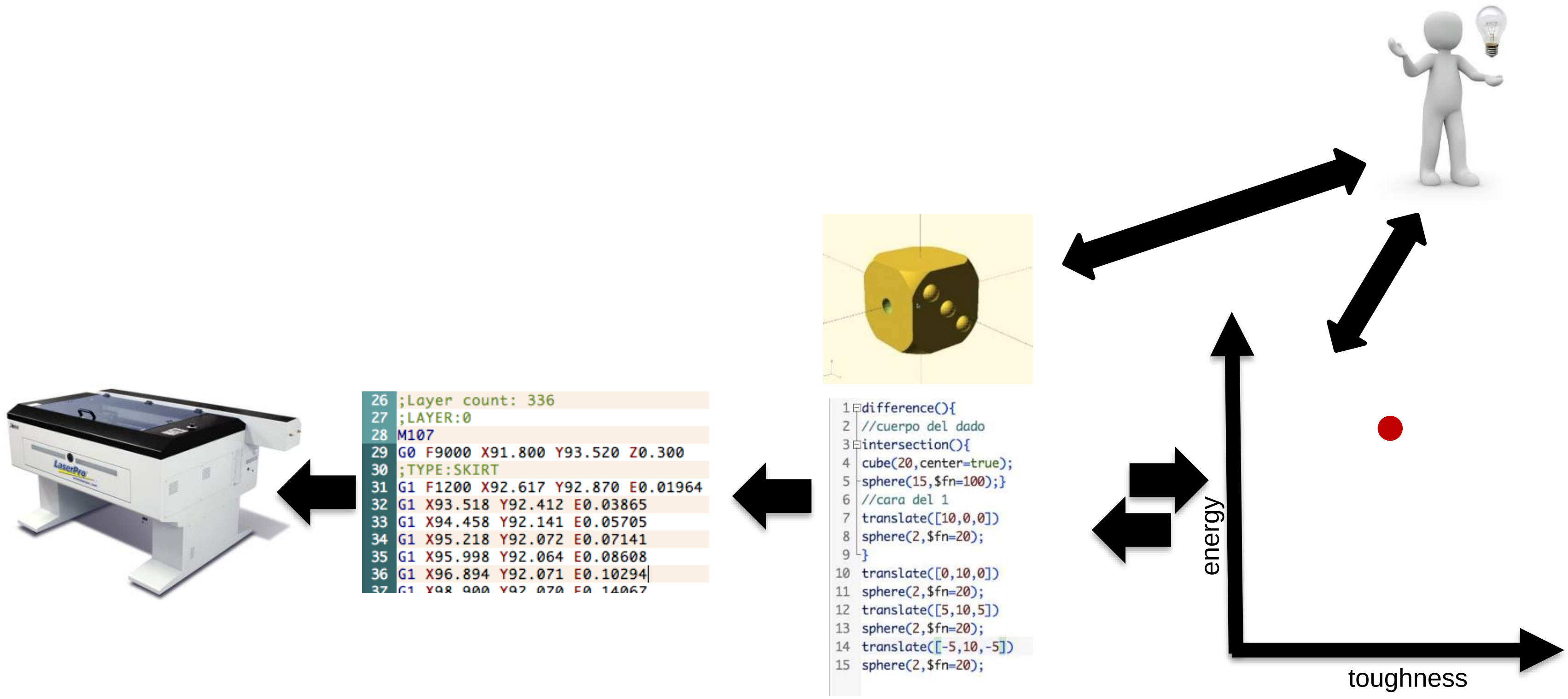
Expert Systems for Computational Design



Data-driven Systems for Computational Design



Computational Design Stack



Hardware **Machine Code** **Design** **Performance**