Creative Evolutionary Computation

Antonios Liapis
Institute of Digital Games
University of Malta
antonios.liapis@um.edu.mt
http://antoniosliapis.com
@SentientDesigns

Georgios N. Yannakakis
Institute of Digital Games
University of Malta
georgios.yannakakis@um.edu.mt
https://yannakakis.net
@yannakakis

GECCO '19 Companion, July 13–17, 2019, Prague, Czech Republic

ACM ISBN 978-1-4503-6748-6/19/07.
https://doi.org/10.1145/3319619.3323371

Who am I?

- Lecturer at the **Institute of Digital Games**, University of Malta.
- **Research** in procedural content generation, computer-aided game design, computational creativity.
- A. Editor of Transactions on Games
- General chair: FDG 2020, GALA 2019
- **Passion** for RPGs and board games.
- More at http://antoniosliapis.com/

Tutorial Outline

- Can computational processes be **creative**?
- **Who** should judge and **what** should be critiqued?
- How can EC **help** such computational processes?
- How can EC **benefit** from comp. creativity?

Table of contents

Introduction to Computational Creativity

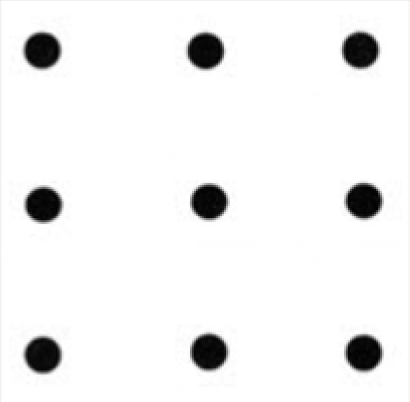
Human Creativity

- Ancient times: creativity treated as a quasi-mystical property, as an activity of the gods in us.
- Recent times: creativity everywhere.
  - **big-c creativity** (individualistic creativity of a genius)
  - **little-c creativity** (every-day, social creativity)
  - **historical creativity** (an idea that is new to the world)
  - **personal creativity** (an idea that is new to the person)

Plato. Ion. In E. Hamilton and H. Cairns, editors, Plato: The Collected Dialogues. Princeton University Press, 1961.
B. Jerey and A. Craft. The universalization of creativity. In A. Craft, B. Jerey, and M. Leibling, editors, Creativity in Education. 2001.
M. A. Boden. The creative mind: Myths and mechanisms. Routledge, 2003.

Creativity Theories

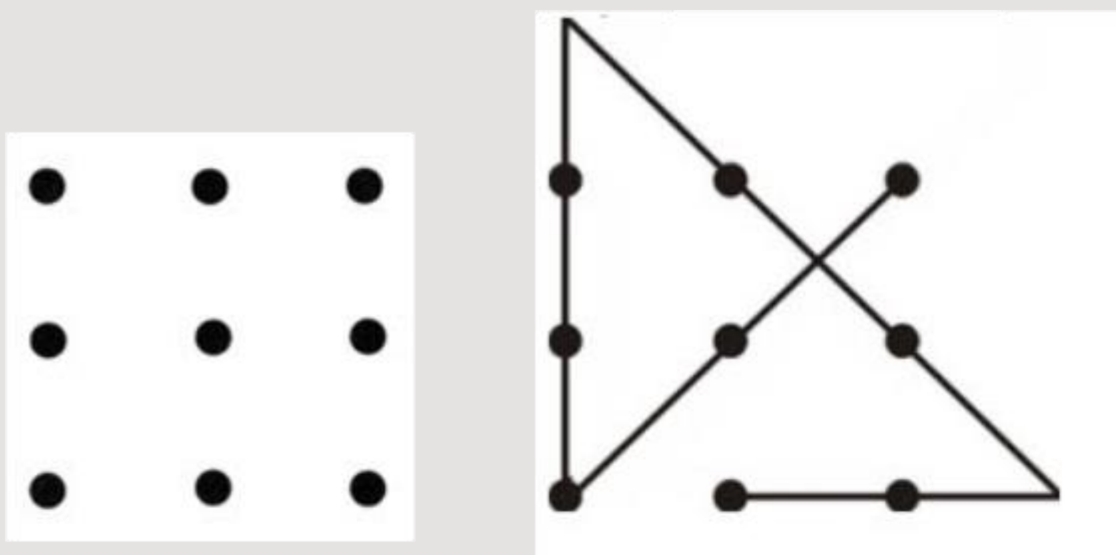
- **Lateral thinking** (thinking outside the box)



E. De Bono. Lateral thinking: Creativity step by step. Harper Collins, 2010.

Creativity Theories

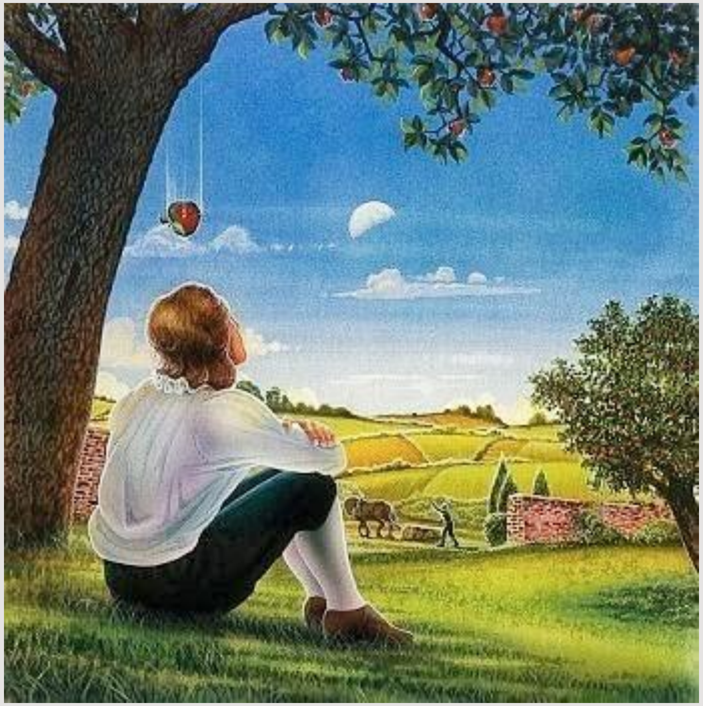
- **Lateral thinking** (thinking outside the box)



E. De Bono. Lateral thinking: Creativity step by step. Harper Collins, 2010.

Creativity Theories

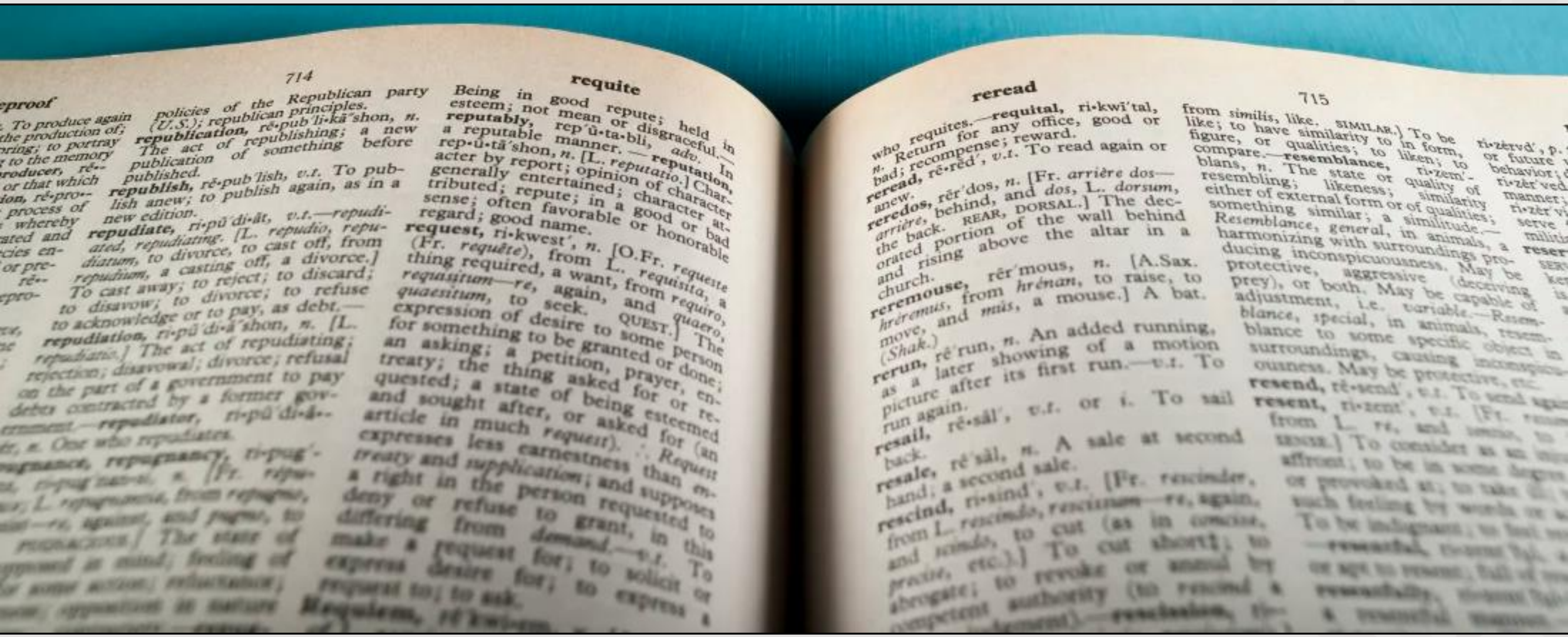
- Lateral thinking (thinking outside the box)
- **Frames:** a routine for tasks, a pattern of associations.
- **Intervention** that disrupts a frame, resulting in re-framing.



T. Scaltsas and C. Alexopoulos. Creating creativity through emotive thinking. In Proceedings of the World Congress of Philosophy, 2013.

Creativity Theories

- Lateral thinking (thinking outside the box)
- **Semantic reasoning** (understanding linguistic structures)



T. Scaltsas and C. Alexopoulos. Creating creativity through emotive thinking. In Proceedings of the World Congress of Philosophy, 2013.

Creativity Theories

- Lateral thinking (thinking outside the box)
- **Semantic lateral thinking**

Q: What kind of berry is a stream?
A: A current currant.

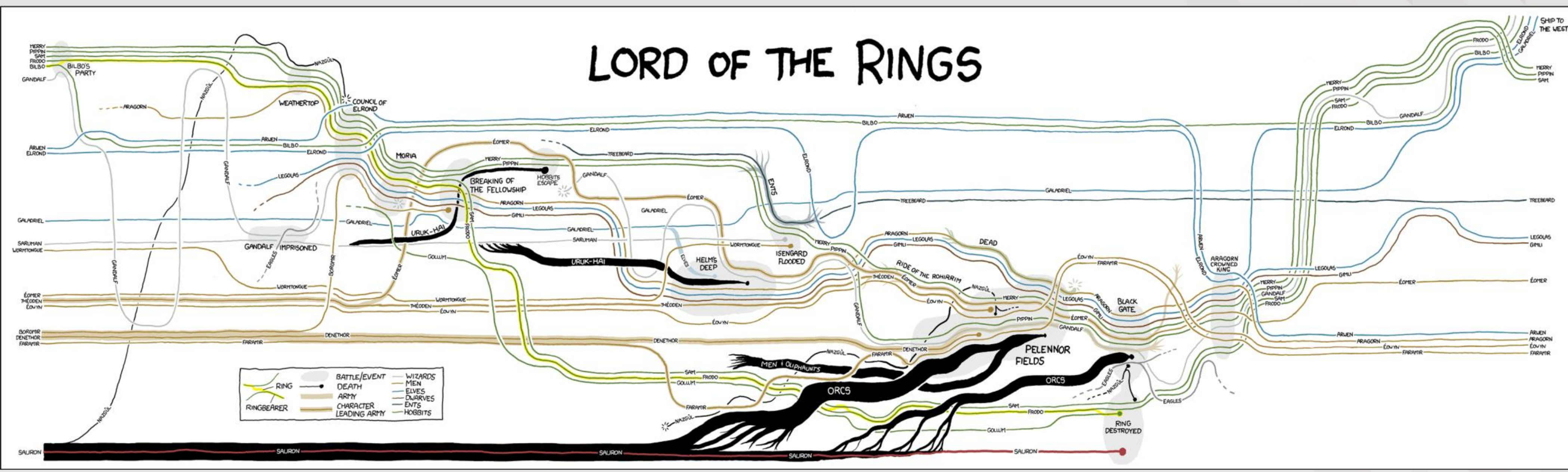
Q: How is an unmannered visitor different from a beneficial respite?
A: One is a rude guest, the other is a good rest.

Ritchie, G., Manurung, R., Pain, H., Waller, A., O'Mara,D. (2006). The STANDUP Interactive Riddle Builder. IEEE Intelligent Systems 21 (2), p. 67-69.

Veale, T., & Bell, N.E. (2016). The shape of tweets to come: Automating language play in social networks. Multiple Perspectives on Language Play.

Creativity Theories

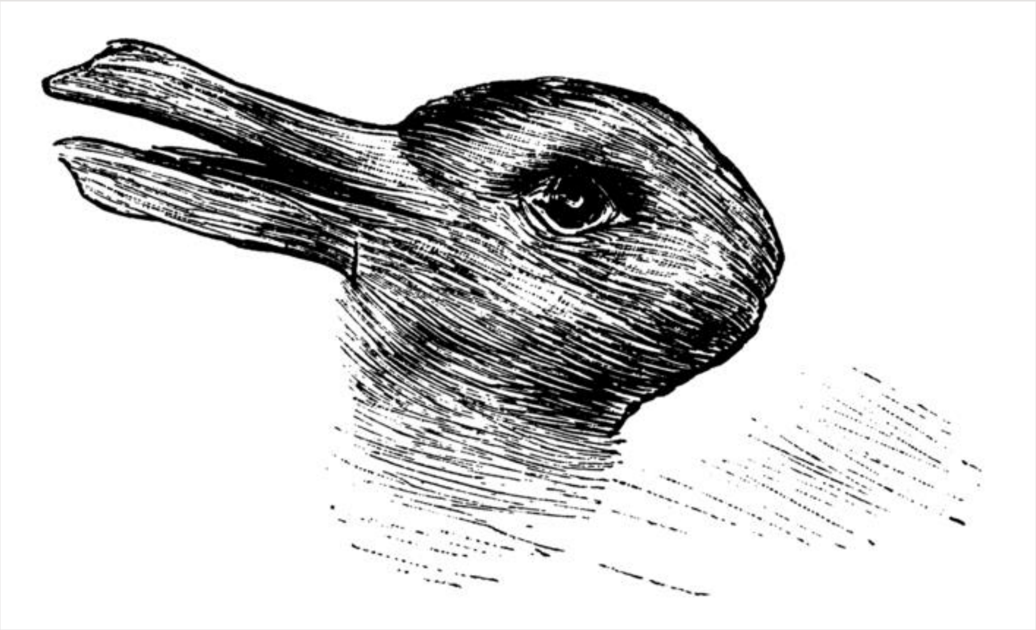
- Lateral thinking (thinking outside the box)
- Semantic lateral thinking
- **Diagrammatic reasoning** (understanding data via diagrams)



P. C.-H. Cheng, R. K. Lowe, and M. Scaife. Cognitive science approaches to understanding diagrammatic representations. Artificial Intelligence Review, 15(1-2):79{94, 2001.

Creativity Theories

- Lateral thinking (thinking outside the box)
- Semantic lateral thinking
- Diagrammatic **visual** and **analogical** lateral thinking.



G. N. Yannakakis, A. Liapis, and C. Alexopoulos. Mixed-initiative co-creativity.
In Proceedings of the 9th Conference on the Foundations of Digital Games, 2014.

Creativity Theories

- Lateral thinking (thinking outside the box)
- Semantic lateral thinking
- Diagrammatic visual and analogical lateral thinking.
- **Emotional** lateral thinking (theory of mind in creativity)

T. Scaltsas and C. Alexopoulos. Creating creativity through emotive thinking. In Proceedings of the World Congress of Philosophy, 2013.

Creativity Theories

- **Lateral thinking** (thinking outside the box)
- **Frames**: a routine for tasks, a pattern of associations.
- **Intervention** that disrupts a frame, resulting in re-framing.
- **Semantic**, **diagrammatic** and **emotional** lateral thinking

G. N. Yannakakis, A. Liapis, and C. Alexopoulos. Mixed-initiative co-creativity. In Proceedings of the 9th Conference on the Foundations of Digital Games, 2014.

What is Computational Creativity?

“Computational Creativity is the art, science, philosophy and engineering of computational systems which, by taking on particular responsibilities, exhibit behaviors that unbiased observers would deem to be creative.”

The Journal of Computational Creativity https://jcc.computationalcreativity.net/

CC Questions

- Which **processes** can be deemed creative?
- Which **output** can be deemed creative?
- Which **domain** can be deemed creative?

CC processes

Combinatorial Creativity:
Pre-fabricated building blocks,
combined together in unexpected ways

M.A. Boden “The Creative Mind: Myths and Mechanisms” Routledge (2003)

CC processes

Exploratory Creativity:
Searching a pre-defined conceptual space for the best/most creative solution

M.A. Boden "The Creative Mind: Myths and Mechanisms" Routledge (2003)

CC processes

Transformational Creativity:
Searching in a conceptual space which changes, and new combinations are possible

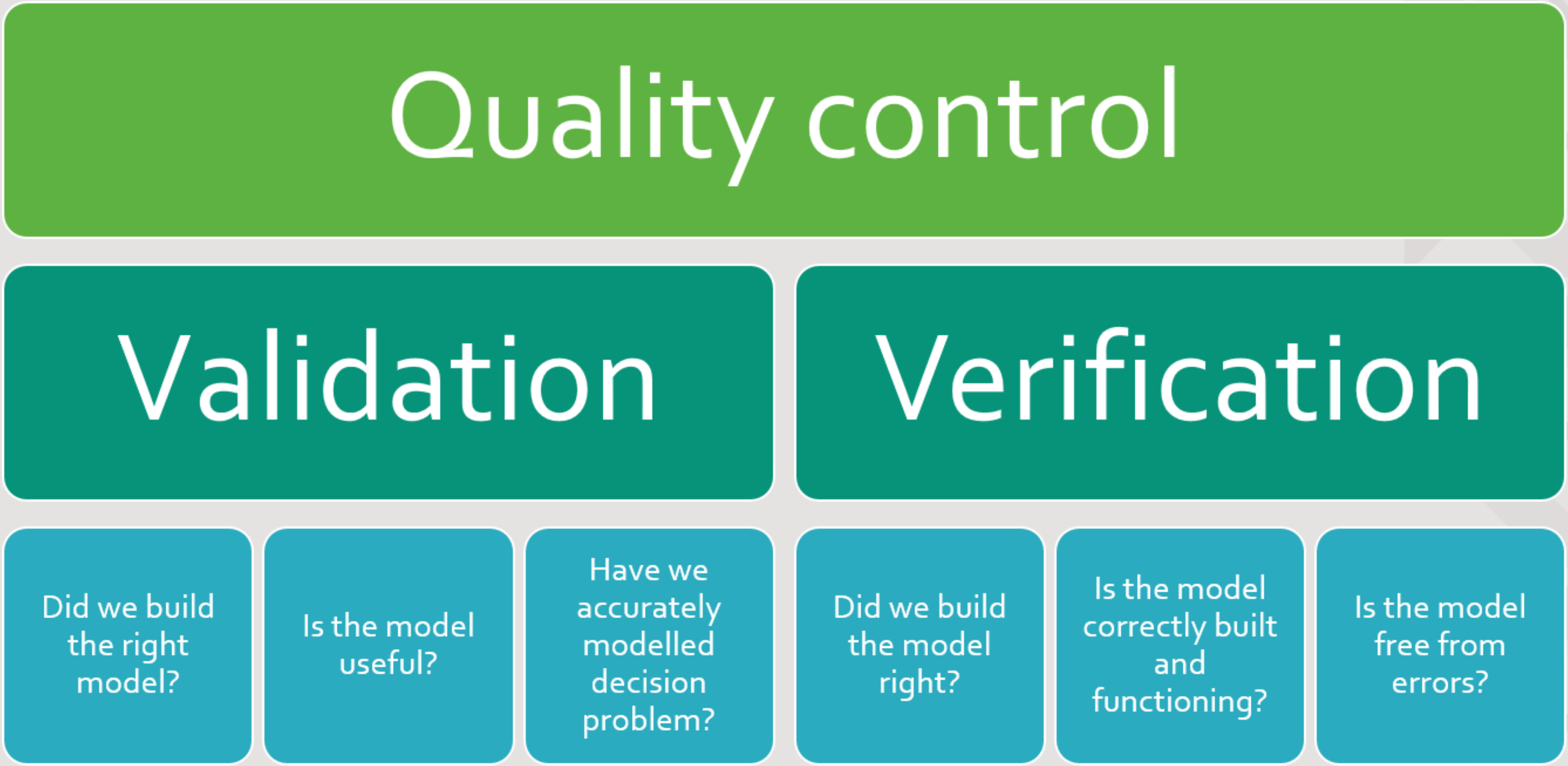
M.A. Boden “The Creative Mind: Myths and Mechanisms” Routledge (2003)

CC Processes

- Combinatorial creativity
- Exploratory creativity
- Transformational Creativity

CC outcomes

- **Quality:** To what extent is the produced item a high quality example of its genre?



G. Ritchie: "Some empirical criteria for attributing creativity to a computer program". Minds and Machines 17:76–99. 2007

Image from https://quantifyresearch.com/2018/03/28/two-vs-model-quality-control-validation-verification/

CC outcomes

- **Novelty:** To what extent is the produced item dissimilar to existing examples of its genre?

G. Ritchie: "Some empirical criteria for attributing creativity to a computer program". Minds and Machines 17:76–99. 2007

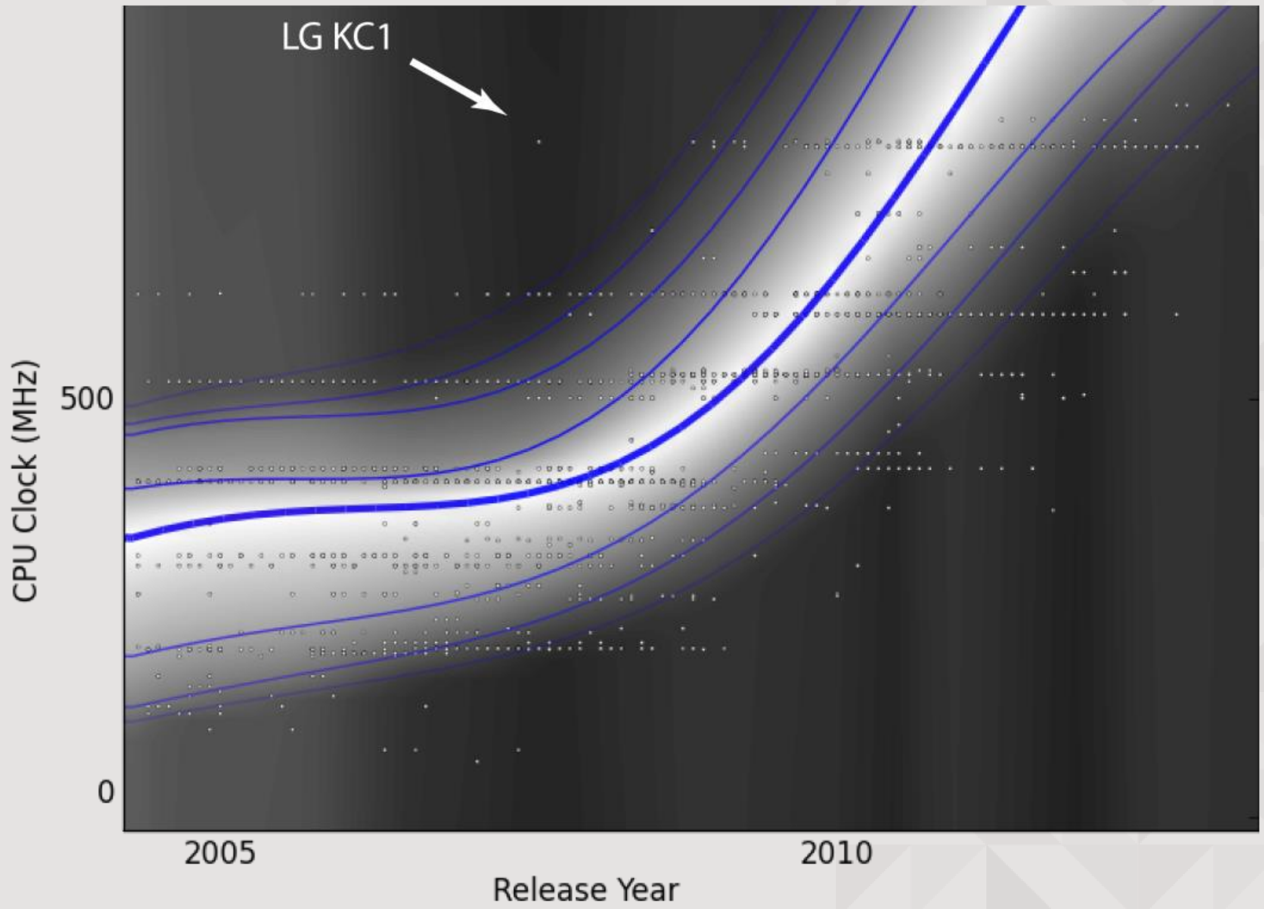
CC outcomes

- **Typicality:** To what extent is the produced item an example of the artefact class in question?

G. Ritchie: “Some empirical criteria for attributing creativity to a computer program”. Minds and Machines 17:76–99. 2007

CC outcomes

- **Surprise:** To what extent is the produced item violating expectations in the trends of both actual and possible designs?



K. Grace and M. Lou Maher : "What to expect when you're expecting: The role of unexpectedness in computationally evaluating creativity". Proceedings of the ICCC, 2014.

CC outcomes

- Value
- Novelty
- Typicality
- Surprise

CC domain

- There is some (usually culturally-defined) class of artefacts which the program is to generate.
- The class is extremely large, possibly infinite.
- Given an item, there may not be a precise definition of whether it is in that class.
- Given an item, humans can rate the (usually subjective) ‘quality’ of the item.

G. Ritchie: “Some empirical criteria for attributing creativity to a computer program”. Minds and Machines 17:76–99. 2007

Artificial Evolution for Computational Creativity

Why is evolution ideal for CC?

Creative Process	**EC**
• Combinatorial Creativity	✓
• Exploratory Creativity	✓ ✓ ✓ ✓ ✓
• Transformational Creativity	✓

Algorithms for CC

Creative Output	**EC**
• Value	✓ ✓ ✓ ✓
• Novelty	✓ ✓
• Typicality	✓
• Surprise	✓

Algorithms for CC

- Divergent Search
- Quality-Diversity
- Constrained Optimization

Divergent Search Algorithms

Divergent Search

- Premise: ignore the **objective** of the problem
  - The fitness landscape may be deceptive
  - The objective function may be ill-formulated
  - “Quality” may be subjective/intractable
- Goal: reward **behavioral** diversity

D. E. Goldberg, “Simple genetic algorithms and the minimal deceptive problem,” in Genetic Algorithms and Simulated Annealing, Research Notes in Artificial Intelligence. Morgan Kaufmann, 1987.

Novelty Search

- Rewards behavioral diversity
- Average distance to nearest neighbors
  - Neighbors in current population & novelty archive

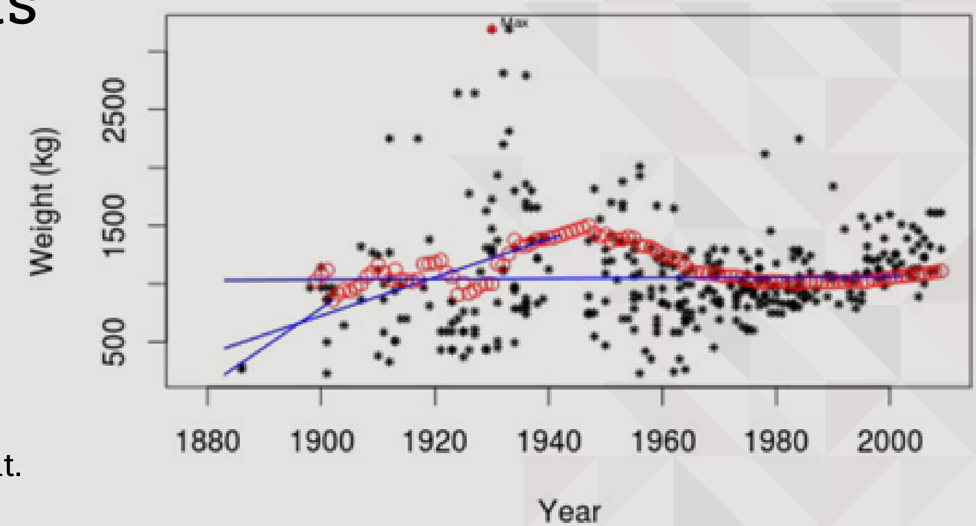
$$\rho(i) = \frac{1}{k} \sum_{j=1}^{k} d(i, \mu_j)$$

- **Novelty archive:** implicit memory
- Distance: based on behavior, not genotype

J. Lehman and K. O. Stanley, “Abandoning objectives: Evolution through the search for novelty alone, ” Evolutionary computation, vol. 19, no. 2,2011.

Surprise

- Theories of surprise
  - curiosity: unexpected stimuli that a predictor can learn (not random, not predictable)
  - regression analysis on temporal dimension to predict the "next" value of the attributes in designs.
  - probabilistic model based on frequencies of objects/events in agent's memory.

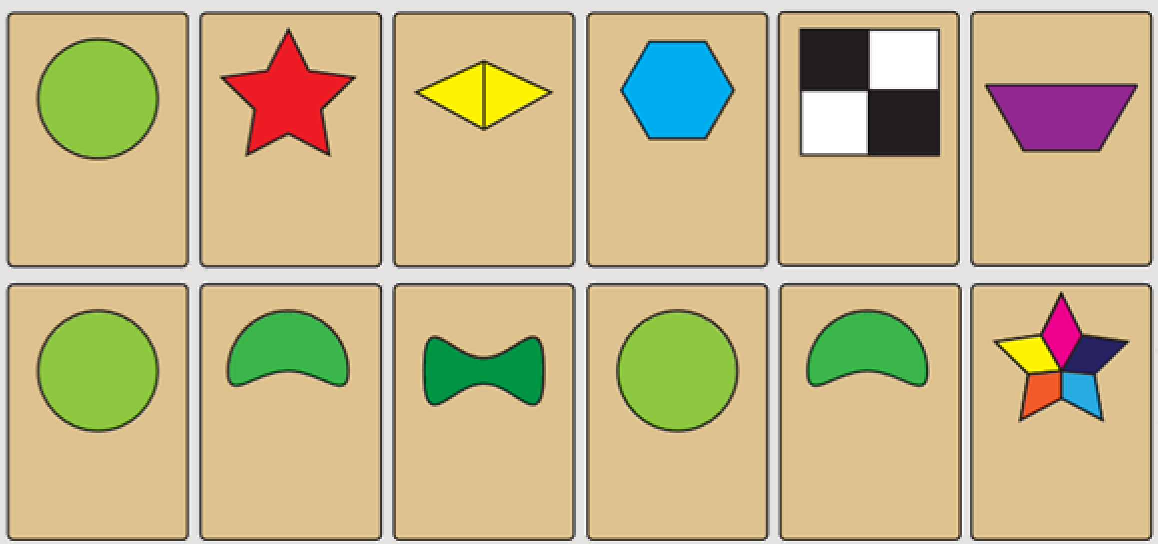


J. Storck, S. Hochreiter, and J. Schmidhuber. Reinforcement-driven information acquisition in non-deterministic environments. In Proc. ICANN'95, vol. 2, pages 159-164. EC2 & CIE, Paris, 1995.
M.L. Maher, D. Fisher, K. Brady: Computational models of surprise in evaluating creative design. Proceedings of the fourth international conference on computational creativity. 2013
L. Macedo and A. Cardoso. Modeling forms of surprise in an artificial agent. In Proc. of the annual Conference of the Cognitive Science Society, 2001.

Surprise

- Differences between Surprise and Novelty:
  - **Novelty**: diverge from **past seen** behaviors
  - **Surprise**: diverge from **expected future** behaviors

High Novelty



High Surprise

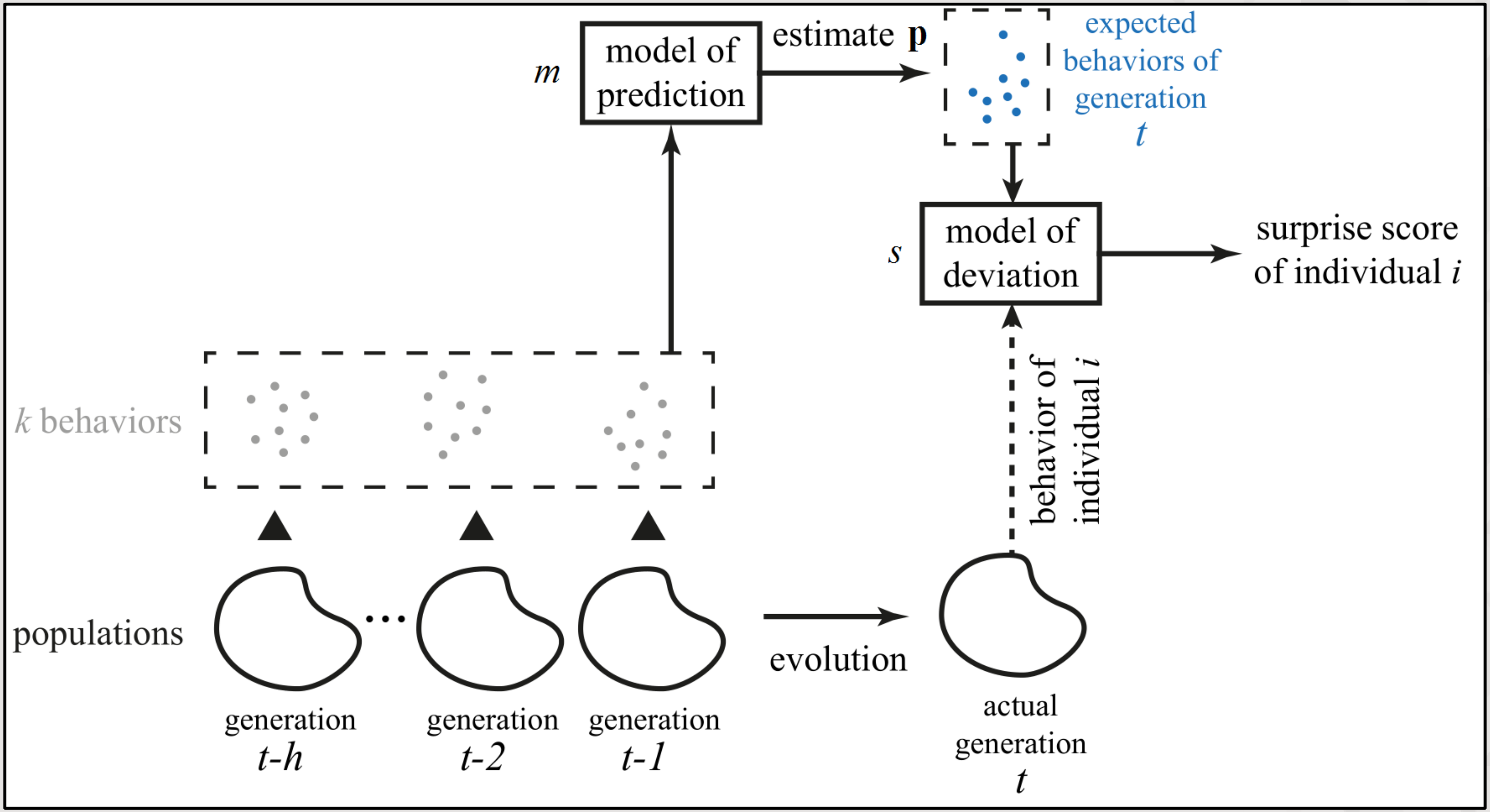
G. N. Yannakakis, A. Liapis: Searching for Surprise, in Proceedings of the International Conference on Computational Creativity. 2016.

Surprise Search

- Reward individuals which exhibit behaviors which diverge from the **expected behaviors** of the current population based on **prior observed behaviors**.
- Two-step process:
  - Predictive model $$\mathbf{p} = m(h, k)$$
  - Divergence model $$s(i) = \frac{1}{n} \sum_{j=0}^{n} d_s(i, p_{i,j})$$

D. Gravina, A. Liapis and G.N. Yannakakis: "Surprise Search: Beyond Objectives and Novelty," in Proceedings of the Genetic and Evolutionary Computation Conference. ACM, 2016.

Surprise Search



http://autogamedesign.eu/?page_id=200

Novelty+Surprise Search

- Optimizing both the novelty score and the surprise score:
  - **NSS:** Linear combination as weighted sum

$$ns(i) = \lambda \cdot n(i) + (1 - \lambda) \cdot s(i)$$

  - **NS-SS:** Two objectives for multi-objective optimization with NSGA-II

D. Gravina, A. Liapis and G. N. Yannakakis: Coupling Novelty and Surprise for Evolutionary Divergence, In Proceedings of the Genetic and Evolutionary Computation Conference, 2017.
D. Gravina, A. Liapis and G. N. Yannakakis: Fusing Novelty and Surprise for Evolving Robot Morphologies, in Proceedings of the Genetic and Evolutionary Computation Conference, 2018.

Quality-Diversity Algorithms

Quality-Diversity

- Premise: a strong convergent force can hide promising areas of the search space.
- Goal: uncover as **many diverse behavioral niches** as possible, but where each niche is represented by a **candidate of the highest possible quality for that niche**.

J.K. Pugh, L.B. Soros, K.O. Stanley. Quality Diversity: A New Frontier for Evolutionary Computation. Frontiers in Robotics and AI (12). 2016.

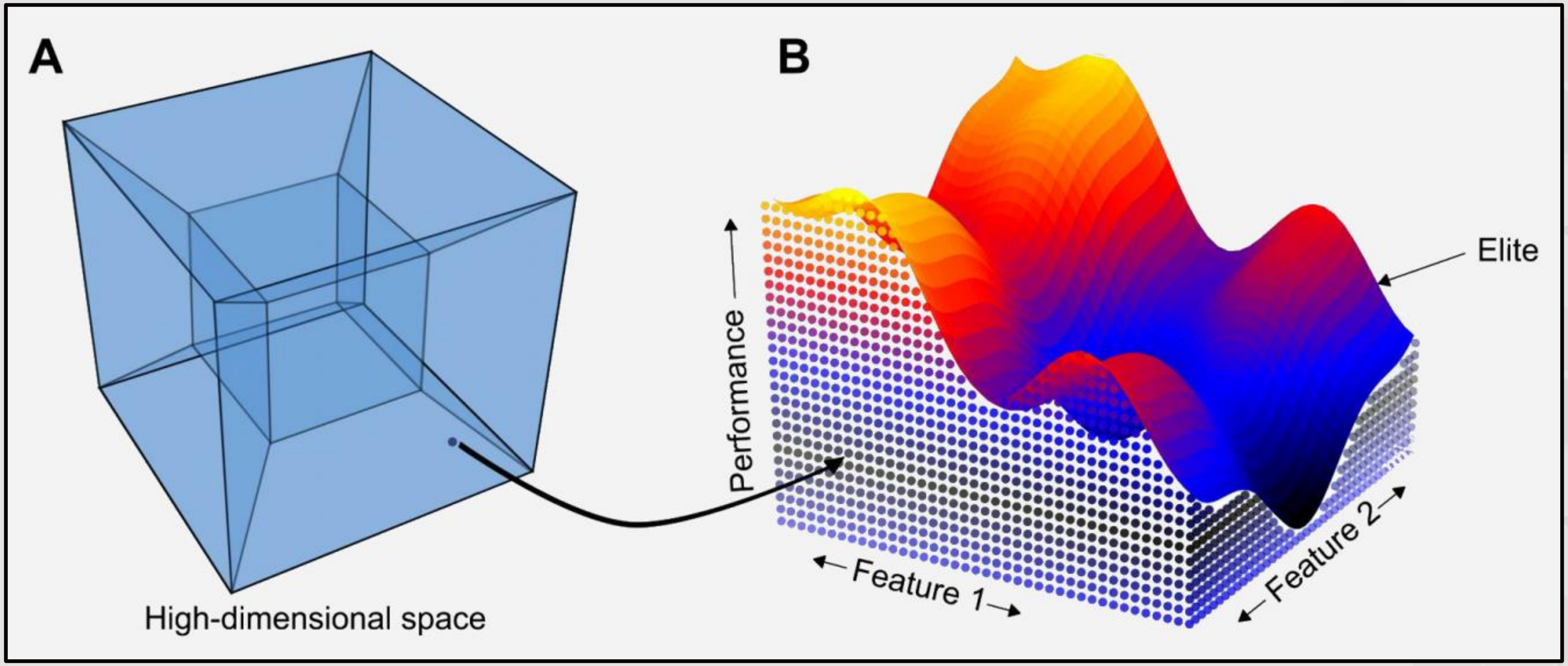
Novelty Search-Local Competition

- Multi-objective optimization (via NSGA-II) of two objectives:
  - **Novelty score** (see novelty search)
  - **Local competition score:** how many of its nearest neighbors in the behavioral space it outperforms.

Lehman, J., and Stanley, K. O. (2011). Evolving a diversity of virtual creatures through novelty search and local competition, in Proceedings of the 13th Annual Conference on Genetic and Evolutionary Computation (GECCO '11), Dublin (New York, NY: ACM), 211–218.

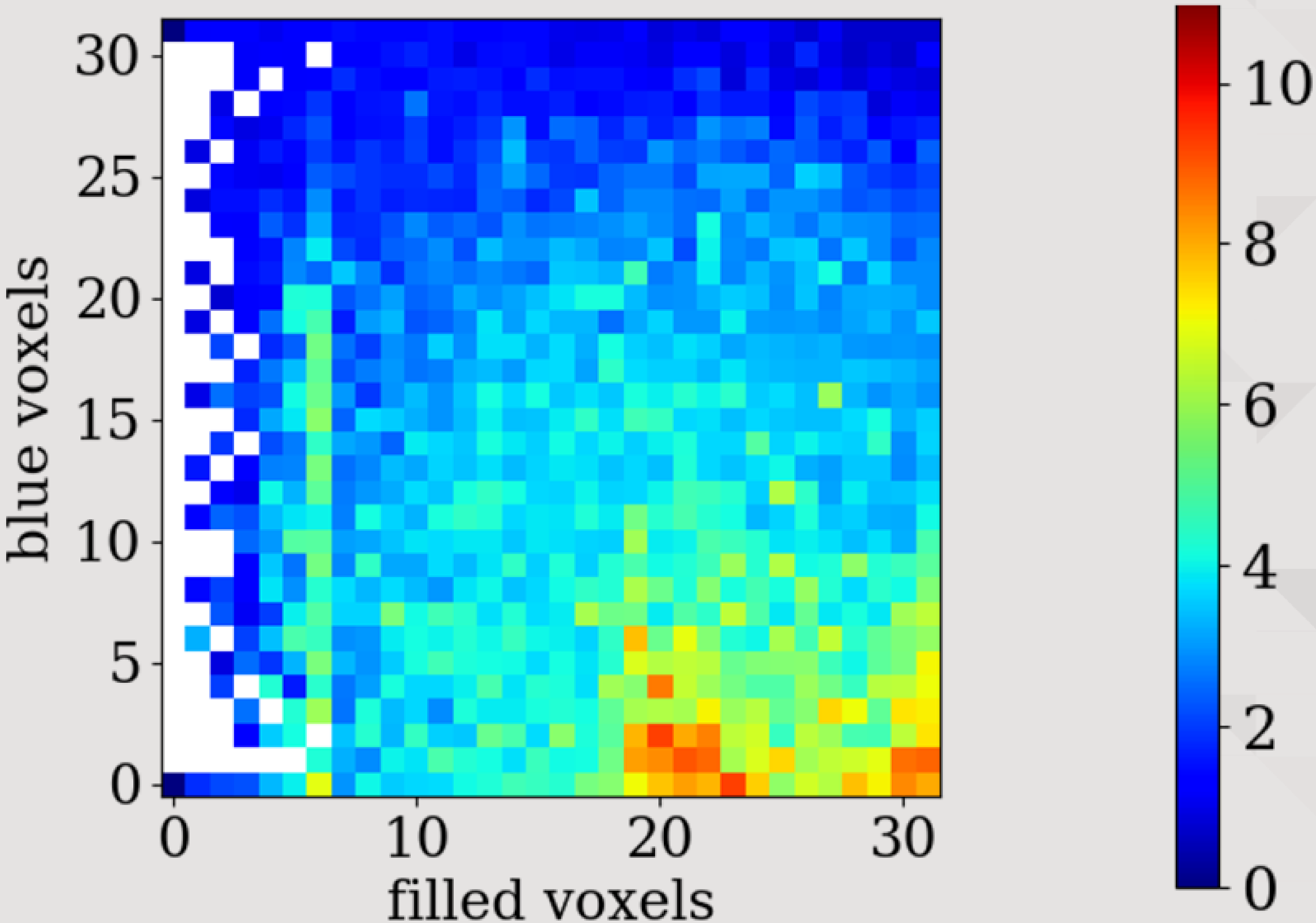
MAP-Elites

- **Partition** a **feature map** of behavioral features
- Store the fittest individual in each cell
- Select parents stochastically from the map



Mouret, J.-B., and Clune, J. (2015). Illuminating search spaces by mapping elites. arXiv preprint arXiv:1504.04909.

MAP-Elites

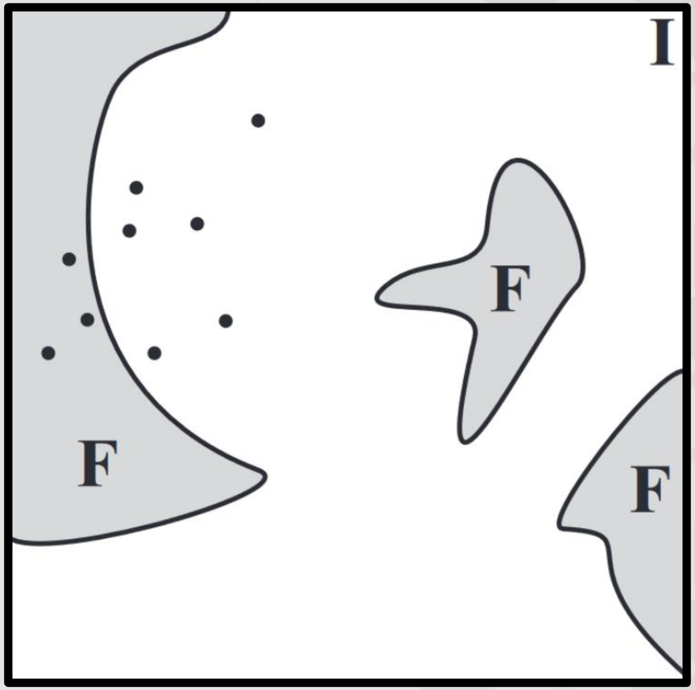


D. Gravina, A. Liapis and G. N. Yannakakis: "Blending Notions of Diversity for MAP-Elites," In Proceedings of the Genetic and Evolutionary Computation Conference, 2017.

Constrained Optimization Algorithms*

Constrained Optimization

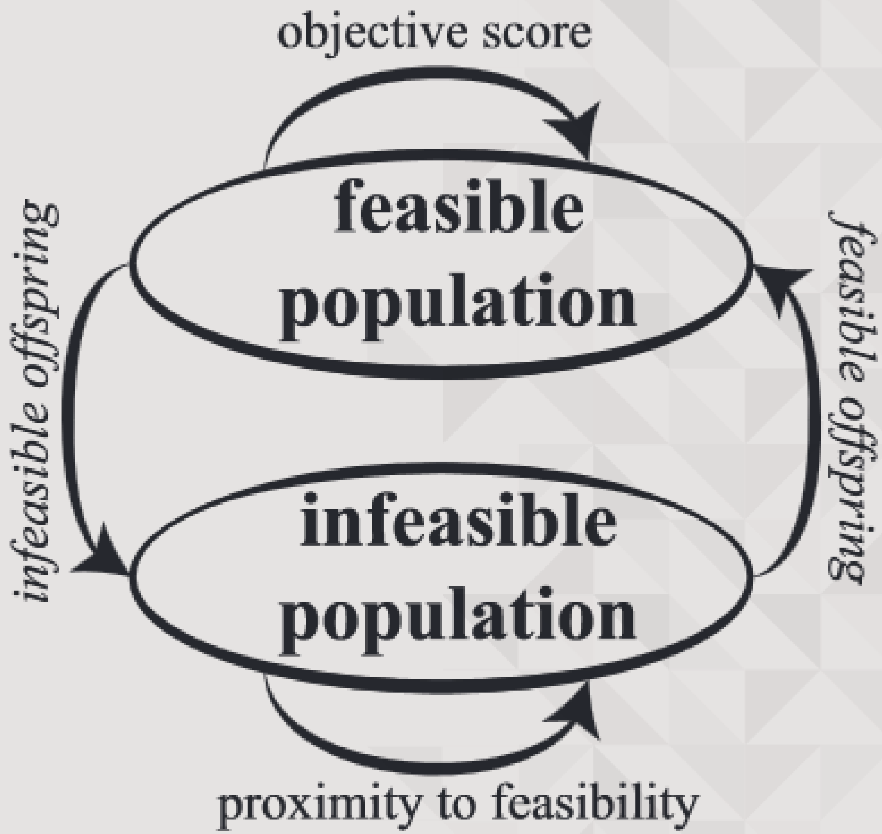
- Premise: hard constraints can split the search space into **islands of feasible solutions among infeasible solutions**
- Solutions:
  - Death penalty
  - Fitness penalty
  - Multi-objective approaches



C.A Coello Coello. A survey of constraint handling techniques used with evolutionary algorithms. 1999
Michalewicz, Z.Do not kill unfeasible individuals. In Proceedings of the Fourth Intelligent Information Systems Workshop. 1995

Constrained Optimization

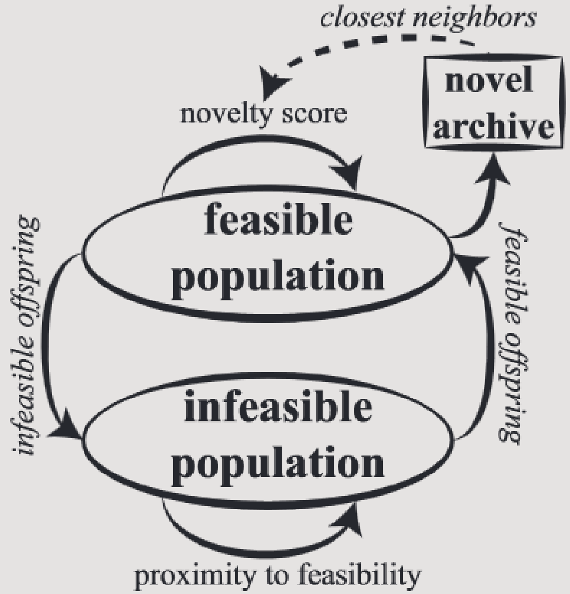
- FI-2pop GA:
  - Feasible pop.: domain-dependent fitness
  - Infeasible pop.: minimize distance to feasibility
  - Indirect form of interbreeding
  - Boost feasible offspring*

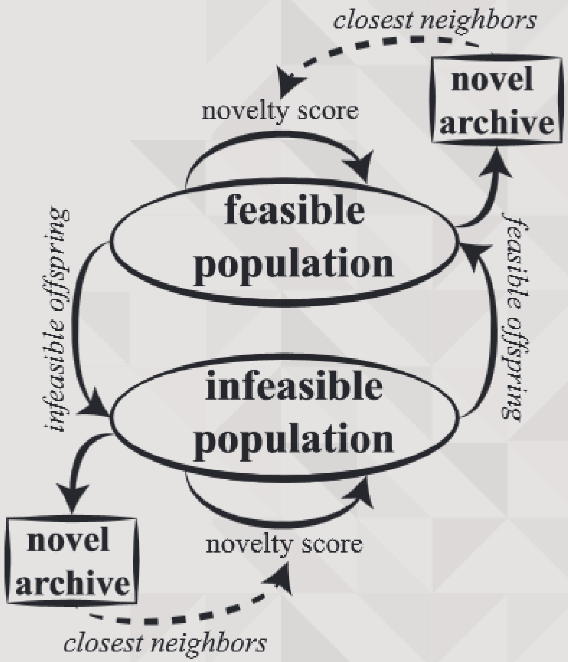


Kimbrough, S.O., Koehler, G.J., Lu, M., Wood, D.H.: On a feasible-infeasible two-population (FI-2Pop) genetic algorithm for constrained optimization: Distance tracing and no free lunch. European Journal of Operational Research 190(2). 2008

Constrained Novelty Search

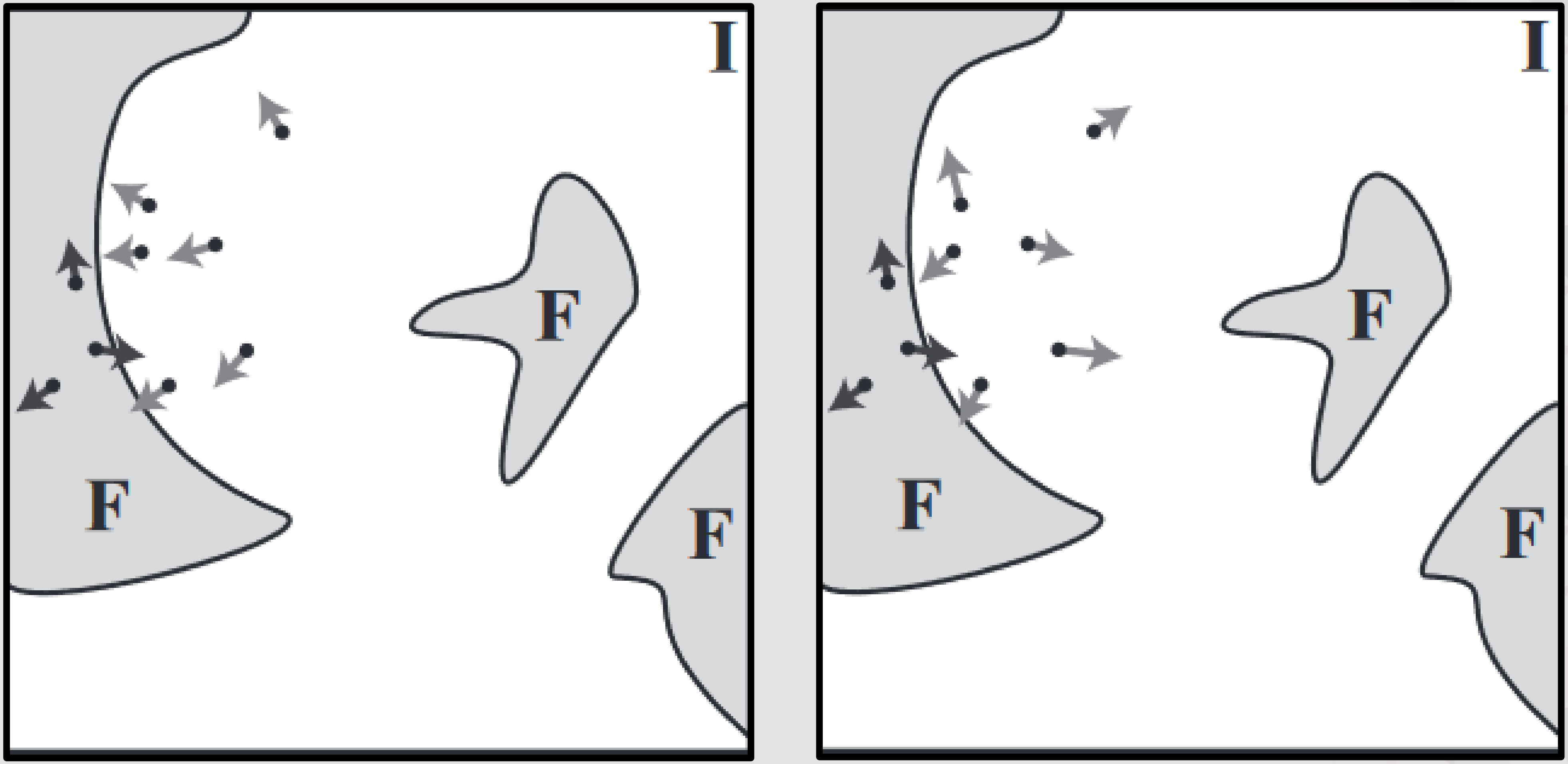
- Feasible-Infeasible Novelty Search:
  - Feasible pop.: maximize novelty score
  - Novelty archive of only feasible solutions
- Feasible-Infeasible Dual Novelty Search





A. Liapis, G. N. Yannakakis and J. Togelius: Constrained Novelty Search: A Study on Game Content Generation, Evolutionary Computation 21(1), 2015, pp. 101-129.

Constrained Novelty Search



A. Liapis, G. N. Yannakakis and J. Togelius: Constrained Novelty Search: A Study on Game Content Generation, Evolutionary Computation 21(1), 2015, pp. 101-129.

Constrained Surprise Search

- Feasible-Infeasible Surprise Search:
    - Feasible pop.: maximize surprise score
    - Predictions made only from feasible individuals

D. Gravina, A. Liapis and G. N. Yannakakis: Constrained Surprise Search for Content Generation.
In Proceedings of the IEEE Conference on Computational Intelligence and Games (CIG), 2016.

Constrained MAP Elites

- As in MAP-Elites, create a feature map
- Each cell holds a **best feasible individual** and a **best infeasible individual**
- Treat as two populations:
  - One selects parents from feasible cells
  - Other selects parents from infeasible cells

A. Khalifa, S. Lee, A. Nealen, and J. Togelius, Talakat: Bullet hellgeneration through constrained MAP-Elites, in Proceedings of The Genetic and Evolutionary Computation Conference. ACM, 2018, pp.1047–1054.

Core Domains of CC via evolution

CC domains

- Representational paintings
- Music
- Mathematical concepts
- Stories
- Jokes
- Poems
- Collages
- Games

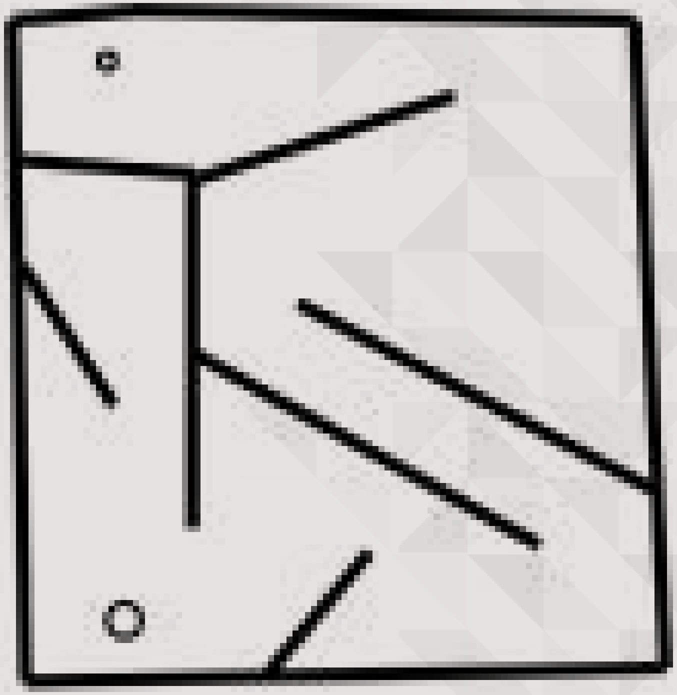
Stealthy swiftness of a leopard,
Happy singing of a bird.

In the morning, I am loyal
Like the comfort of a friend.
But the morning grows more lifeless
Than the fabric of a rag.
And the mid-day makes me nervous
Like the spirit of a bride.

Krzeczkowska, A., El-Hage J., Colton S, and Clark S: Automated Collage Generation – With Intent, Proc. of the ICCC 2010
Colton, S., Goodwin, J., & Veale, T. Full-FACE Poetry Generation. Proc. of the ICCC 2012.
Graeme Ritchie: “Some empirical criteria for attributing creativity to a computer program”. Minds and Machines 17:76–99. 2007

Creative Problem Solving

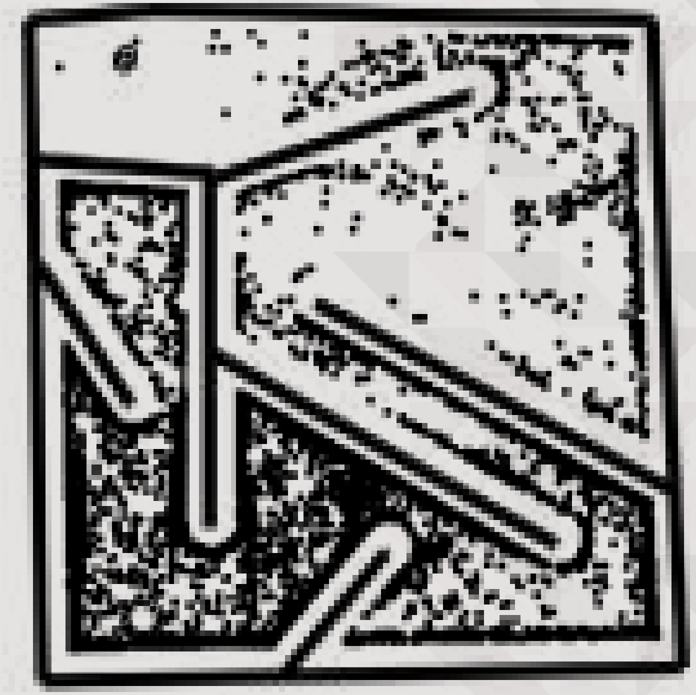
- Problems usually have one solution.
- Objective functions may lead away from solutions.
- Stepping stones towards the solution are unknown.
- Creative solutions (novel, surprising) may be more useful in the long run than ‘better’ ones.



J. Lehman, K.O. Stanley. Abandoning objectives: Evolution through the search for novelty alone. Evolutionary computation 19 (2), 189-223. 2011.

Problem: Maze Navigation

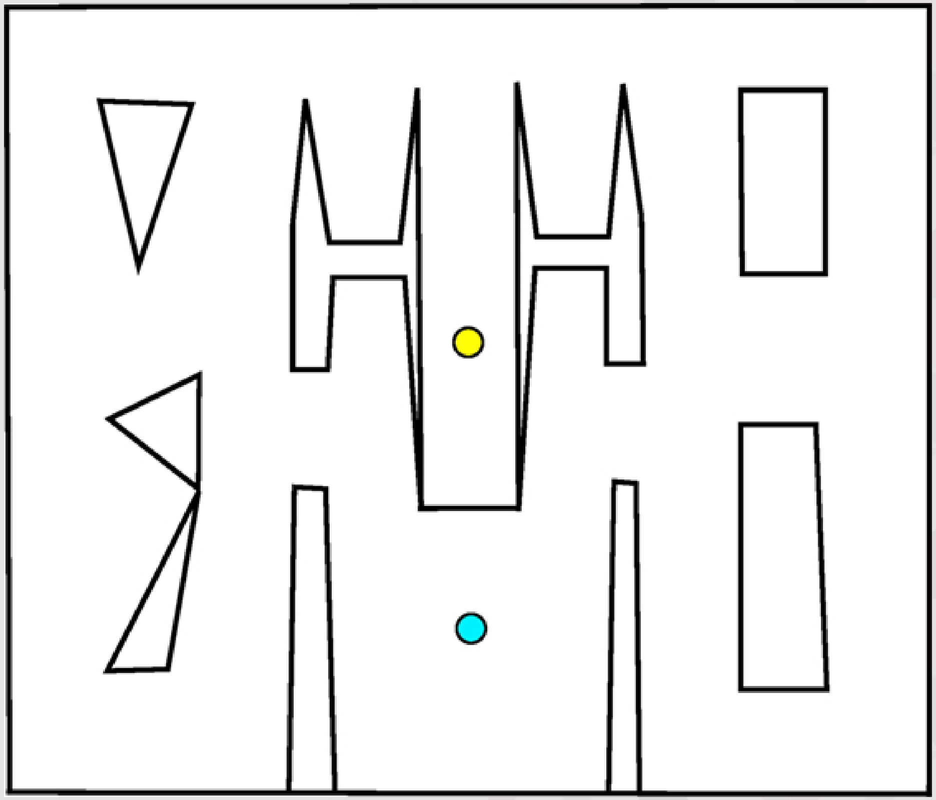
- Robot controller: 4 goal sensors, 6 collision sensors
- ANN evolved via NEAT to decide on turning & speed
- Solution: goal reached
- Quality: ???
- Diversity: distance between final positions after simulation



J. Lehman, K.O. Stanley. Abandoning objectives: Evolution through the search for novelty alone. Evolutionary computation 19 (2), 189-223. 2011.

Problem: Maze Navigation

- Novelty search with local competition:
  - **Novelty:** pairwise distance of points along robots’ trails
  - **Local competition:** # individuals further to final goal



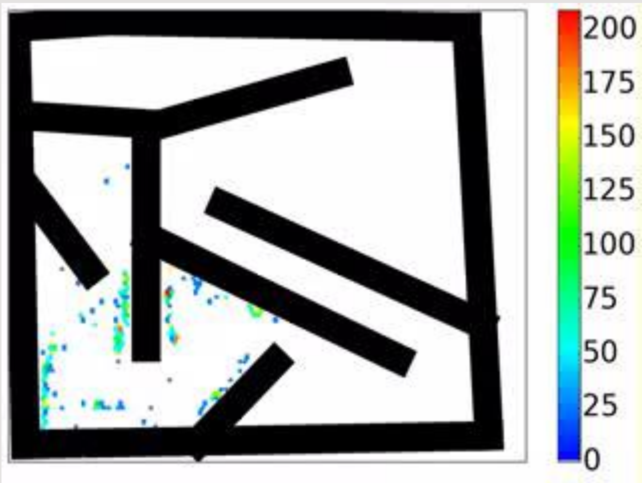
J. K. Pugh, L. B. Soros, and K. O. Stanley, Quality diversity: A new frontier for evolutionary computation, Frontiers in Robotics and AI, vol. 3, 2016

Problem: Maze Navigation

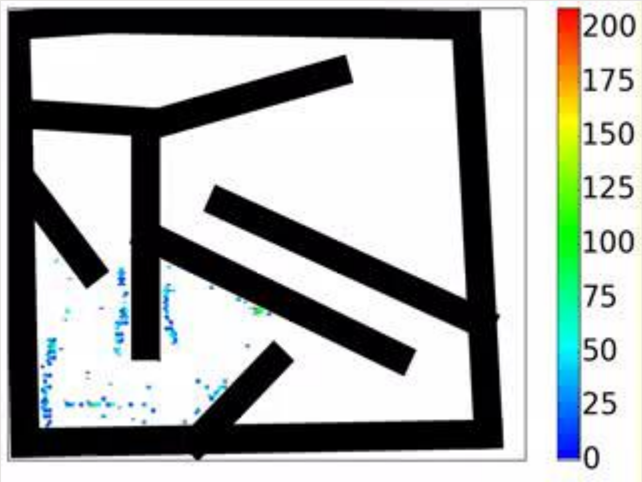
- Surprise Search:
  - *k*-means clustering of robots' final positions
  - Predicted positions via linear interpolation

D. Gravina, A. Liapis and G. N. Yannakakis: Quality Diversity Through Surprise, in Transactions on Evolutionary Computation, 2019.

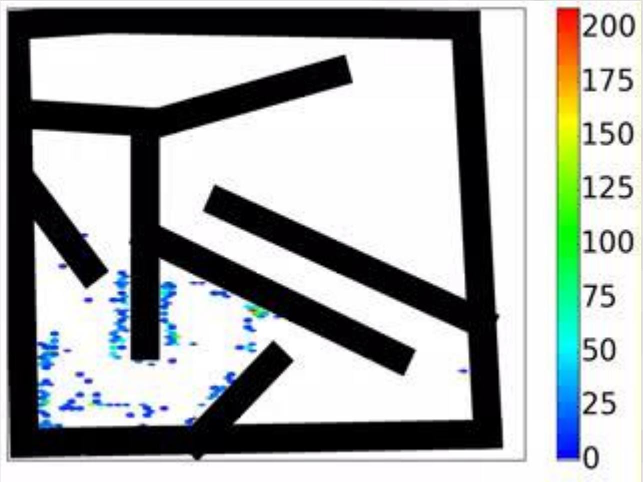
Problem: Maze Navigation



Quality



Novelty

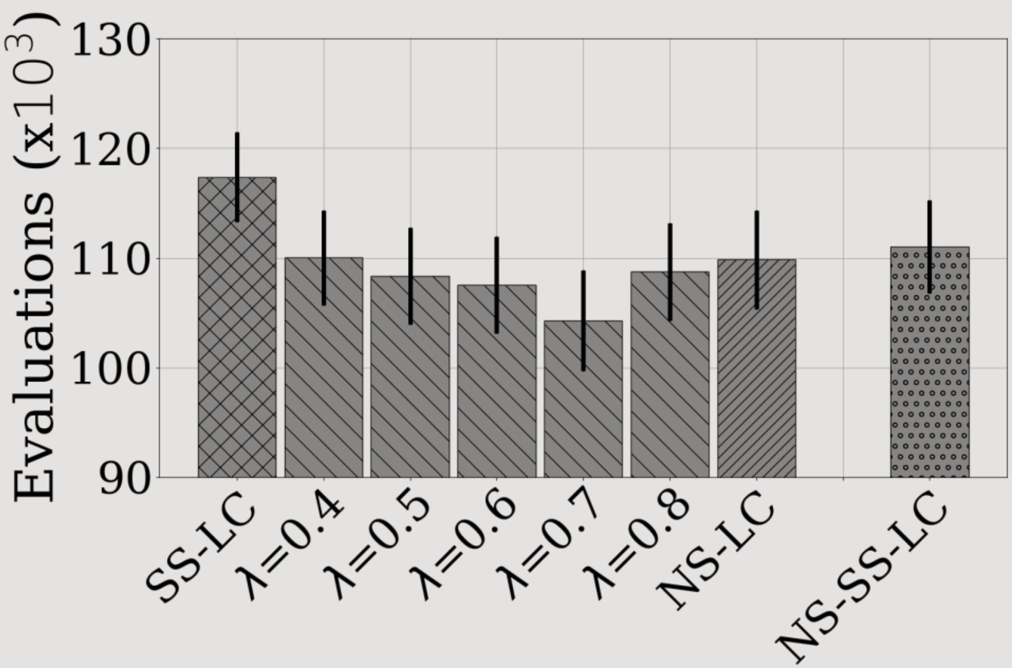


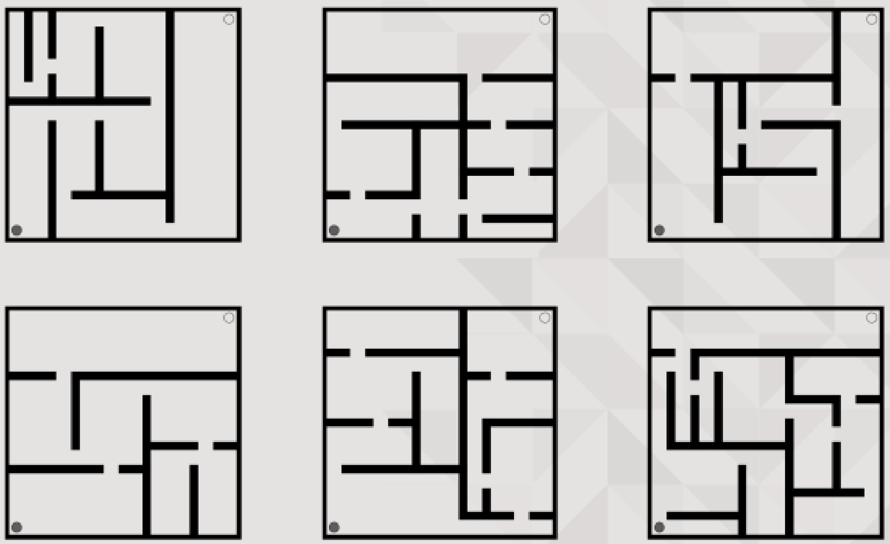
Surprise

D. Gravina, A. Liapis and G.N. Yannakakis: "Surprise Search: Beyond Objectives and Novelty," in Proceedings of the Genetic and Evolutionary Computation Conference. ACM, 2016.

Problem: Maze Navigation

- Surprise Search + Novelty Search + Local Competition
  - NSGA-II two- or three-objective optimization
  - Novelty + Surprise as linear combination or two objectives

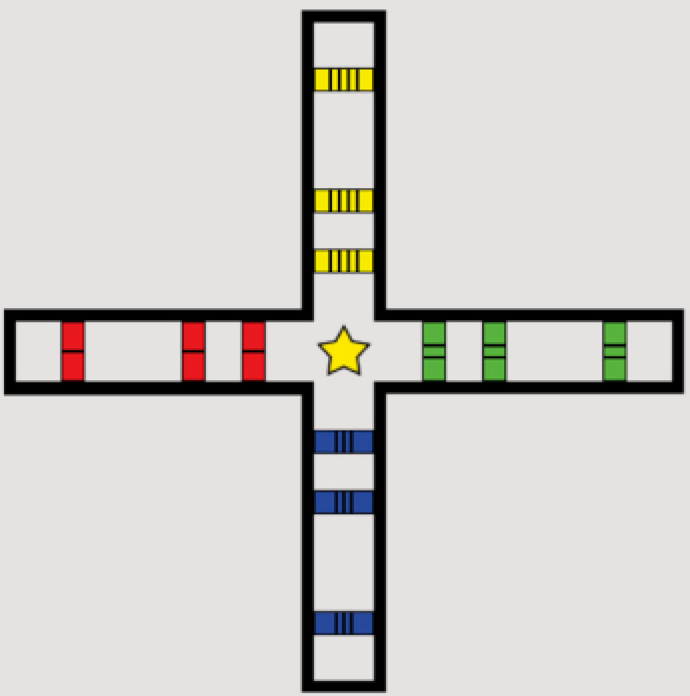


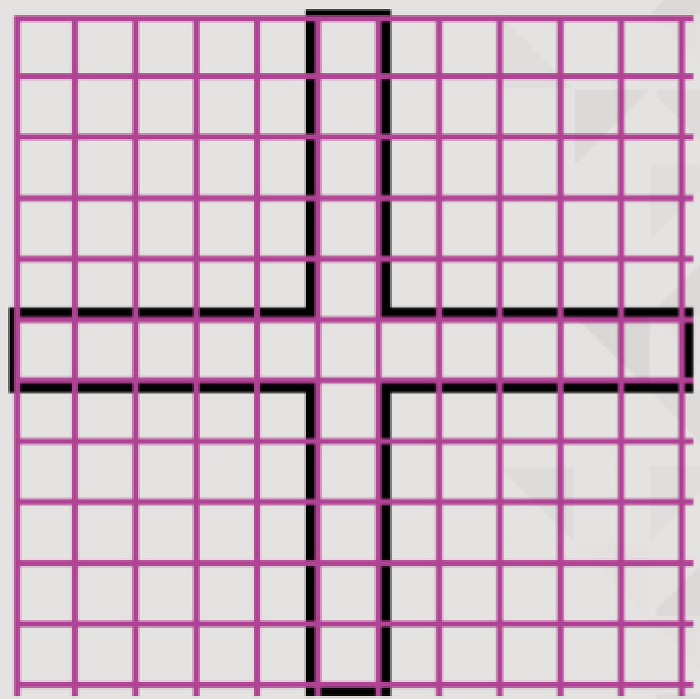


D. Gravina, A. Liapis and G. N. Yannakakis: Quality Diversity Through Surprise, in Transactions on Evolutionary Computation, 2019.

Problem: Maze Navigation

- Curiosity Search with an **intra-life novelty score**
  - Number of distinct behaviors exhibited in one simulation
  - For mazes: # unique grid tiles touched + # doors opened

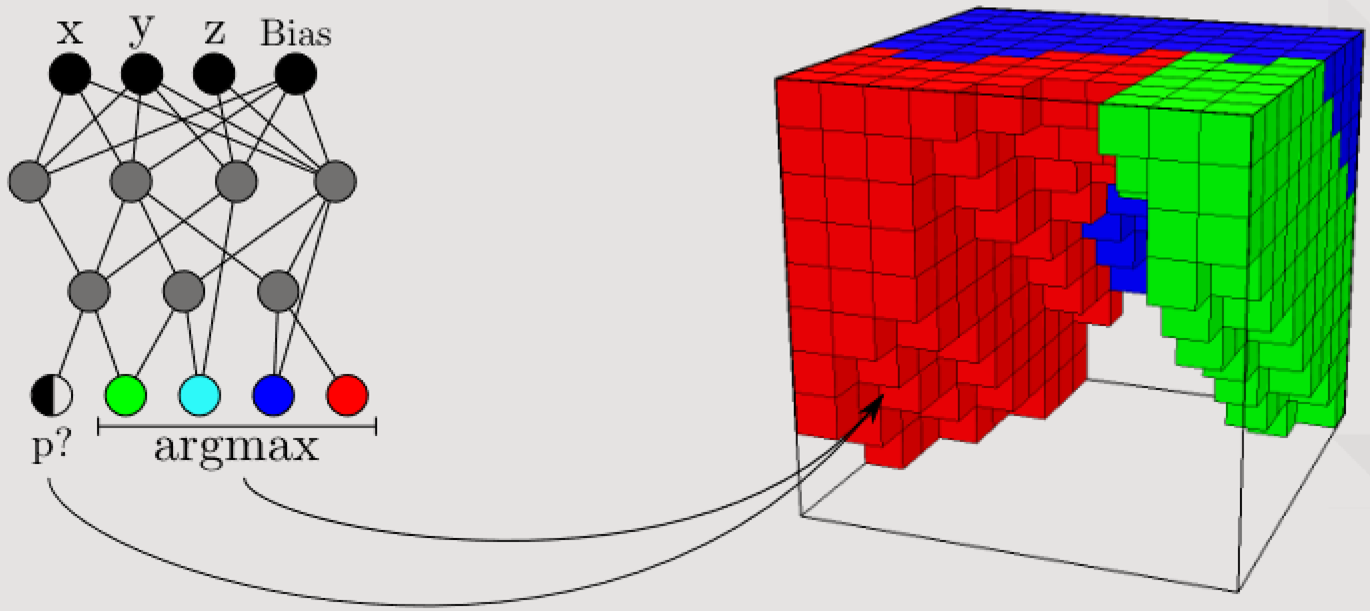




C. Stanton, J. Clune: Curiosity Search: Producing Generalists by Encouraging Individuals to Continually Explore and Acquire Skills throughout Their Lifetime. PLoS ONE 11(9): e0162235. doi:10.1371/journal.pone.0162235

Problem: Virtual Creatures

- Soft robots with voxel-based materials
  - 4 types: active (contract or expand), inactive (soft or stiff)
  - CPPN decides material, if any



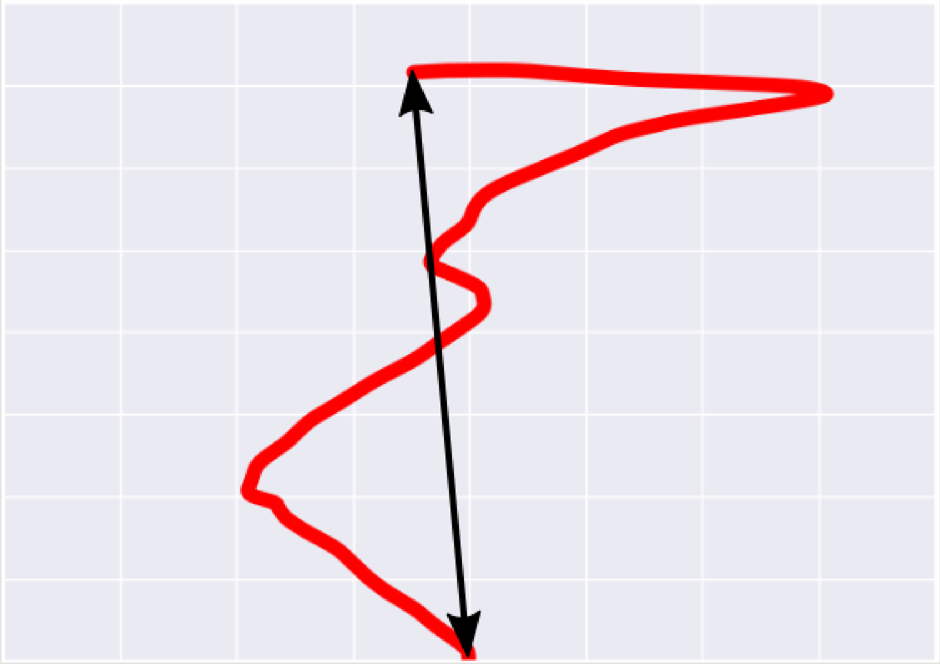
G. Methenitis, D. Hennes, D. Izzo, and A. Visser. 2015. Novelty search for soft robotic space exploration. In Proceedings of the 2015 Annual Conference on Genetic and Evolutionary Computation. ACM, 193–200

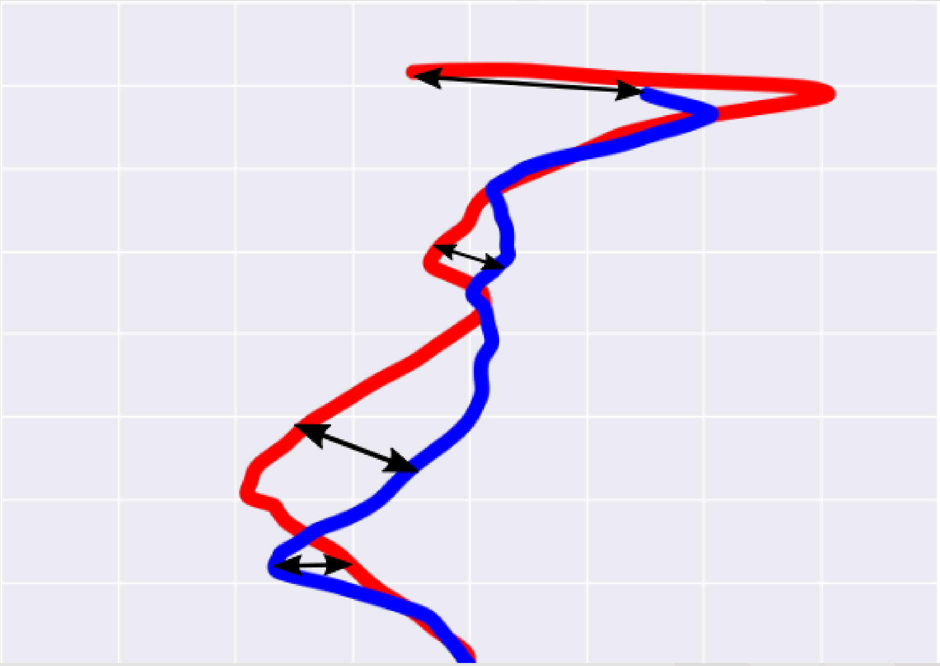
Problem: Virtual Creatures

Cheney N, MacCurdy R, Clune J, Lipson H (2013) Unshackling evolution: Evolving soft robots with multiple materials and a powerful generative encoding. Proceedings of the Genetic and Evolutionary Computation Conference. 167-174.

Problem: Virtual Creatures

- **Quality:** distance from start to end position after sim
- **Novelty:** distance of points along robots’ trails
  - Trail is rotation-invariant and z-axis flattened.

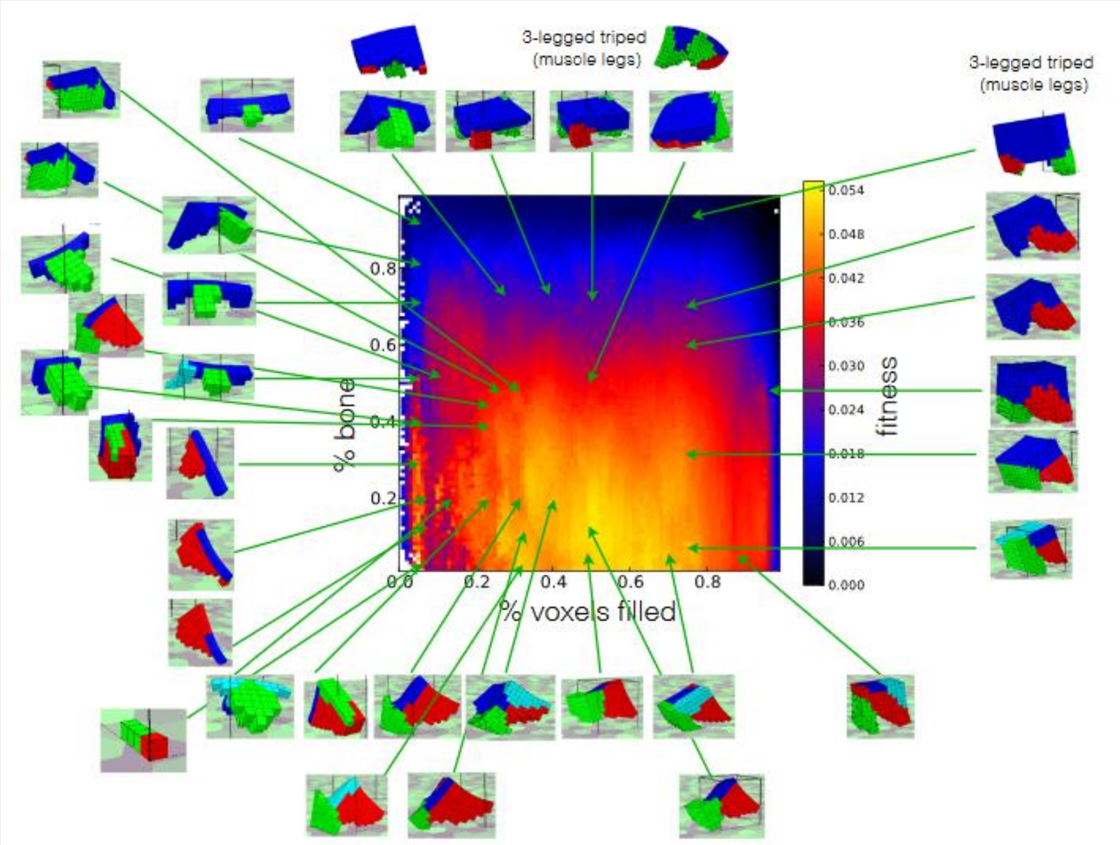




D. Gravina, A. Liapis and G. N. Yannakakis: "Fusing Novelty and Surprise for Evolving Robot Morphologies," in Proceedings of the Genetic and Evolutionary Computation Conference, 2018.

Problem: Virtual Creatures

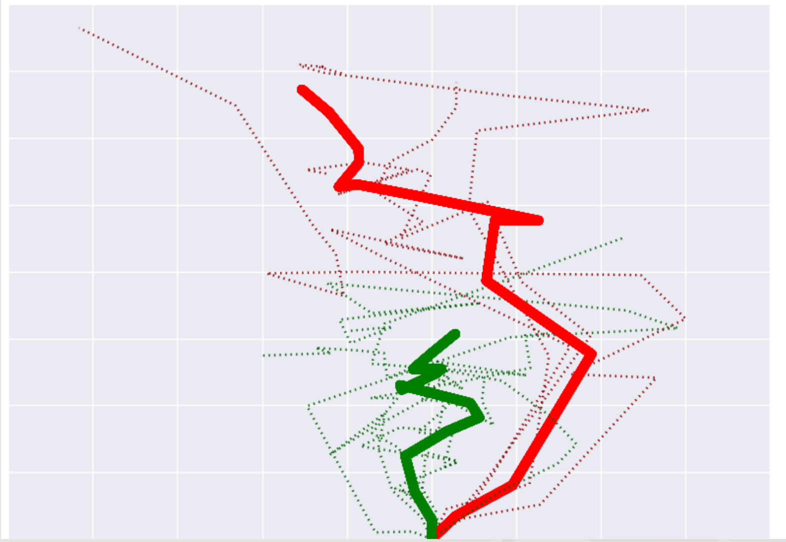
- **MAP-Elites:** feature map of 128x128
  - Features: % of stiff voxels, % of filled voxels

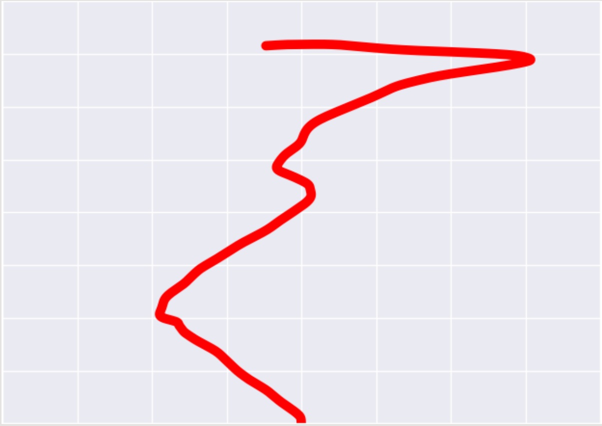


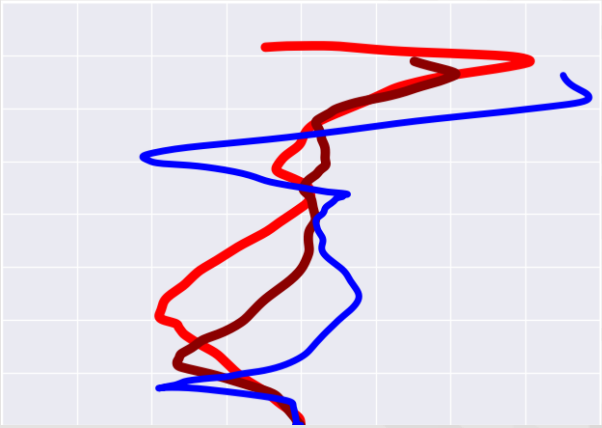
J-B. Mouret and J. Clune. 2015. Illuminating search spaces by mapping elites. arXiv preprint arXiv:1504.04909 (2015).

Problem: Virtual Creatures

- Surprise search:
  - K-means clustering of trails
  - Predicted trails via linear interpolation
  - Deviation as distance along robots' trails

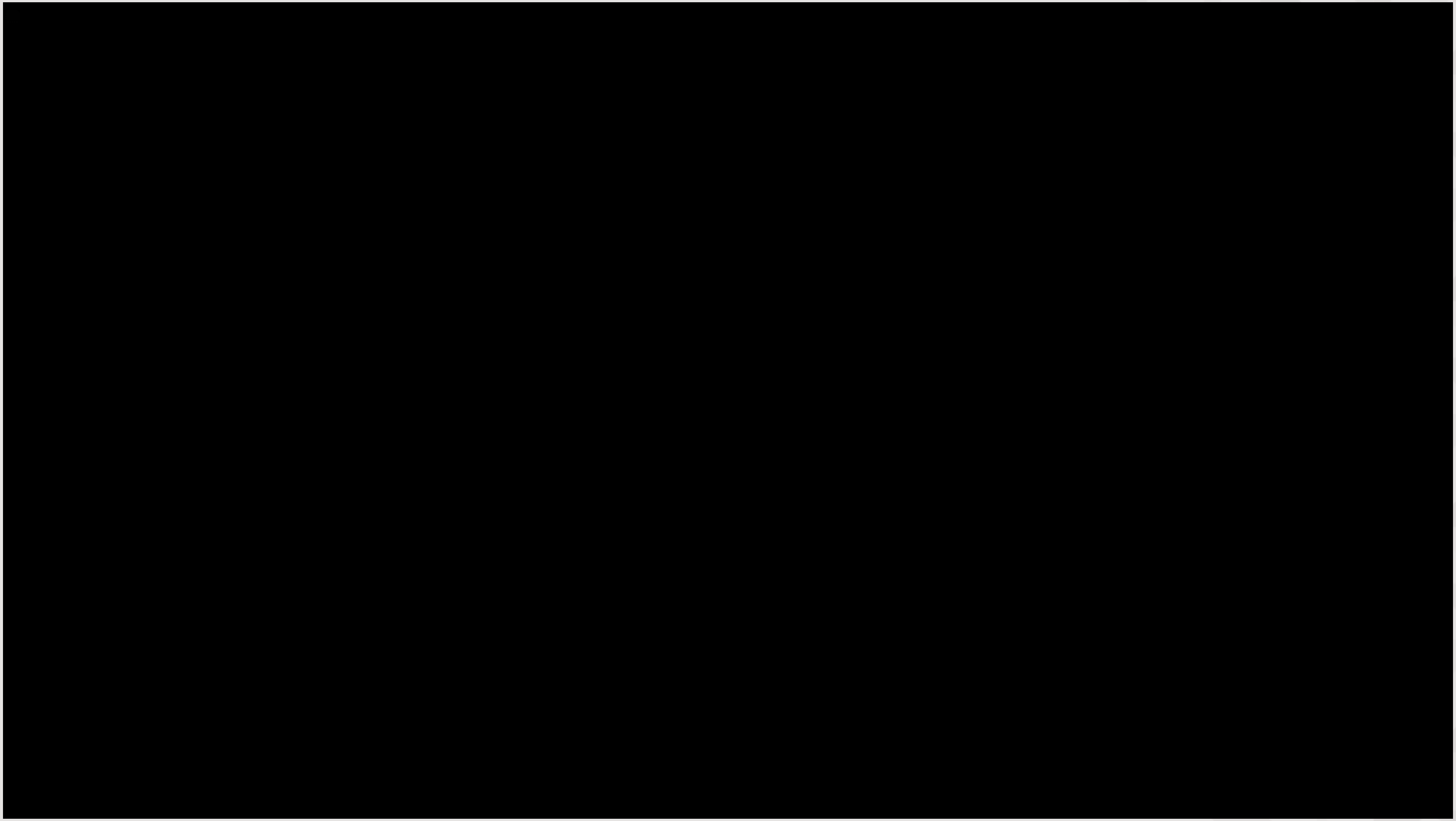






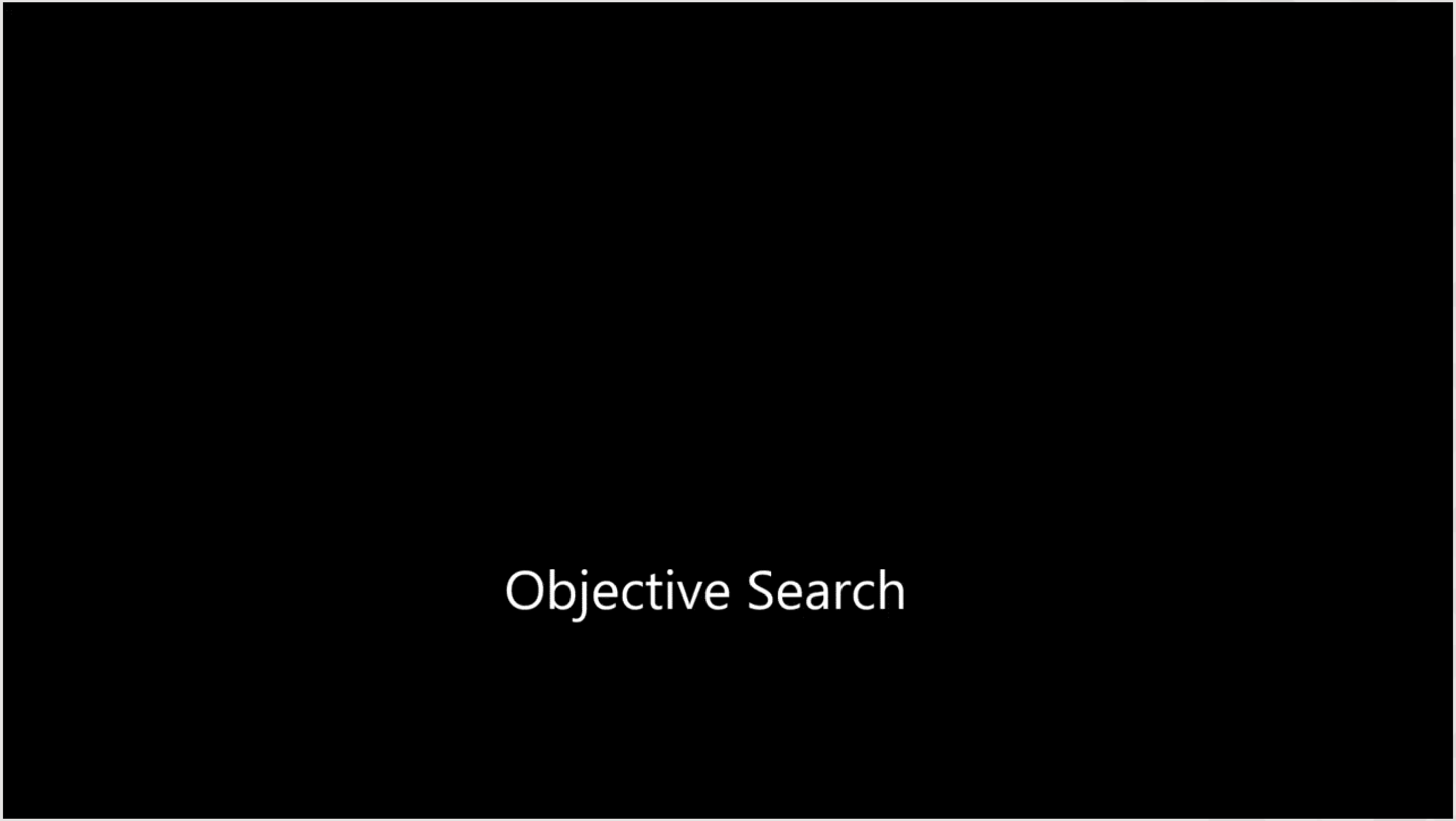
D. Gravina, A. Liapis and G. N. Yannakakis: "Fusing Novelty and Surprise for Evolving Robot Morphologies," in Proceedings of the Genetic and Evolutionary Computation Conference, 2018.

Problem: Virtual Creatures



D. Gravina, A. Liapis and G. N. Yannakakis: "Exploring Divergence for Soft Robot Evolution," in Proceedings of the Genetic and Evolutionary Computation Conference, 2017.

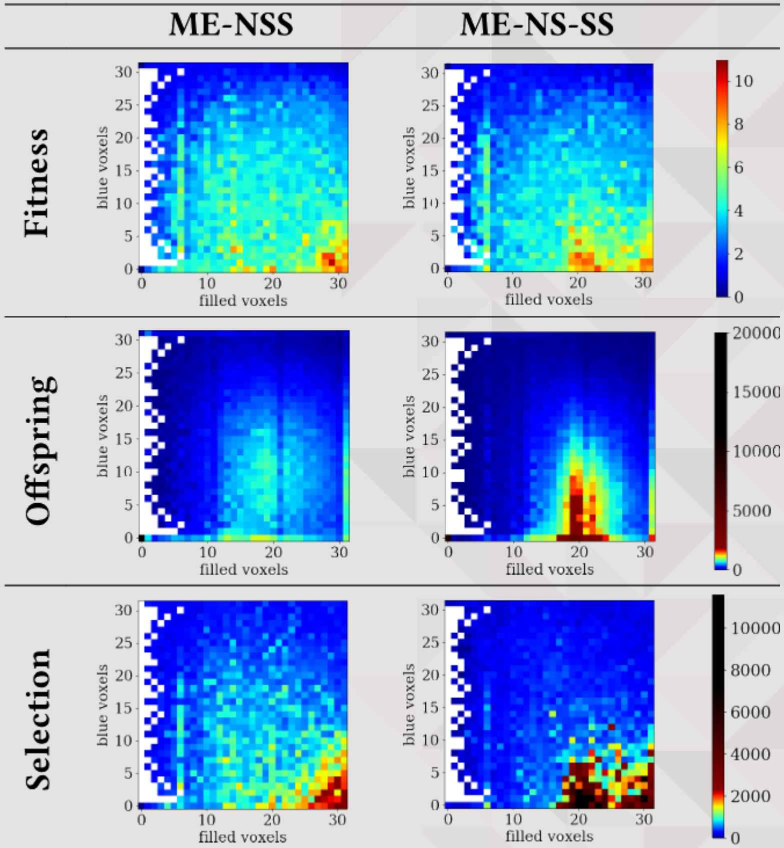
Problem: Virtual Creatures



D. Gravina, A. Liapis and G. N. Yannakakis: "Fusing Novelty and Surprise for Evolving Robot Morphologies," in Proceedings of the Genetic and Evolutionary Computation Conference, 2018.

Problem: Virtual Creatures

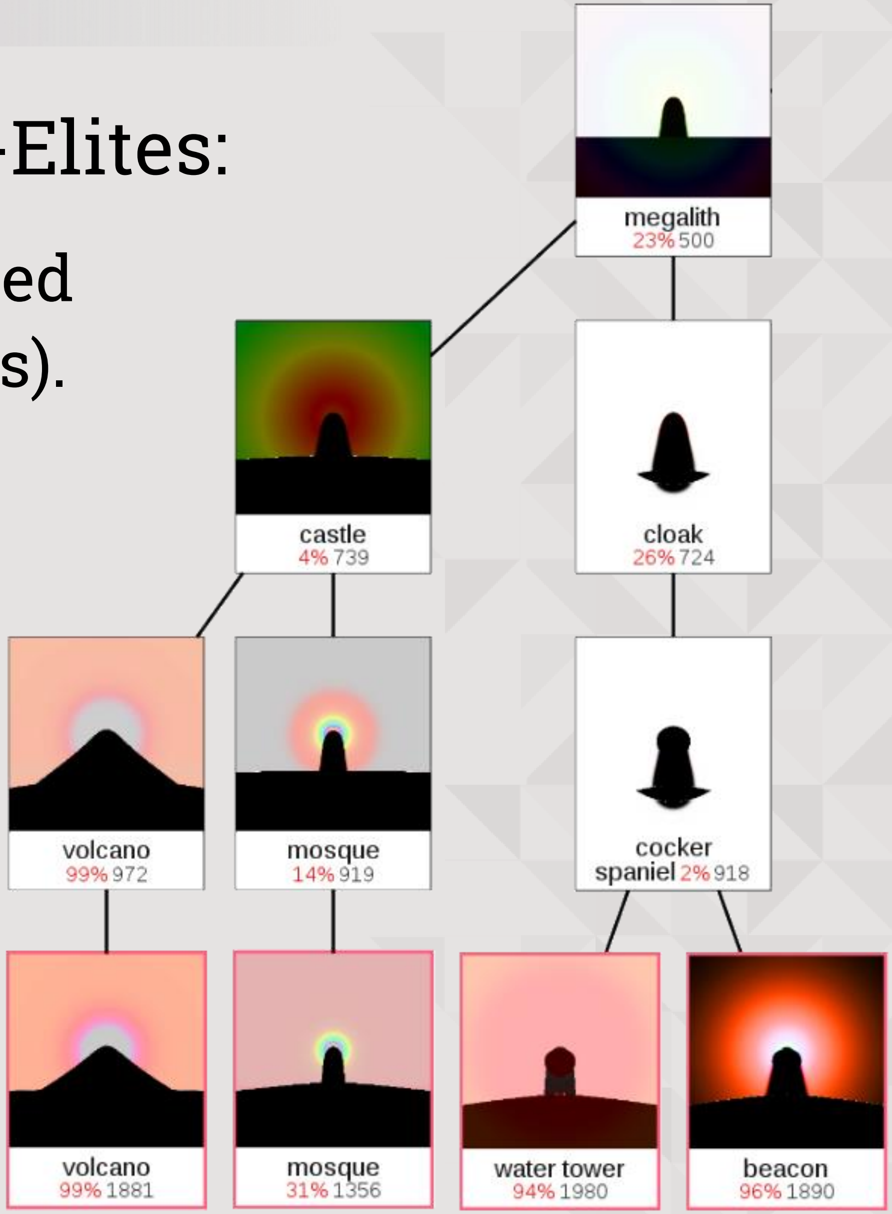
- MAP-Elites with parent selection based on novelty or surprise:
  - Space partition based on voxels
  - Distance characterization based on trails (real or predicted)
  - Come see the poster!



D. Gravina, A. Liapis and G. N. Yannakakis: "Blending Notions of Diversity for MAP-Elites," in Proceedings of the Genetic and Evolutionary Computation Conference, 2019

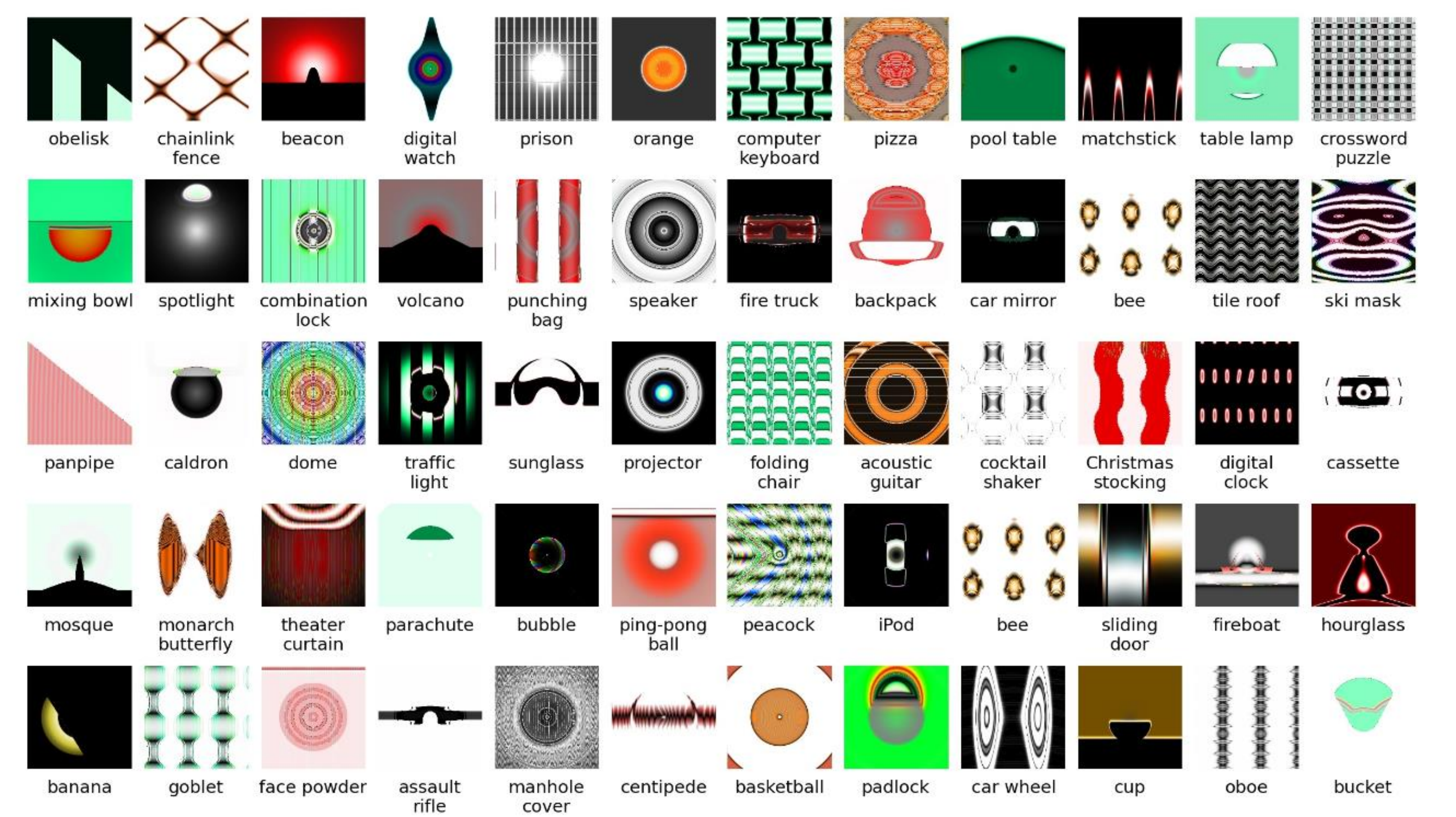
Computational Artworks

- Innovation engines via MAP-Elites:
  - Space partitioned via DNN-based object recognition (1000 classes).
  - Quality based on respective confidence of detected object.



Nguyen, A.; Yosinski, J.; and Clune, J. 2015. Innovation engines: Automated creativity and improved stochastic optimization via deep learning. In Proceedings of the Genetic and Evolutionary Computation Conference.

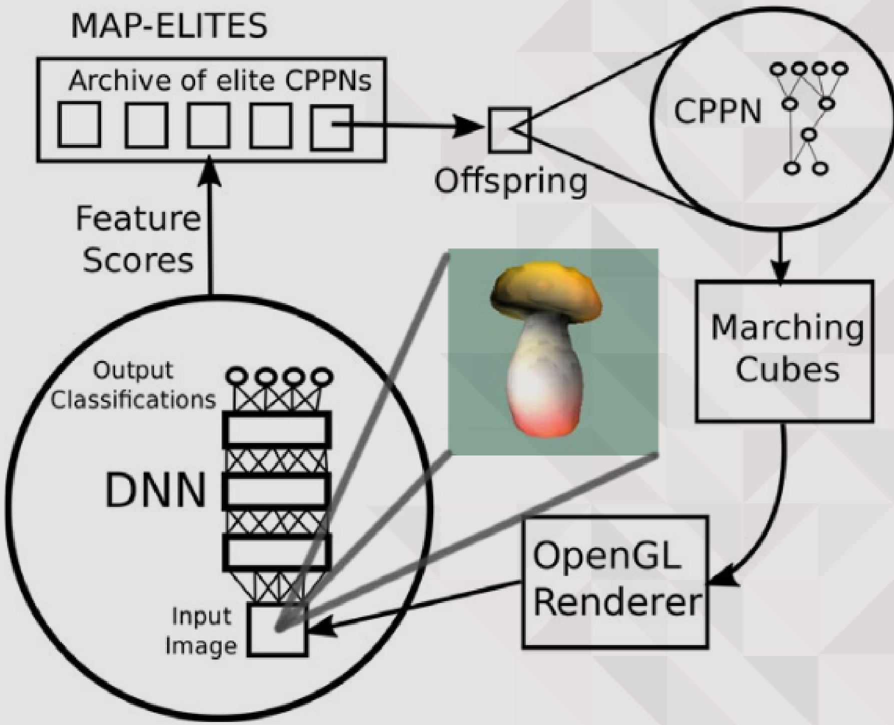
Computational Artworks



Nguyen, A.; Yosinski, J.; and Clune, J. 2015. Innovation engines: Automated creativity and improved stochastic optimization via deep learning. In Proceedings of the Genetic and Evolutionary Computation Conference.

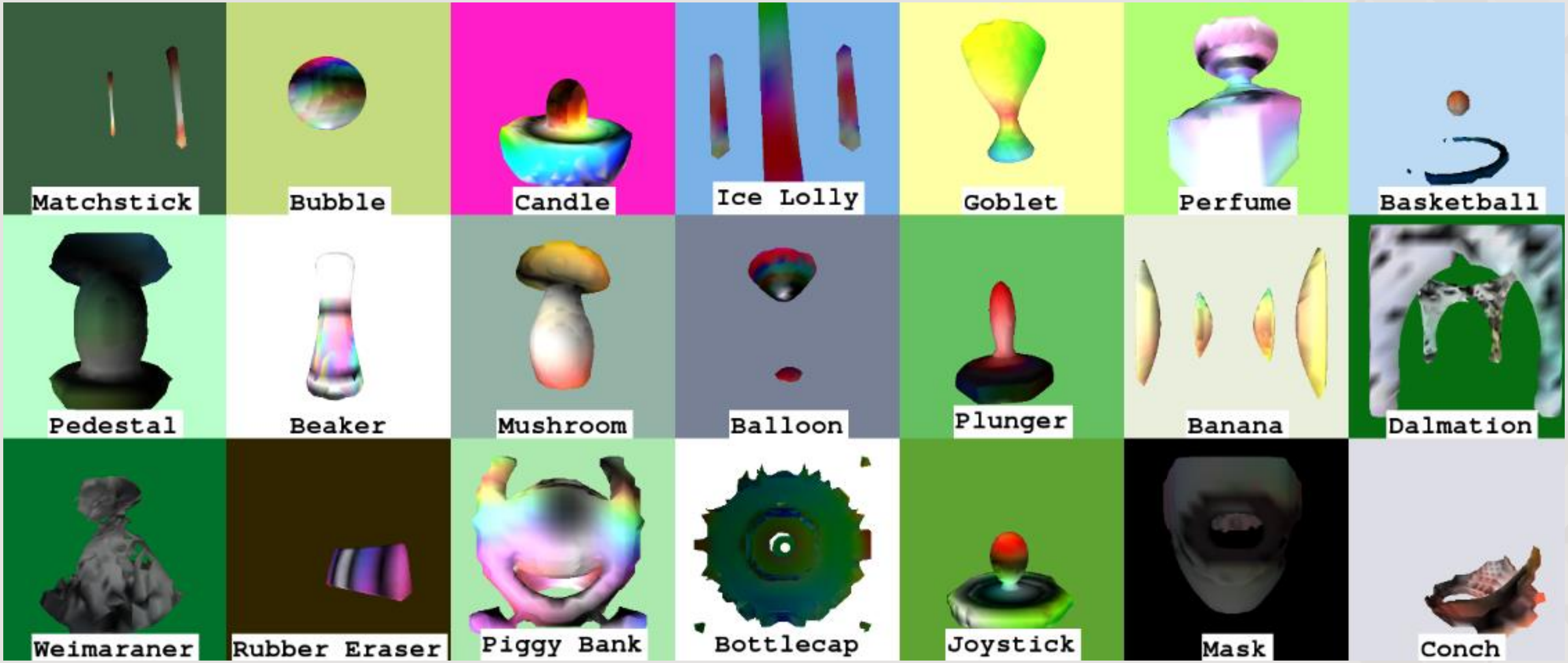
Computational Artworks

- MAP-Elites for 3D models:
  - 3D model created by evolved CPPN, rendered in 6 perspectives.
  - Cell is a category detected via ImageNet, made abstract via Wordnet hypernyms.
  - MAP-Elites selects stochastically, but penalized if unproductive.



J. Lehman, S. Risi, J. Clune: "Creative Generation of 3D Objects with Deep Learning and Innovation Engines," in Proceedings of the Seventh International Conference on Computational Creativity, June 2016

Computational Artworks



J. Lehman, S. Risi, J. Clune: “Creative Generation of 3D Objects with Deep Learning and Innovation Engines," in Proceedings of the Seventh International Conference on Computational Creativity, June 2016

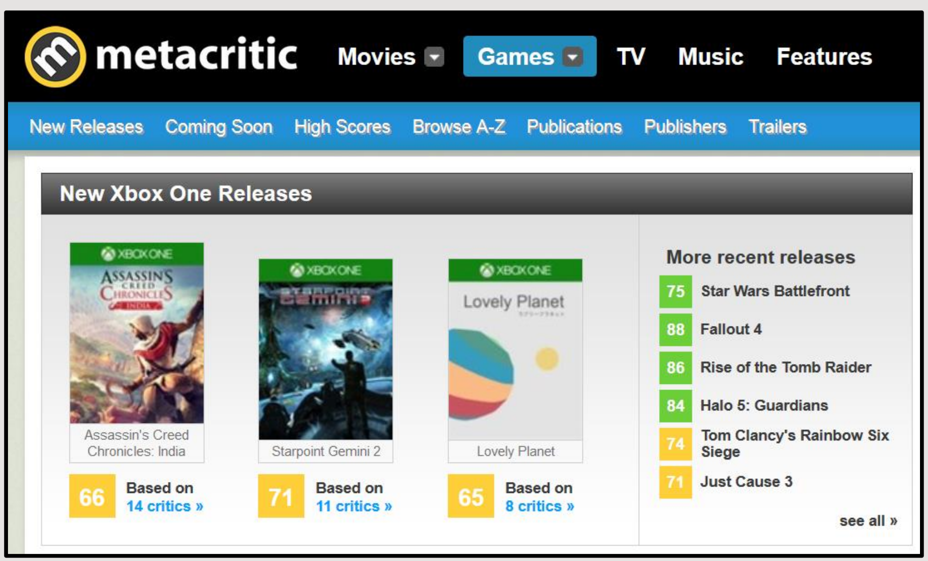
Creativity in Games (with Evolution)

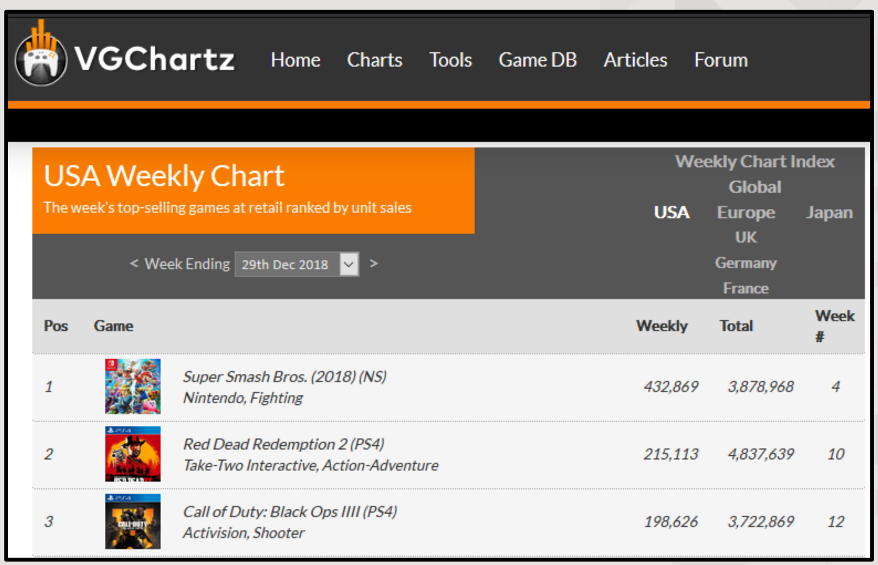
Games rely on creativity

A. Liapis, G. N. Yannakakis and J. Togelius: Computational Game Creativity, in Proc. of the Intl. Conf. on Computational Creativity, 2014.

Games as a creative domain

- Games fall into a **large class** (possibly with subclasses, e.g. casual, shooter, RPG)
- this class has somewhat fuzzy boundaries.
- this class has extensive human-based evaluations of quality.

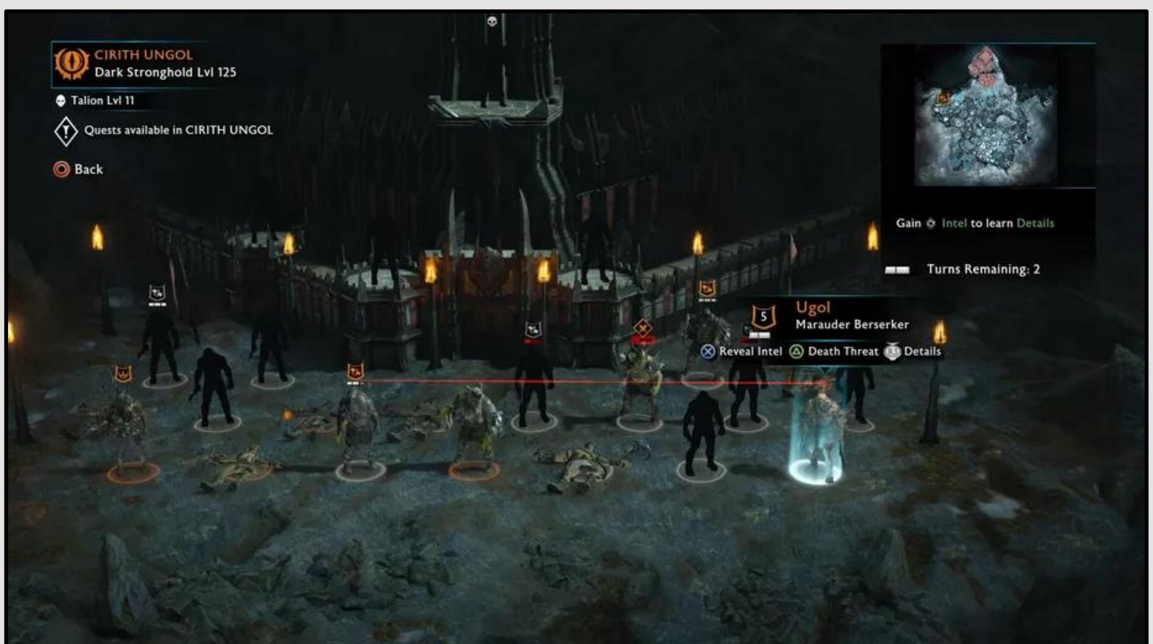




A. Liapis, G. N. Yannakakis and J. Togelius: Computational Game Creativity, in Proc. of the Intl. Conf. on Computational Creativity, 2014.

Games rely on procedural creation

- PCG is a commercial necessity.
  - fast development cycles, replayability, retention.
- The game industry proudly displays its CC.

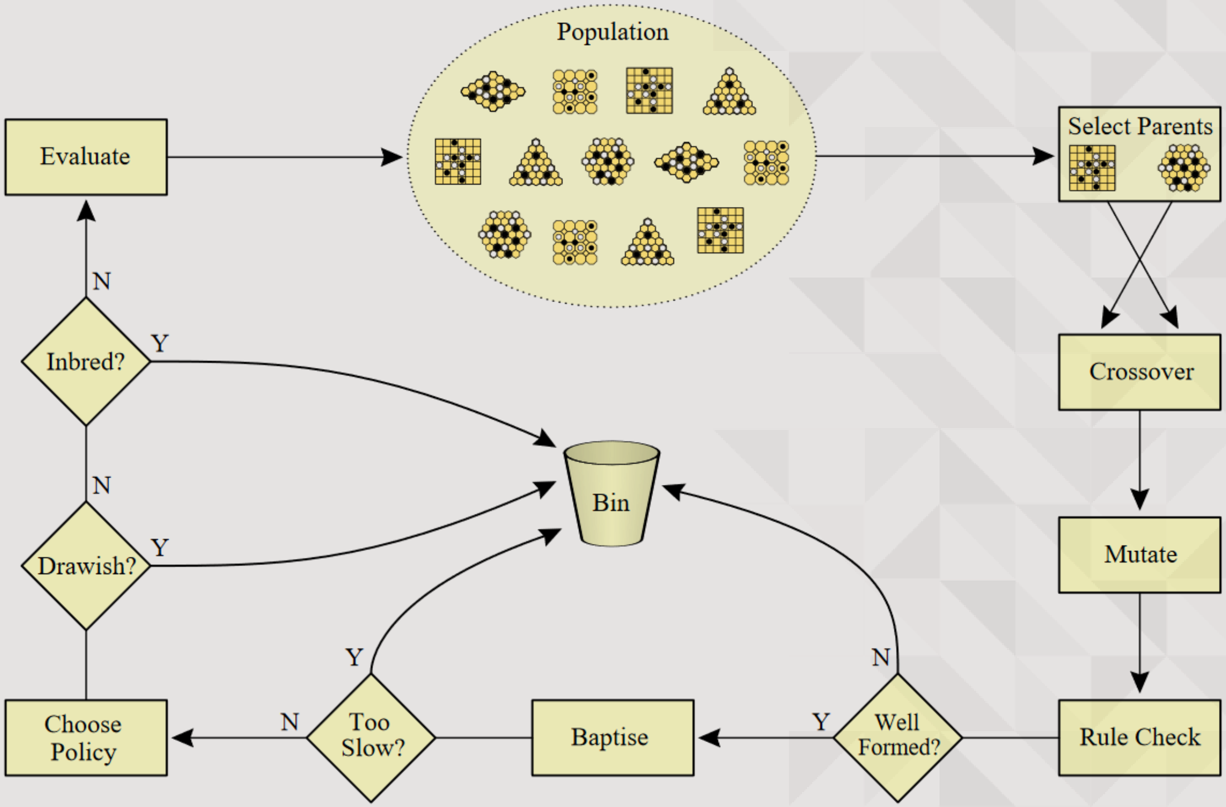


The thought "of creating a near infinite universe should pretty much make a game developer have a nervous breakdown."

A. Liapis, G. N. Yannakakis and J. Togelius: Computational Game Creativity, in Proc. of the Intl. Conf. on Computational Creativity, 2014.

Evolution in Content Generation

- Search-based Procedural Content Generation
  - Testing and improving content iteratively
  - Unlike constructive or generate-and-test methods



Togelius, J.; Yannakakis, G.; Stanley, K.; and Browne, C. 2011. Search-based procedural content generation: A taxonomy and survey. IEEE Trans. on Computational Intelligence and AI in Games 3(3):172-186.

PCG is a Quality-Diversity Problem

- Premise: game content usually has hard **playability** requirements, but also must provide **replayability** (and avoid repetition)
- Game content must be:
  - Good (playable, balanced, etc.)
  - Diverse (inspire new gameplay)

D. Gravina, A. Khalifa, A. Liapis, J. Togelius and G. N. Yannakakis: Procedural Content Generation through Quality-Diversity, in Proceedings of the IEEE Conference on Games, 2019.

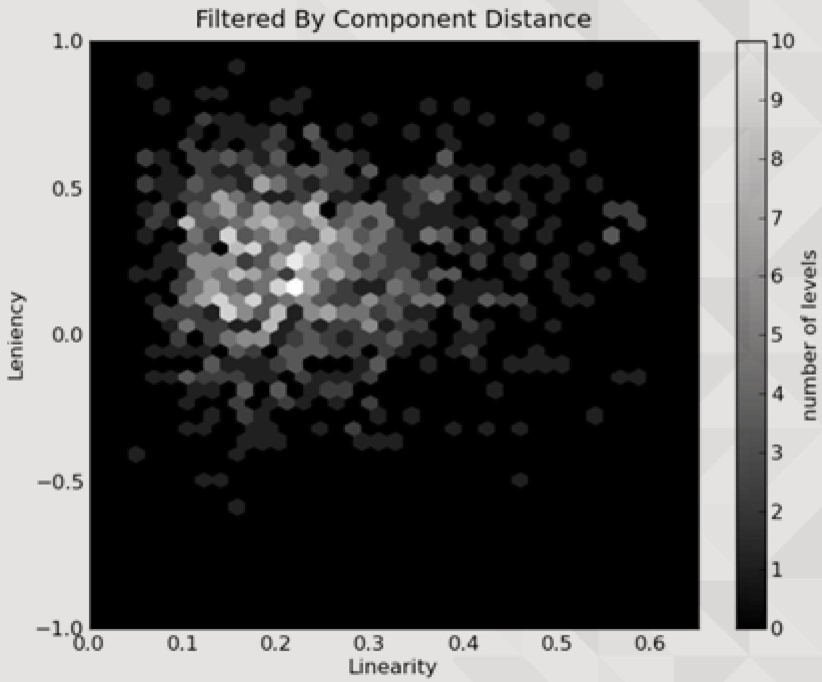
Dimensions of PCG-QD

- **Divergence Components:**
  - Behavior Space Distance
  - Behavior Space Partitioning
- **Quality Components:**
  - Local Competition
  - Constraints

D. Gravina, A. Khalifa, A. Liapis, J. Togelius and G. N. Yannakakis: Procedural Content Generation through Quality-Diversity, in Proceedings of the IEEE Conference on Games, 2019.

Benefits of PCG-QD

- **Generative Efficiency:** one run, many good results (diverse from each other)
- **Fitness-Free Search:** exploring more than one dimension of interest
- **Online Expressivity Analysis**
- **Human-Machine Co-Creation**
- **Explainability**



D. Gravina, A. Khalifa, A. Liapis, J. Togelius and G. N. Yannakakis: Procedural Content Generation through Quality-Diversity, in Proc. of the IEEE Conference on Games, 2019.
G. Smith, J. Whitehead: Analyzing the Expressive Range of a Level Generator, in Proc. of the FDG Workshop on Procedural Content Generation in Games, 2010
J. Zhu, A. Liapis, S. Risi, R. Bidarra and G. M. Youngblood: Explainable AI for Designers: A Human-Centered Perspective on Mixed-Initiative Co-Creation, in Proc. of the IEEE Conference on Computational Intelligence and Games, 2018.

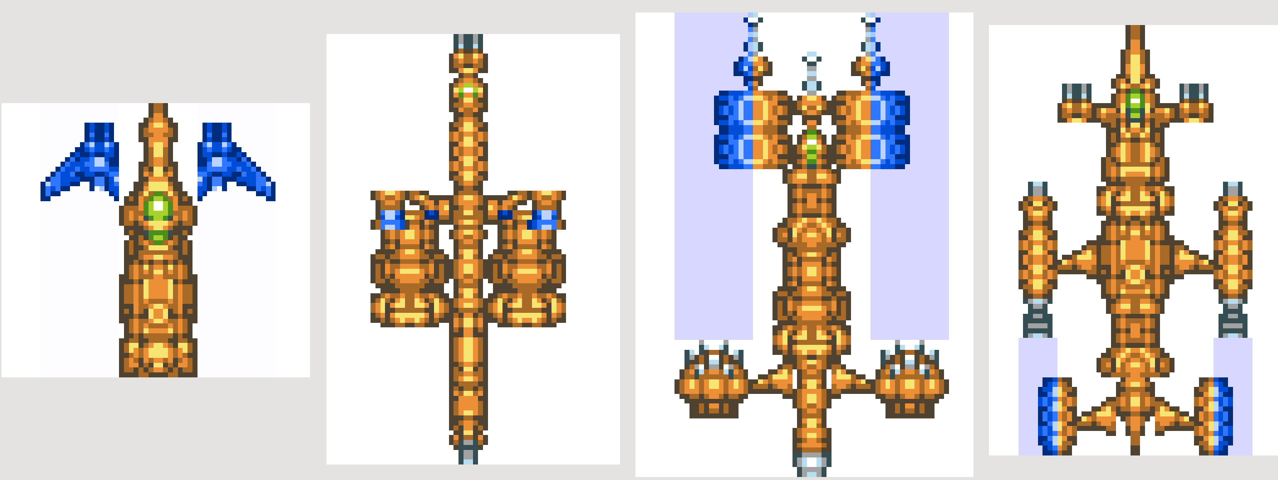
Instances of PCG-QD

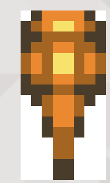
Algorithm	Components				Characterization		Artifact
	Divergence		Quality		Divergence	Quality	
	D	P	LC	C			
MAP-Elites	-	✓	✓	-	DNN Output	DNN Confidence	2D and 3D objects [37], [38]
MESB	-	✓	✓	-	Mana Distribution	Health Difference	Hearthstone Decks [13]
CME	-	✓	✓	✓	Playthrough Properties	Validity and Playability	Bullet-Hell Scripts [18]
	-	✓	✓	✓	Triggered Mechanics	Playability and Simplicity	Mario Scenes [19]
	-	✓	✓	✓	Linearity, Simmetry, Similarity, and Patterns	Playability, Room properties, and Design patterns	Dungeons [39]
CNS	✓	-	-	✓	Visual Diversity	Playability	Map Sketches [14], [15]
	✓	-	-	✓	Visual Diversity	Believability	Arcade-Style Spaceships [40]
	✓	-	-	✓	DNN Latent Space	Believability	2D Spaceship Hulls [16]
CSS	✓	-	-	✓	Map Locations	Balance and Playability	FPS Weapons [17]
NS-LC	✓	-	✓	-	Block Presence	Complexity	Minecraft-like Structures [41]

D. Gravina, A. Khalifa, A. Liapis, J. Togelius and G. N. Yannakakis: Procedural Content Generation through Quality-Diversity, in Proceedings of the IEEE Conference on Games, 2019.

Spaceship Generation

- Generated spaceships via turtle commands
- Mutations add/remove commands
- **Quality:** 5 plausibility constraints



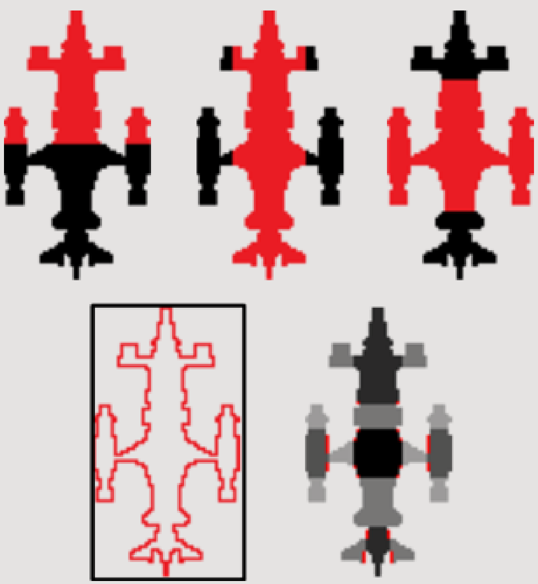


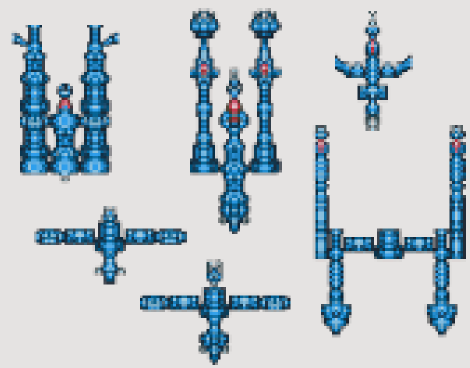
UT15

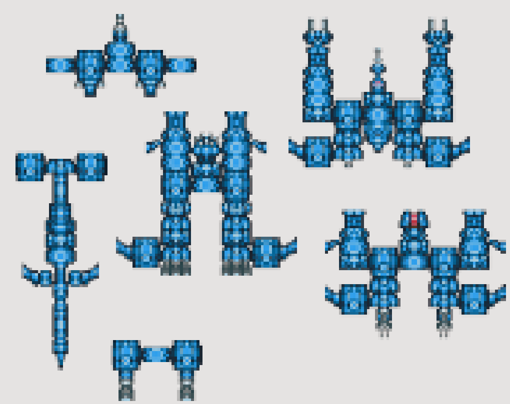
A. Liapis, “Exploring the visual styles of arcade game assets,” in Proceedings of Evolutionary and Biologically Inspired Music, Sound,Art and Design (EvoMusArt). Springer, 2016

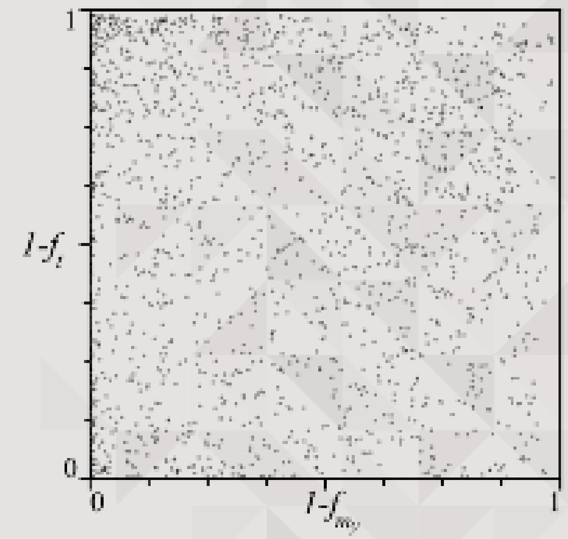
Spaceship Generation

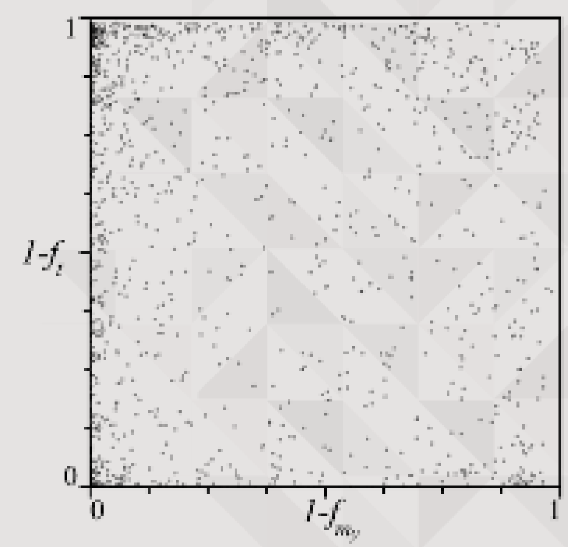
- **Diversity:** 7 visual properties
- FINS to maximize distance on 3 or all visual dimensions







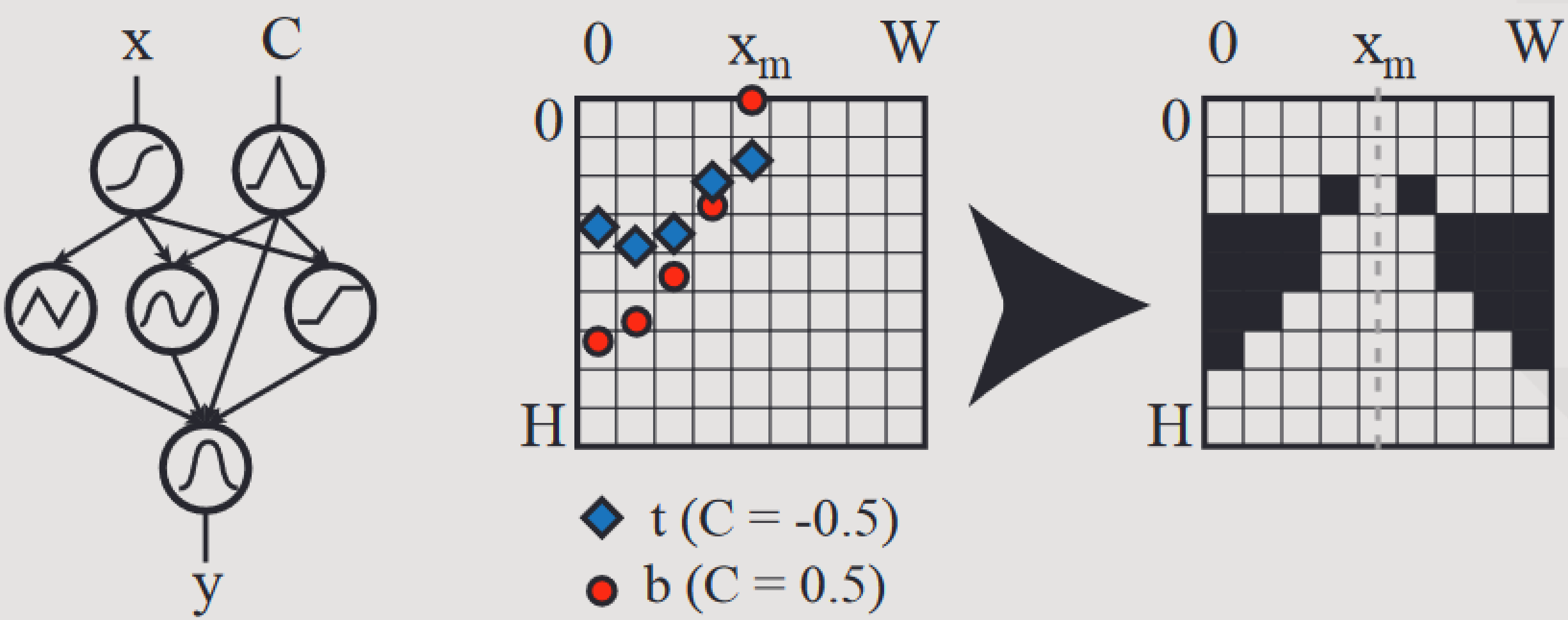


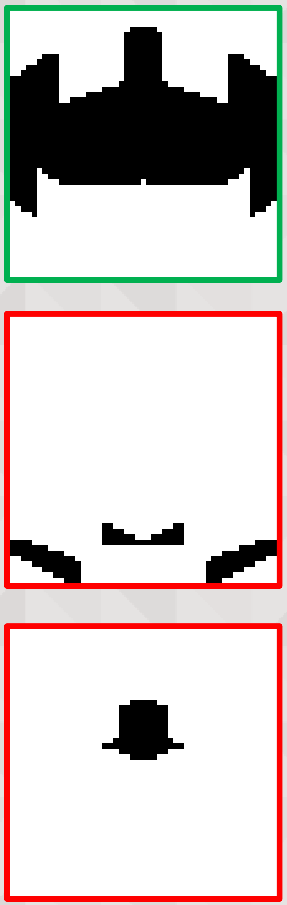


A. Liapis, "Exploring the visual styles of arcade game assets," in Proceedings of Evolutionary and Biologically Inspired Music, Sound,Art and Design (EvoMusArt). Springer, 2016

DeLeNoX Spaceship Generation

- Spaceship hull generation (line overlap)
- Points evolved via CPPN
- **Quality:** two plausibility constraints

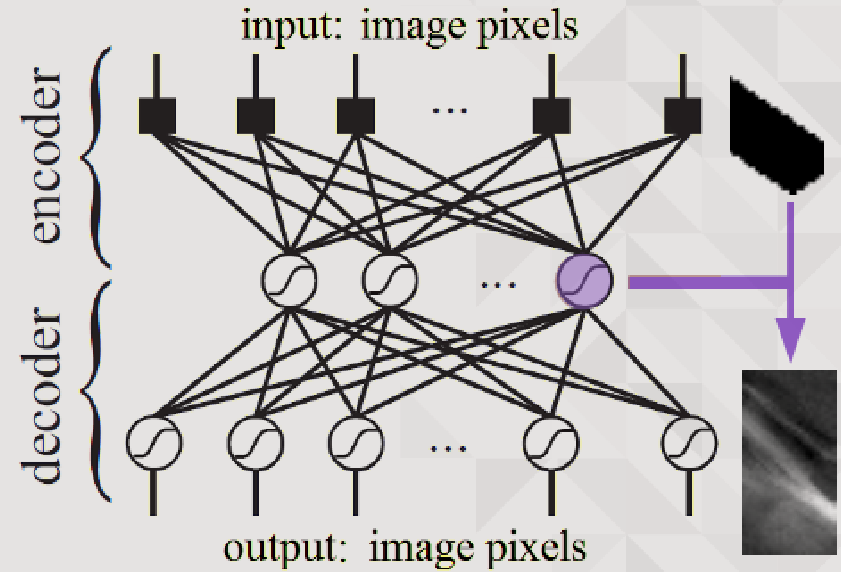


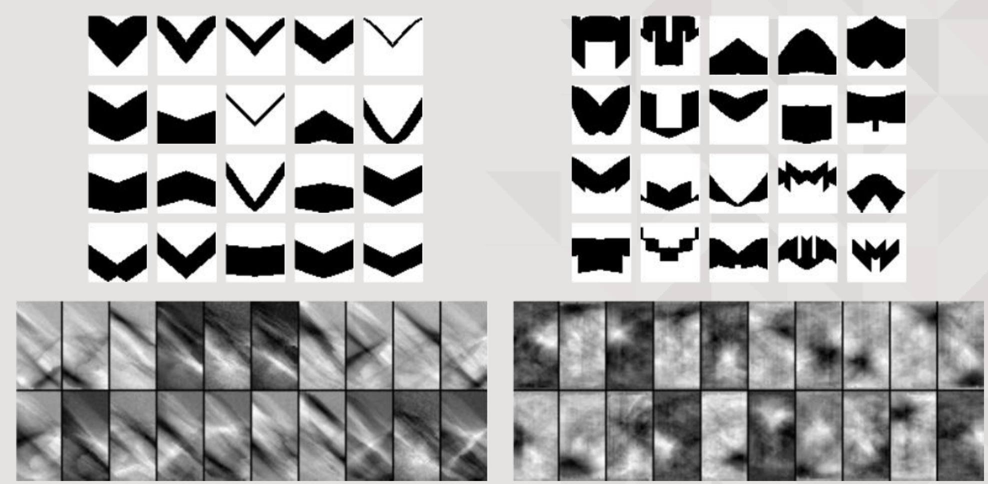


A. Liapis, H. P. Martınez, J. Togelius, and G. N. Yannakakis, "Transforming exploratory creativity with DeLeNoX,." in ICCC, 2013, pp. 56–63.

DeLeNoX Spaceship Generation

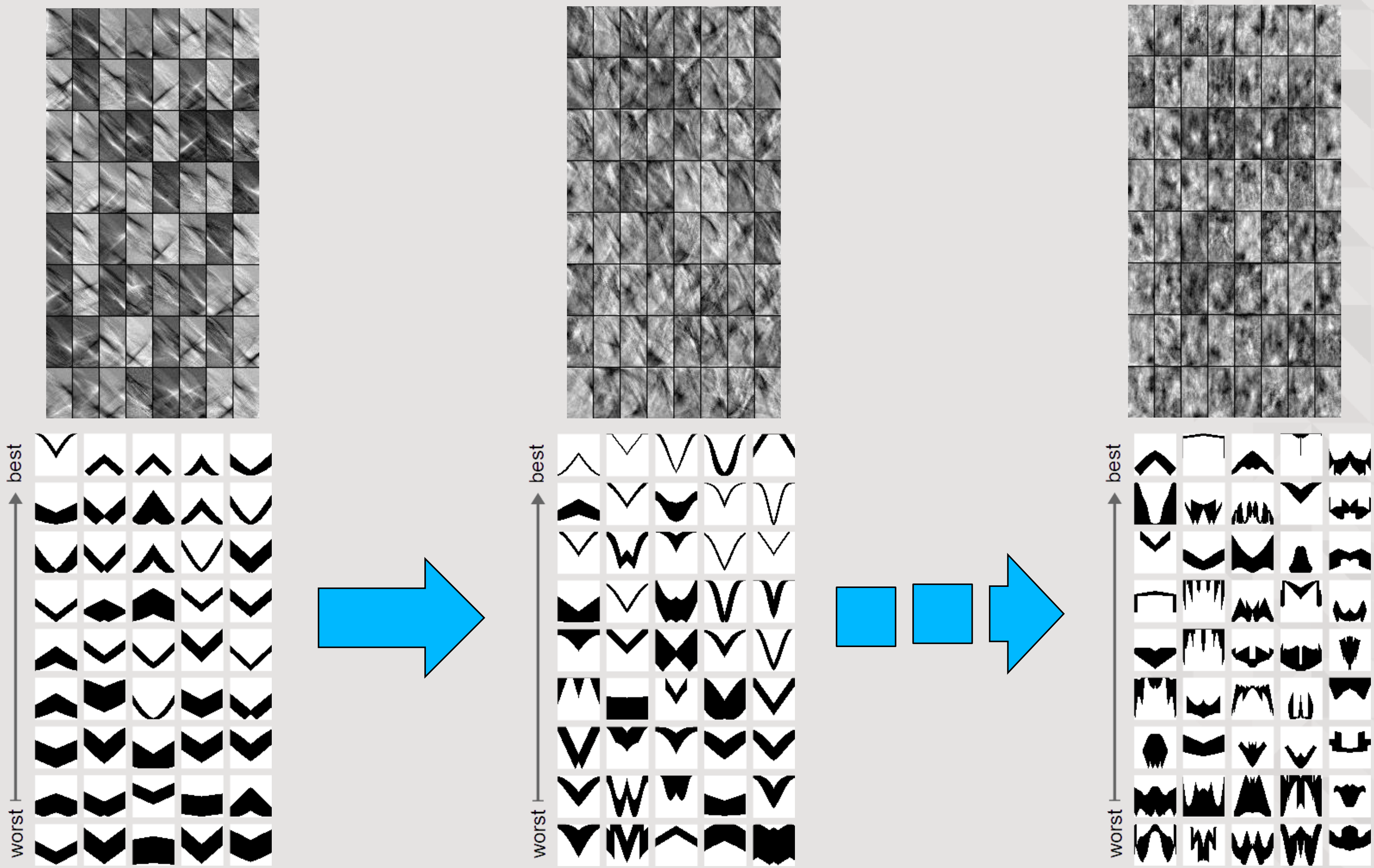
- **Novelty:** distance based on latent representation
- Autoencoder trained on all results of 100 evol. runs
- New evol. runs based on vector distance in hidden nodes of autoencoder
- Re-train autoencoder on new results, repeat.





A. Liapis, H. P. Martınez, J. Togelius, and G. N. Yannakakis, Transforming exploratory creativity with DeLeNoX, in ICCC, 2013

DeLeNoX Spaceship Generation

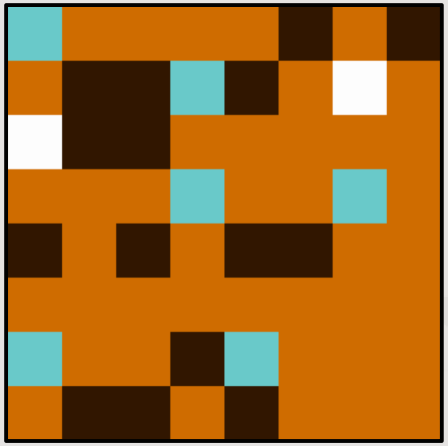


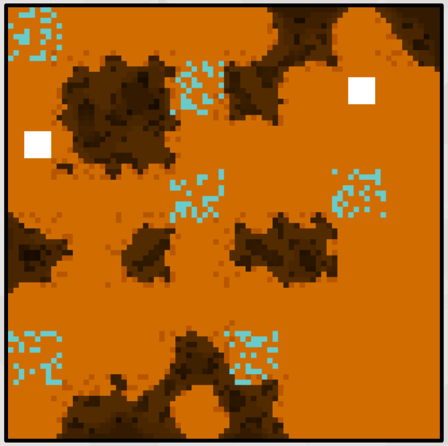
A. Liapis, H. P. Martınez, J. Togelius, and G. N. Yannakakis, “Transforming exploratory creativity with DeLeNoX,.” in ICCC, 2013, pp. 56–63.

http://sentientsketchbook.com

Novel Suggestions for Designers

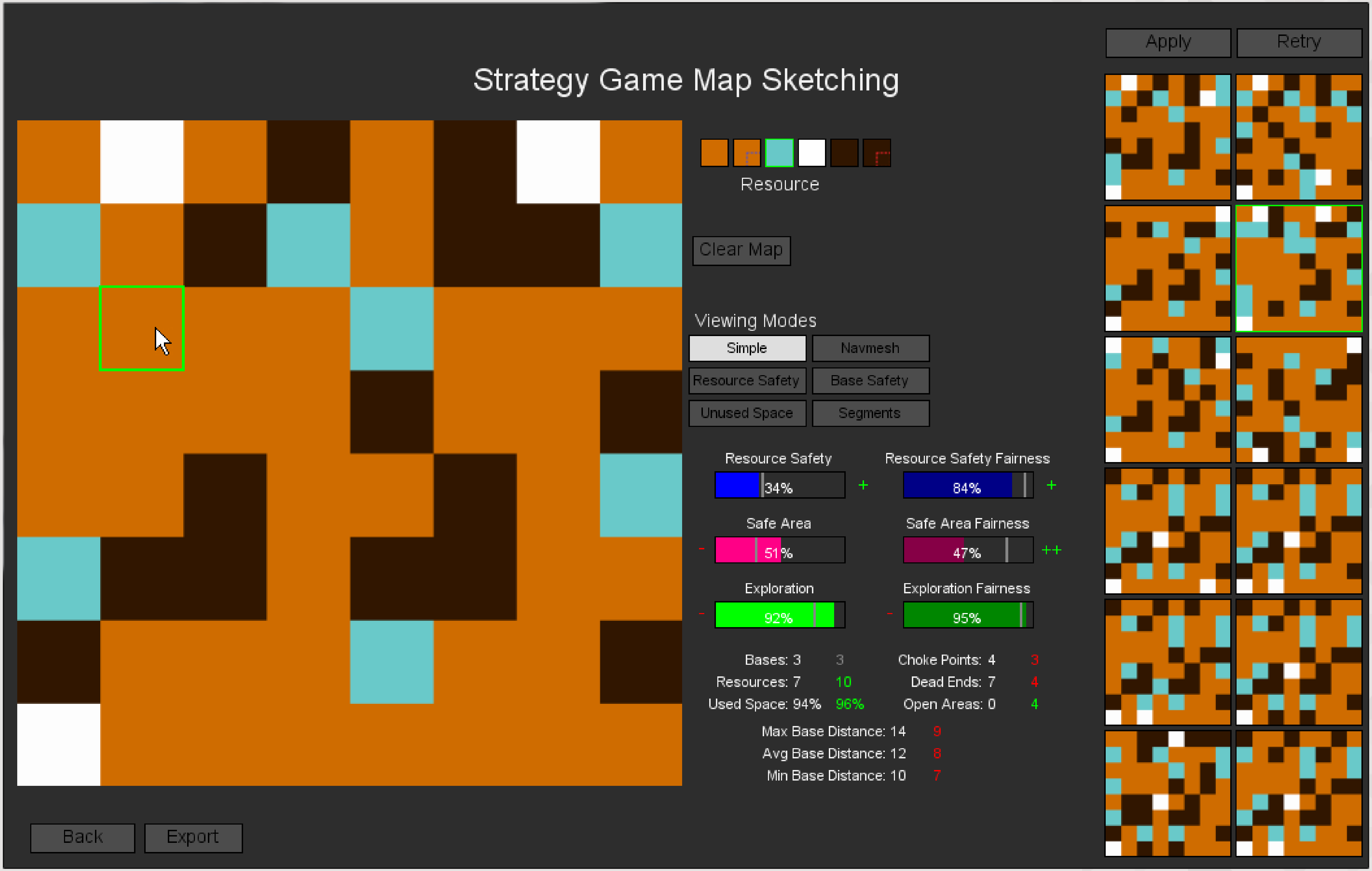
- Sentient Sketchbook: CAD tool for level design, with real-time alternatives generated by the computer (inspired by human user)
- Low-fidelity map sketches
- Constraints:
  - Number of 'special' tiles
  - All 'special' tiles must be reachable from one another





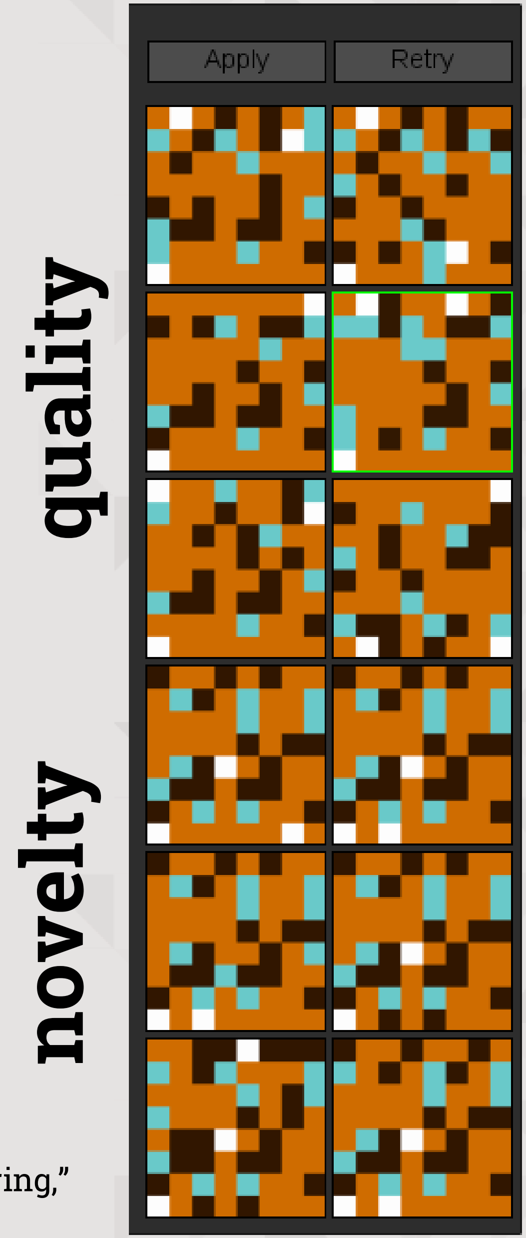
A. Liapis, G. N. Yannakakis, and J. Togelius, "Sentient sketchbook: Computer-aided game level authoring," in Proceedings of the 8th Conference on the Foundations of Digital Games, 2013, pp. 213–220.

Novel Suggestions for Designers



Novel Suggestions for Designers

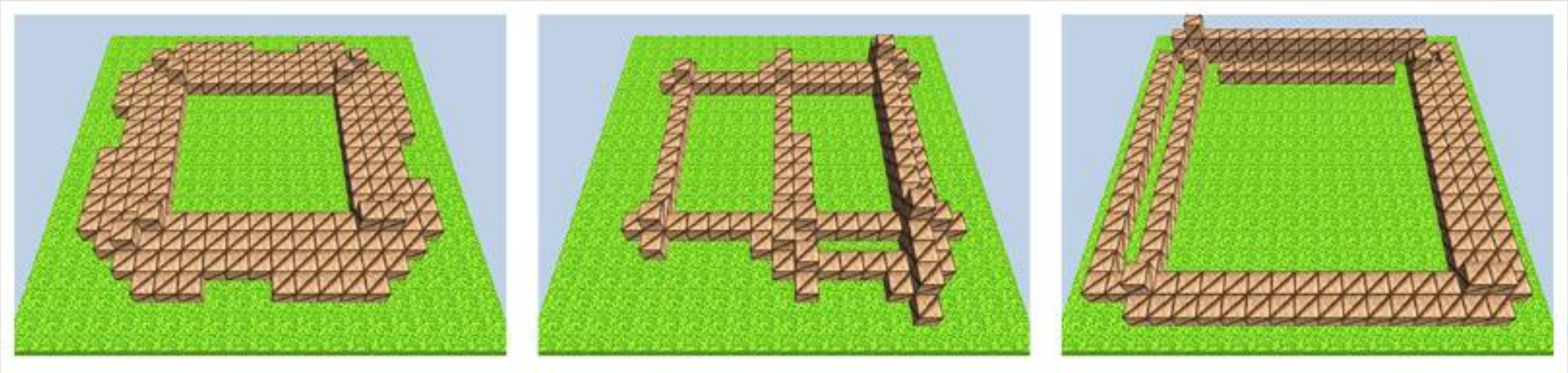
- Genetic algorithms running multiple threads.
- Initial population seeded from the user's sketch.
- Two-population constrained evolution ensures playable results.
- Quality: different path operations
- Novelty: tile-to-tile similarity



A. Liapis, G. N. Yannakakis, and J. Togelius, “Sentient sketchbook: Computer-aided game level authoring,” in Proceedings of the 8th Conference on the Foundations of Digital Games, 2013, pp. 213–220.

Minecraft Structure Generation

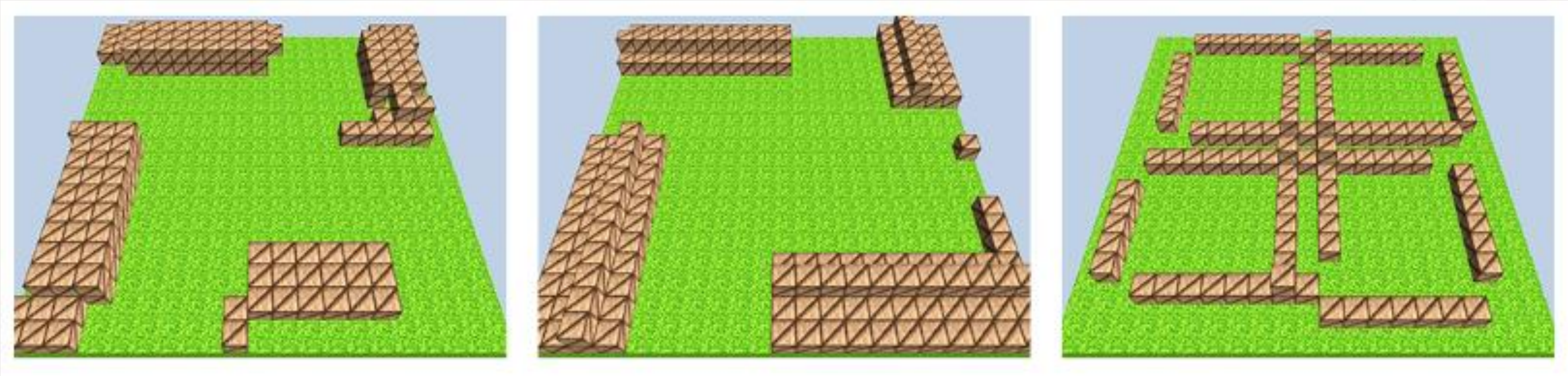
- **Minecraft structures created by agents**
- Agents controlled by evolved ANN
  - Input: 11x11 blocks around agent (block, boundary, empty)
  - Output: 6 actions (move, add block, remove block)



J. K. Pugh, L. B. Soros, R. Frota, K. Negy and K. O. Stanley, “Major Evolutionary Transitions in the Voxelbuild Virtual Sandbox Game”, in Proceedings of the European Conference on Artificial Life. 2017.

Minecraft Structure Generation

- Neuroevolution guided by NS-LC:
  - **Quality:** larger and taller structures (blocks * max. height)
  - **Diversity:** voxel-by-voxel similarity



J. K. Pugh, L. B. Soros, R. Frota, K. Negy and K. O. Stanley, “Major Evolutionary Transitions in the Voxelbuild Virtual Sandbox Game”, in Proceedings of the European Conference on Artificial Life. 2017.

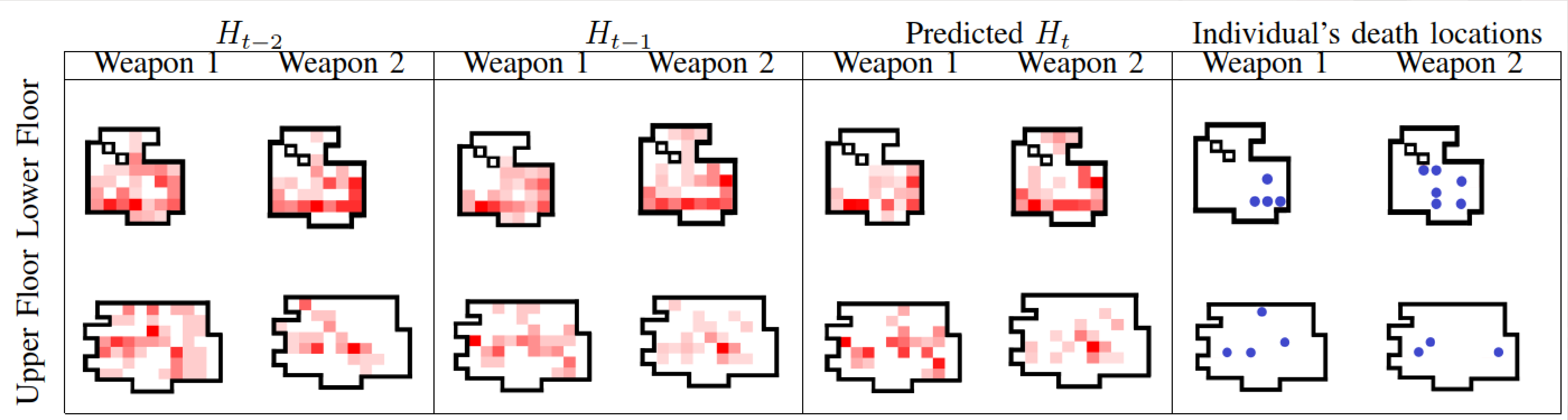
Surprising Weapon Generation

- Evolving **pairs of weapons** for a one-versus-one match in an Unreal Tournament 3 map.
- 22 parameters (11 per weapon), e.g. bullet speed
- Constraints via simulation:
  - Effectiveness (kills achieved)
  - Safety (harm to wielder)
  - Balance (entropy of kills)

D. Gravina, A. Liapis, and G. N. Yannakakis, “Constrained surprise search for content generation,” in Proceedings of the IEEE Conference on Computational Intelligence and Games. IEEE, 2016.

Surprising Weapon Generation

- **Surprise:** computed on death location heatmaps aggregated from the entire feasible population.
- Predicting next heatmap of death locations.



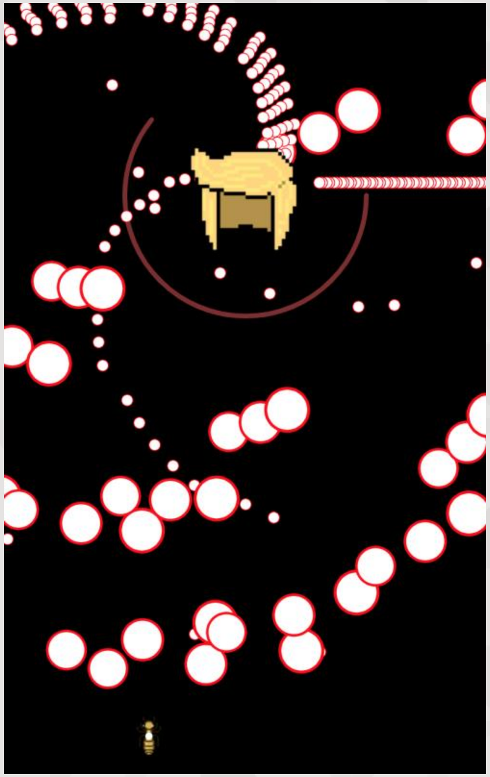
D. Gravina, A. Liapis, and G. N. Yannakakis, "Constrained surprise search for content generation," in Proceedings of the IEEE Conference on Computational Intelligence and Games. IEEE, 2016.

Surprising Weapon Generation

D. Gravina, A. Liapis, and G. N. Yannakakis, “Constrained surprise search for content generation,” in Proceedings of the IEEE Conference on Computational Intelligence and Games. IEEE, 2016.

Coding Shoot'em'up Scripts

- Shoot-em-up script for placing enemy or bullet spawners, evolved via Constrained MAP Elites
- Chromosome: 11 arrays of 23 integers each mapped to the custom Talakat script
- Constraints via simulation:
  - # spawners below a max value.
  - At least 10 bullets in more than 50% of frames.



A. Khalifa, S. Lee, A. Nealen, and J. Togelius, "Talakat: Bullet hell generation through constrained MAP-Elites," in Proc. of The Genetic and Evolutionary Computation Conference. ACM, 2018, pp.1047–1054

Coding Shoot'em'up Scripts

- **Quality** following simulated A* playthrough:
  - Progress: # frames survived
  - Lose: if player has died
  - Safety: # frames a stationary agent would survive
  - Future location: distance from fewest bullets
- **Space Partition** following simulated A* playthrough:
  - Entropy: # times player changed direction
  - Risk: # bullets near player
  - Distribution: amount of space occupied by bullets

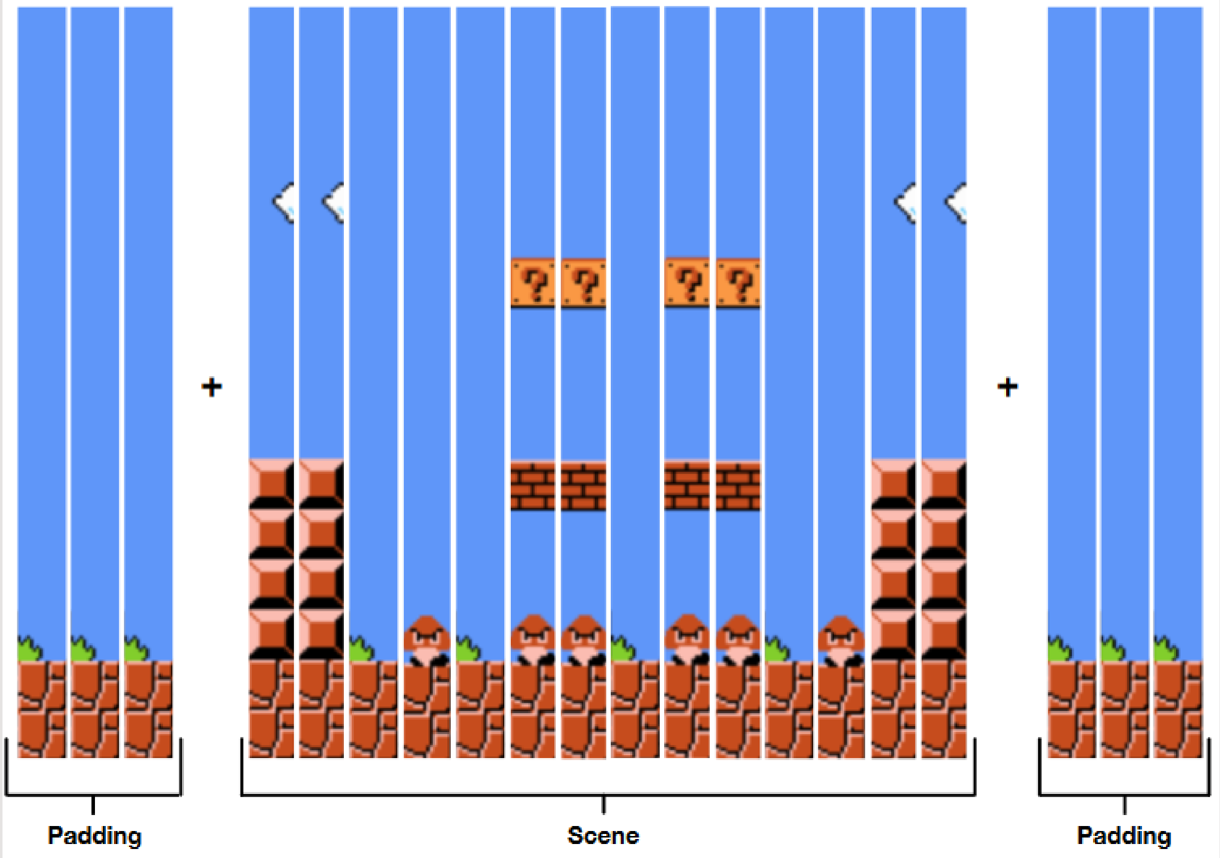
A. Khalifa, S. Lee, A. Nealen, and J. Togelius, "Talakat: Bullet hell generation through constrained MAP-Elites," in Proc. of The Genetic and Evolutionary Computation Conference. ACM, 2018, pp.1047–1054

Coding Shoot'em'up Scripts

A. Khalifa, S. Lee, A. Nealen, and J. Togelius, "Talakat: Bullet hell generation through constrained MAP-Elites," in Proc. of The Genetic and Evolutionary Computation Conference. ACM, 2018, pp.1047–1054

Novel Mechanics for Mario Levels

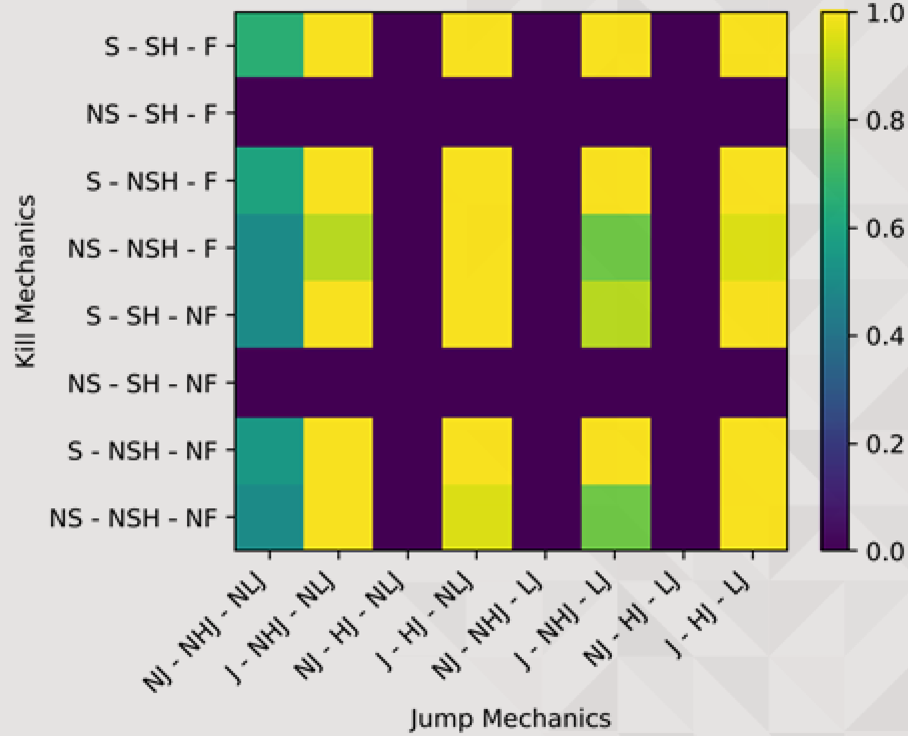
- “Scenes” (level fragments) for Super Mario Bros.
- Representation: 14 + 3 + 3 floor slices (premade)



A. Khalifa, M. C. Green, G. Barros, and J. Togelius, Intentional computational level design, in Proceedings of The Genetic and Evolutionary Computation Conference. ACM, 2019

Novel Mechanics for Mario Levels

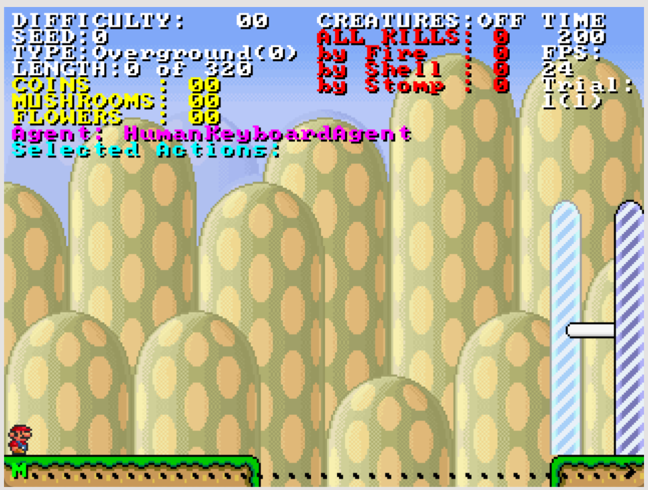
- Simulations with "perfect" (A*) and "limited" agent
- **Constraints:** same performance between perfect & limited agents
- **Quality:** simplicity (entropy of tiles in a scene)
- **Diversity:** mechanics used



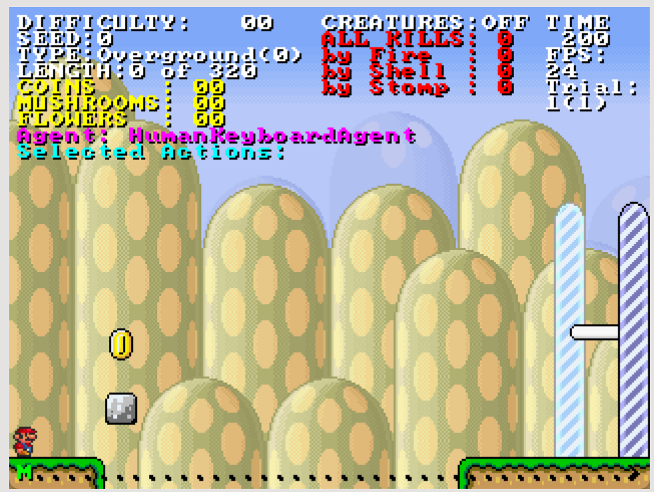
A. Khalifa, M. C. Green, G. Barros, and J. Togelius, Intentional computational level design, in Proceedings of The Genetic and Evolutionary Computation Conference. ACM, 2019

Novel Mechanics for Mario Levels

- “Limited” agent may also punish certain mechanics



Speed Punishing Model



Coin Punishing Model

Shell Kill Punishing Model

A. Khalifa, M. C. Green, G. Barros, and J. Togelius, Intentional computational level design, in Proceedings of The Genetic and Evolutionary Computation Conference. ACM, 2019

Novel Mechanics for Mario Levels

0 Mechanics

100 Mechanics

A. Khalifa, M. C. Green, G. Barros, and J. Togelius, Intentional computational level design,
in Proceedings of The Genetic and Evolutionary Computation Conference. ACM, 2019

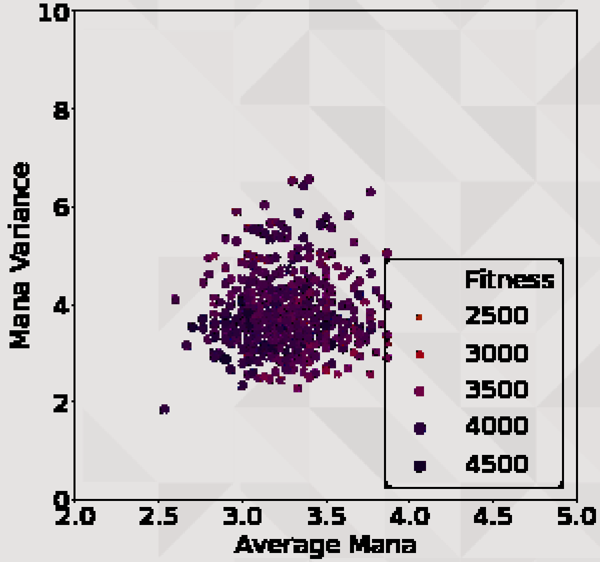
Diverse Mana Use in Hearthstone

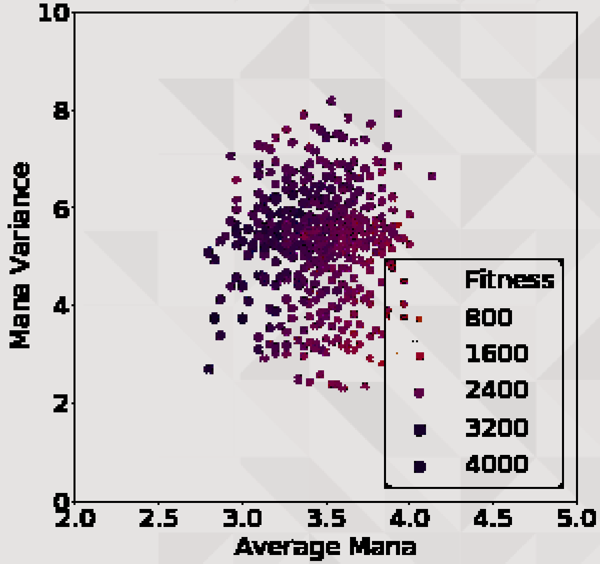
- Generating decks for Hearthstone
- Mutation by replacing cards from starter and classic decks, resulting in valid decks.
- **Quality:** average difference in health after 200 games against opponent*

M. C. Fontaine, S. Lee, L. B. Soros, F. D. M. Silva, J. Togelius, and A. K. Hoover, "Mapping hearthstone deck spaces with MAP-Elites with sliding boundaries," in Proceedings of The Genetic and Evolutionary Computation Conference. ACM, 2019.

Diverse Mana Use in Hearthstone

- **Space Partition:**
  - Average mana cost of 30 cards in deck
  - Deviation in mana use of 30 cards
- MAP-Elites with Sliding Boundaries:
  - boundaries placed uniformly at percentage marks of the distribution
  - boundaries re-calculated every 100 individuals





M. C. Fontaine, S. Lee, L. B. Soros, F. D. M. Silva, J. Togelius, and A. K. Hoover, "Mapping hearthstone deck spaces with MAP-Elites with sliding boundaries," in Proceedings of The Genetic and Evolutionary Computation Conference. ACM, 2019.

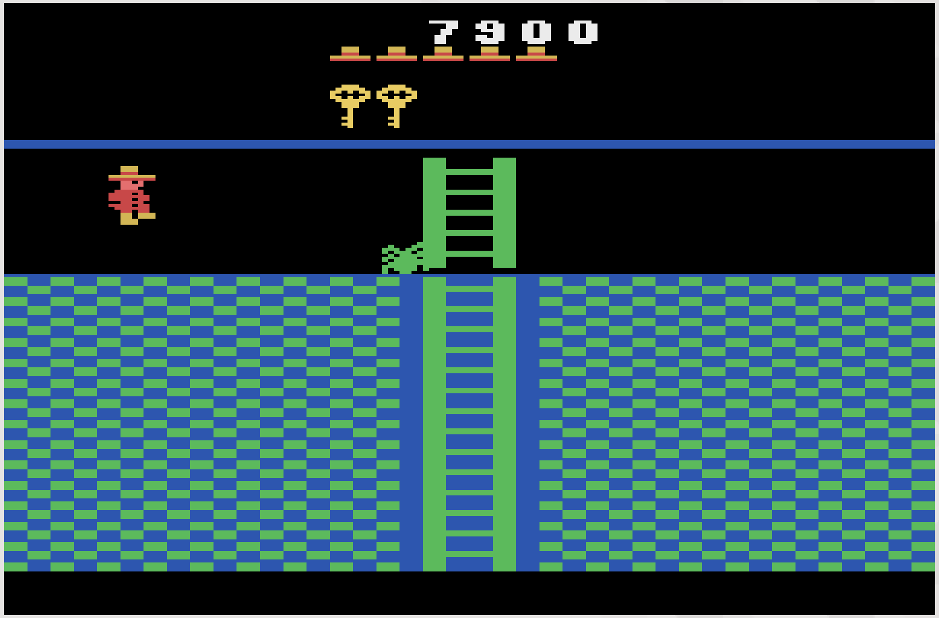
Instances of PCG-QD

Algorithm	**Components**				**Characterization**		**Artifact**
	Divergence		Quality		Divergence	Quality	
	D	P	LC	C			
MAP-Elites	-	✓	✓	-	DNN Output	DNN Confidence	2D and 3D objects [37], [38]
MESB	-	✓	✓	-	Mana Distribution	Health Difference	Hearthstone Decks [13]
CME	-	✓	✓	✓	Playthrough Properties	Validity and Playability	Bullet-Hell Scripts [18]
	-	✓	✓	✓	Triggered Mechanics	Playability and Simplicity	Mario Scenes [19]
	-	✓	✓	✓	Linearity, Simmetry, Similarity, and Patterns	Playability, Room properties, and Design patterns	Dungeons [39]
CNS	✓	-	-	✓	Visual Diversity	Playability	Map Sketches [14], [15]
	✓	-	-	✓	Visual Diversity	Believability	Arcade-Style Spaceships [40]
	✓	-	-	✓	DNN Latent Space	Believability	2D Spaceship Hulls [16]
CSS	✓	-	-	✓	Map Locations	Balance and Playability	FPS Weapons [17]
NS-LC	✓	-	✓	-	Block Presence	Complexity	Minecraft-like Structures [41]

D. Gravina, A. Khalifa, A. Liapis, J. Togelius and G. N. Yannakakis: Procedural Content Generation through Quality-Diversity, in Proceedings of the IEEE Conference on Games, 2019.

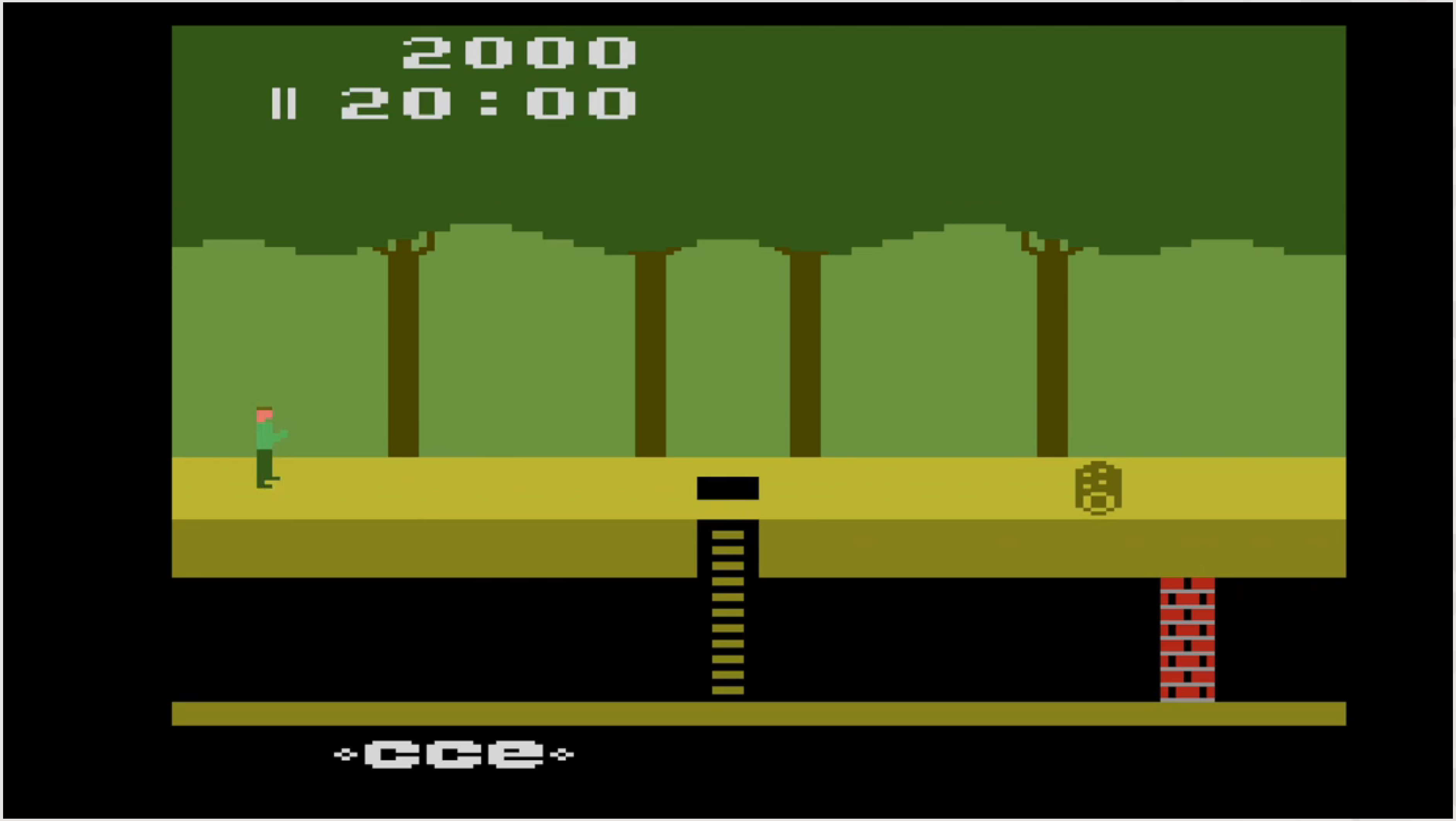
Beyond Game Content Generation

- Example of QD for agents that play games:
  - **Go-Explore:** enhanced QD based on MAP-Elites
  - States represented as low-res screen captures + metadata
  - Exploration done randomly, adds/updates states
  - Robustification via ANN and imitation learning to maximize score



A. Ecoffet, J. Huizinga, J. Lehman, K. O. Stanley, and J. Clune. Montezuma's Revenge Solved by Go-Explore, a New Algorithm for Hard-Exploration Problems (Sets Records on Pitfall, Too). 2018. https://eng.uber.com/go-explore/

Beyond Game Content Generation



A. Ecoffet, J. Huizinga, J. Lehman, K. O. Stanley, and J. Clune. Montezuma's Revenge Solved by Go-Explore, a New Algorithm for Hard-Exploration Problems (Sets Records on Pitfall, Too). 2018. https://eng.uber.com/go-explore/

Next Steps

Future challenges

- **Orchestrating** multiple facets: how to assess value when audio, visuals, plot, (rules? levels?) all contribute to the same artifact?
- **Deep learning** to drive novelty, surprise, and diversity? And from which **data sources**?
- **Human creativity** back in the loop: interfacing & explaining EC/ML approaches.

A. Liapis, G. N. Yannakakis, M. J. Nelson, M. Preuss and R. Bidarra: "Orchestrating Game Generation," in Transactions on Games, vol. 11, no 1, pp. 48-68, 2019.

Emotion as a driver for CC

- Mathematical models of surprise are one thing…
- Can we drive EC on computational models of surprise, joy, arousal that match human notions (e.g. from crowdsourcing?)

D. Melhart, A. Liapis, G. N. Yannakakis: PAGAN: Video Affect Annotation Made Easy. In Proc. of the 8th International Conference on Affective Computing andIntelligent Interaction (ACII), 2019.

Parting words

- **Computational Creativity** is (and has been) an ideal application for evolutionary computation.
- Creativity hinges on transformation, reframing, surprise, novelty, typicality, and quality.
- EC methods that promote such properties are ideal candidates (QD, novelty/surprise search)
- **Game content generation** is especially suited for this as it has playability constraints & quality and structural/gameplay diversity concerns too.

Thank you!

?