Generative Art via Grammatical Evolution

Erik Fredericks, Abigail Diller, and Jared Moore
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Grand Valley State University
www.gvsu.edu

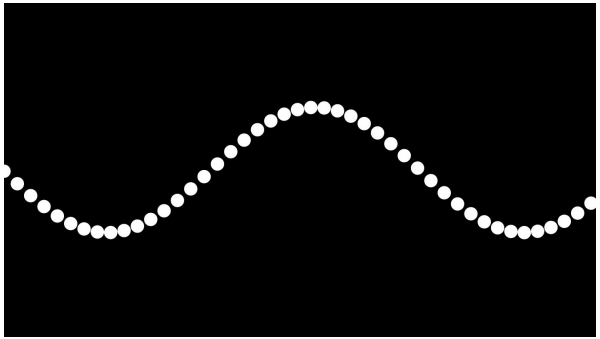
Motivation

Daniel Shiffman - TheCodingTrain

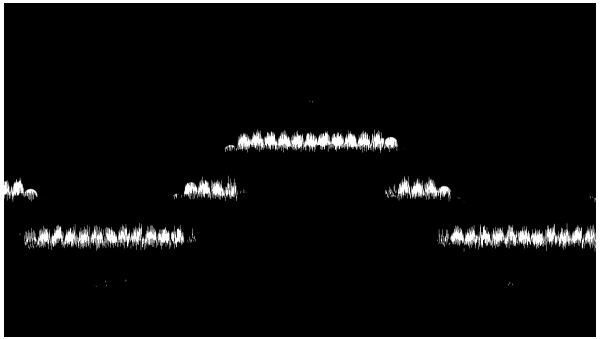
Background - Generative Art

Visualization of algorithms and/or mathematical functions [1-5]

- Creative coding [11-15]
- Real-world displays [16]



y = 75.0 *sin(x)

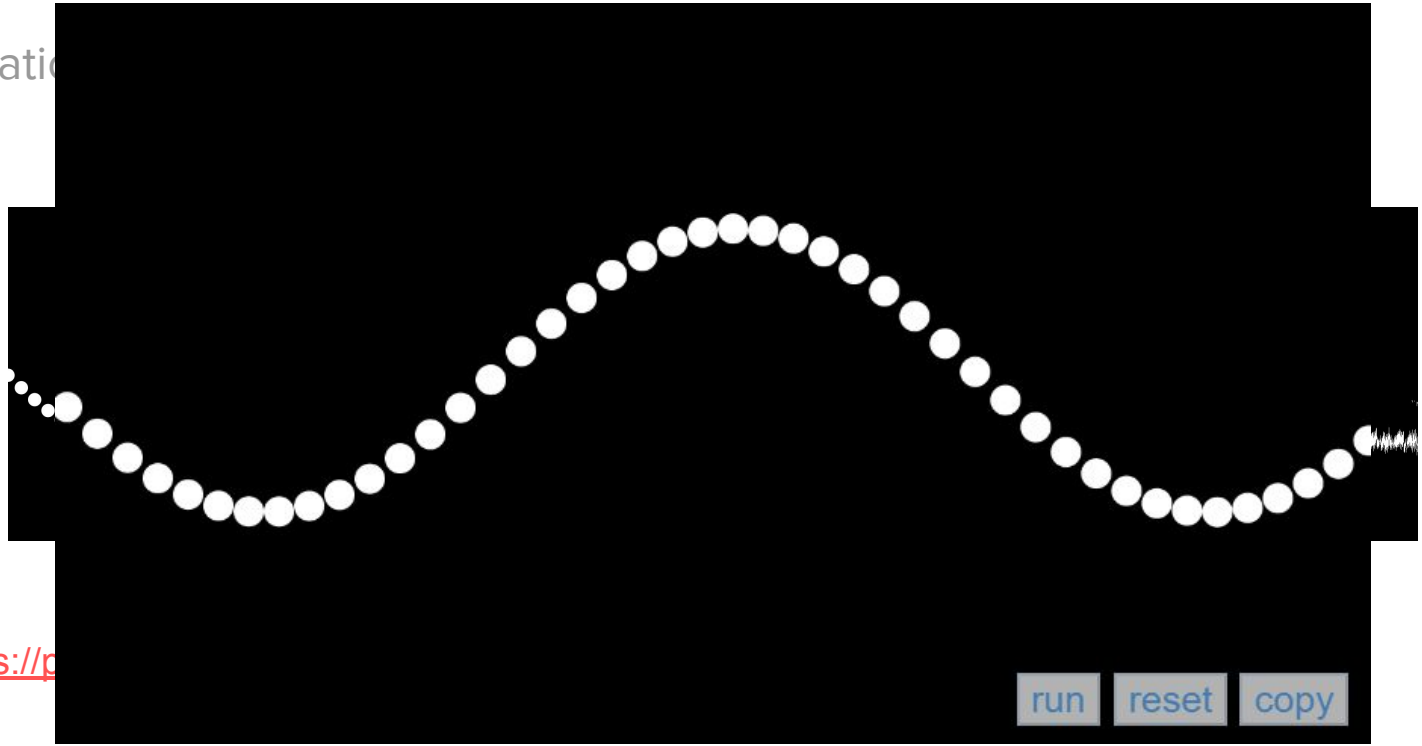


Pixel sorted

https://p5js.org/examples/math-sine-wave.html

Background - Generative Art

Visualizati



https://p

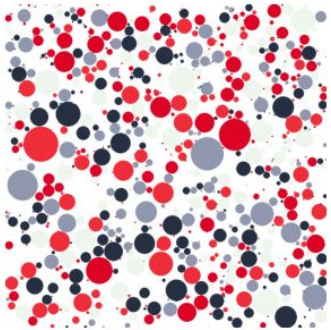
https://editor.p5js.org/frederer/sketches/DbWjEErKy

Included techniques

Stippling
Cellular automata
Circle packing
Flow fields (two implementations)
Drunkard's walk
Dithering
Pixel sorting
– any technique is viable!

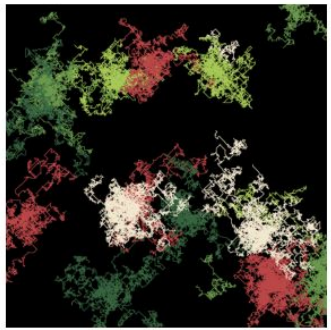
(a) Stippled

(b) Cellular Automata



(c) Circle Packing

(d) Flow Field



(e) Drunkard's Walk

Background - Grammatical Evolution

Subset of evolutionary computation (generally genetic programming-based) [24]

- Grammar-based genome [6-7]
- Uses very similar genetic operators (e.g., mutation, crossover, etc.)

Effective at constraining the *solution space*

- Target for genetic improvement! [7]

```
rules = {
  'ordered_pattern': ['#techniques#'],
  'techniques': ['#technique#','#techniques#,#technique#'],
  'technique': ['stippledBG','flowField'],
  ...
}
```

Tracery [9] grammar

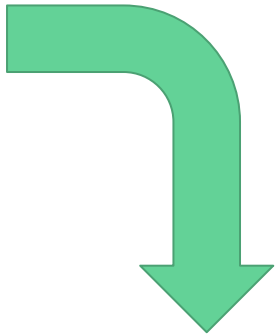
Background - Grammars

Top-level rule is "flattened" and production rules expanded

- Tracery enables randomness (among other things)

```
rules = {
  'ordered_pattern': ['#techniques#'],
  'techniques': ['#technique#','#techniques#,#technique#'],
  'technique': ['stippledBG','flowField'],
  ...
}
```

Tracery [9] grammar

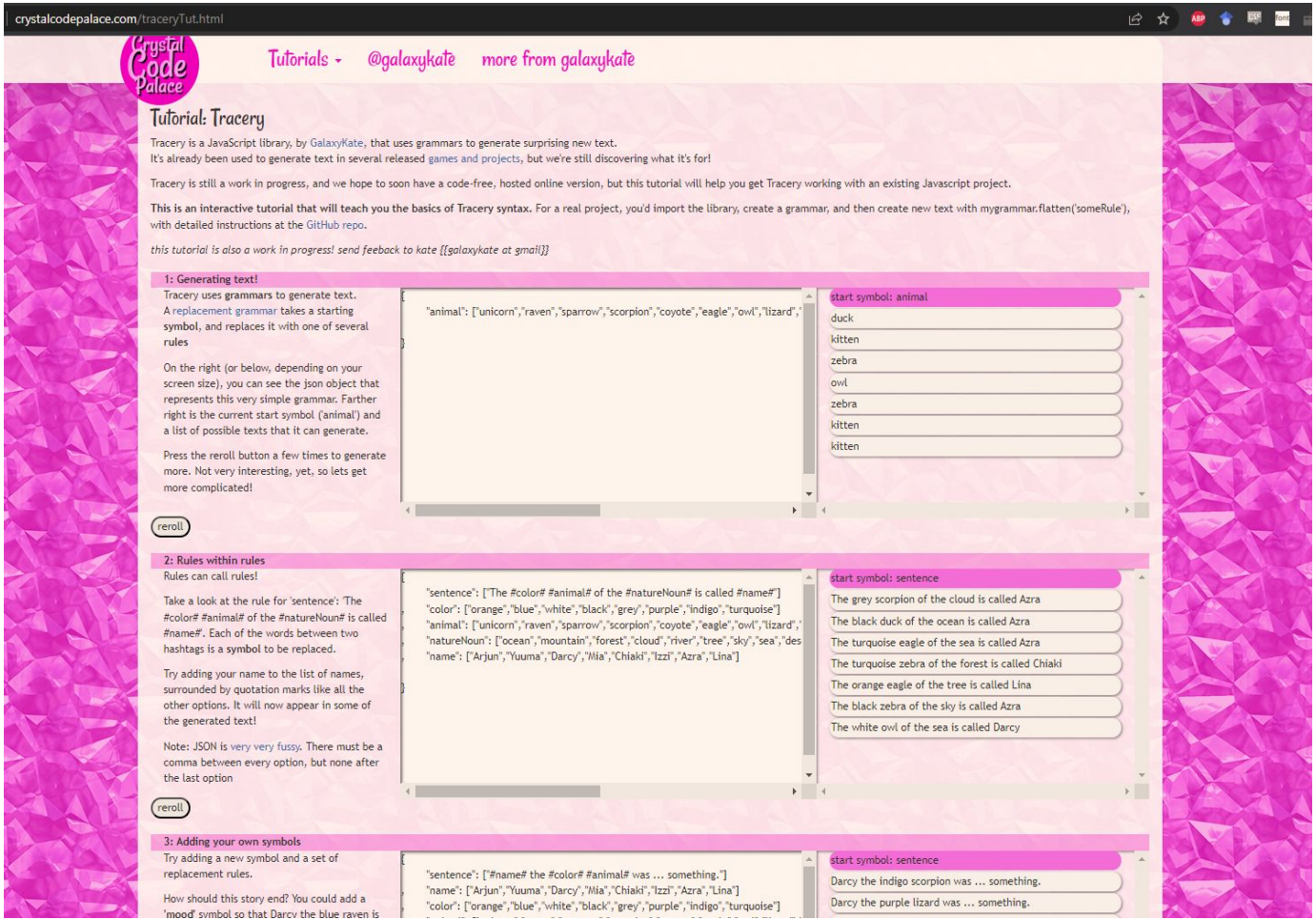


`stippledBG(params`$_a$`),stippledBG(params`$_b$`),flowField(params`$_c$`),stippledBG(params`$_d$`)`

Expanded output

Tracery [9]

http://www.crystalcodepalace.com/traceryTut.html



Background - Lexicase Selection [10]

Many-objective selection operator
- Not pareto-based!

Evaluates individuals on an objective-by-objective basis

Each selection:
- Sample of population taken
- Comparison on first objective
  - If one individual better, selected
  - Else, advance to next objective
- If all objectives exhausted
  - Random selection

ϵ-Lexicase selection [30]
- Individuals tied if within ϵ
- Important for real-valued fitness objectives (observable output may not change)

ϵ = **0.85**

Project

Apply GI techniques to **optimize the grammar** defining the order and parameters of a set of generative art techniques

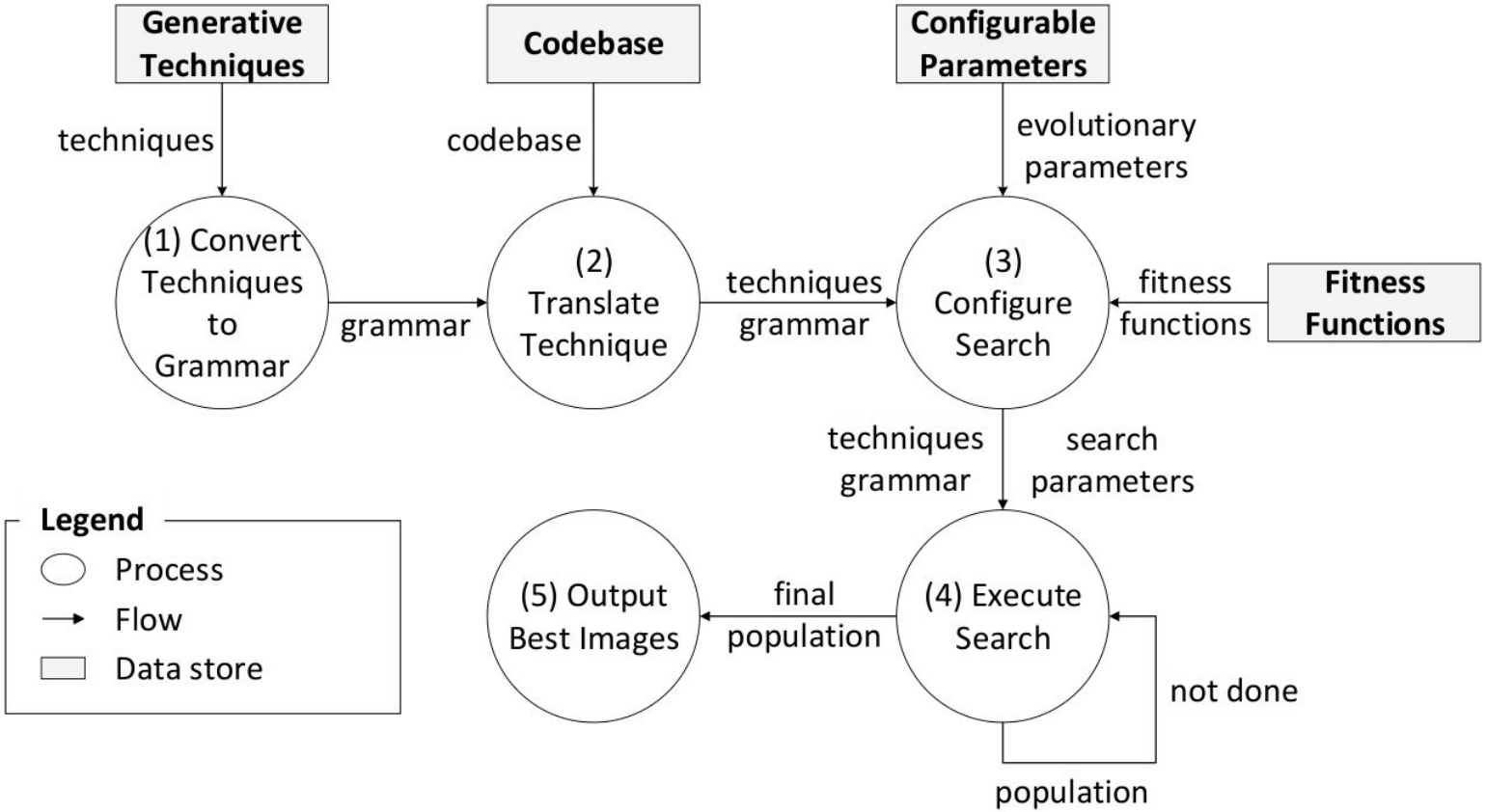
- I like glitch art, which makes for a lovely (and naive) proof of concept
  - (Pixel sorting below ➜ https://github.com/satyarth/pixelsort)

Original

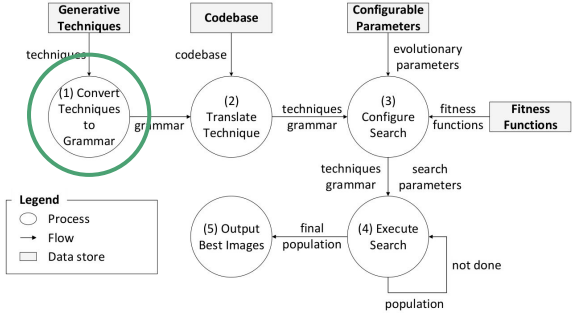
Pixel sorted

Color shifted

Approach


Generative Techniques
Codebase
Configurable Parameters
techniques
codebase
evolutionary parameters
(1) Convert Techniques to Grammar
grammar
(2) Translate Technique
techniques grammar
(3) Configure Search
fitness functions
Fitness Functions
techniques grammar
search parameters
Legend
Process
Flow
Data store
(5) Output Best Images
final population
(4) Execute Search
not done
population

(1) Convert Techniques to Grammar

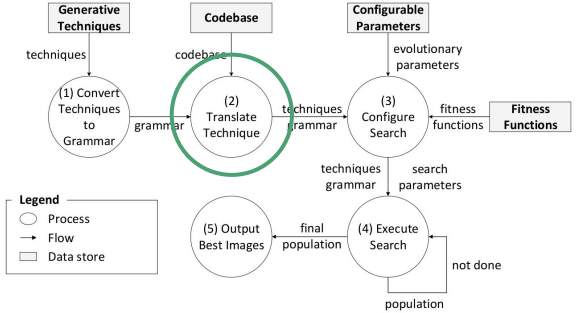


Suite of generative art techniques required as input

```
def flowField(type, palette, zoom):
  # type: ['edgy', 'curves']
  # palette: list of colors
  # zoom: float between 0.001 and 0.500
```

```
'flow-field' : '#flow-field-type#:#palette#:#flow-field-zoom#',
'flow-field-type' : ['edgy', 'curves'],
'flow-field-zoom': [str(x) for x in np.arange(0.001, 0.5, 0.001)],
…
```

(2) Translate Technique



Each generative art technique must also be translated to framework requirements

E.g., flow field must (minimally) accept a Pillow Image object

```
def flowField(image, type, palette, zoom)
  # image: PIL image object
  # type: ['edgy', 'curves']
  # palette: list of colors
  # zoom: float between 0.001 and 0.500
```

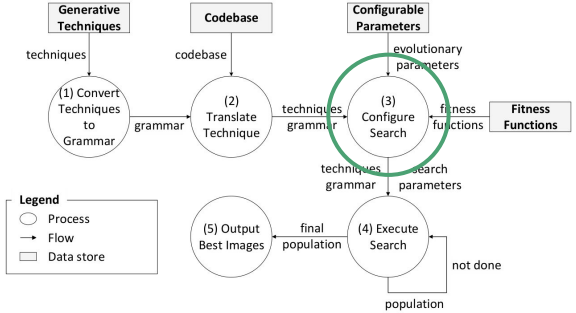
(3) Configure Search

Selection operator:

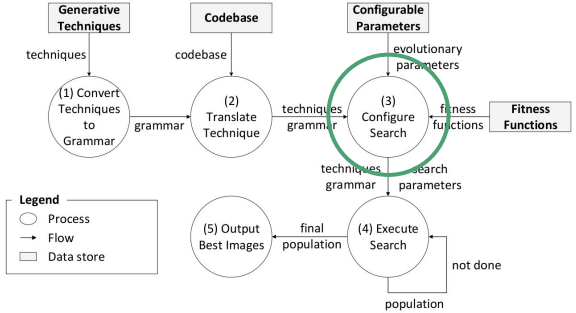
- Many-objective (Lexicase selection)
- Single-objective (Tournament selection)
- Random (No selection)

Standard configurable parameters

- E.g., population size, mutation rate, etc.



(3) Configure Search



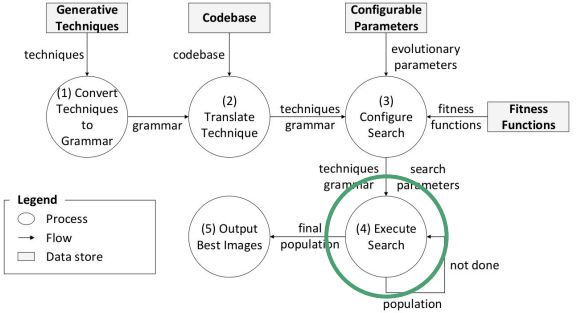
Fitness functions

$ff_{min(genome)}$: minimize duplicate genes
$ff_{max(techniques)}$: maximizing diversity of included techniques
$ff_{max(RMS|Chebyshev)}$: maximize pixel differences between images

Many-objective search uses all four fitness functions

Single-objective search only uses $ff_{max(RMS)}$

(4) Execute Search



Search executed according to (3)

- Each genome evaluated on flattened grammar

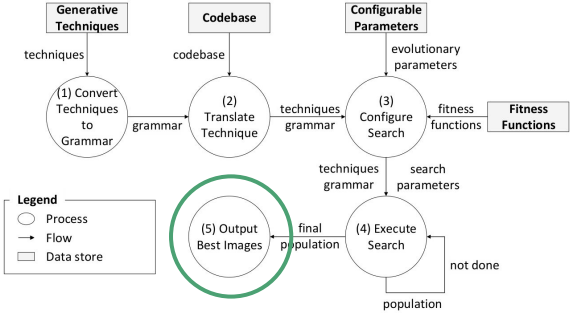
- *For this work*, image object **not** cleared
  - Subject of future work

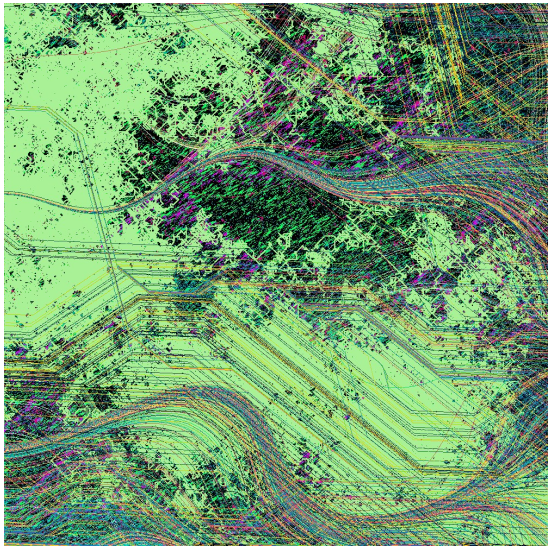
Depending on configuration

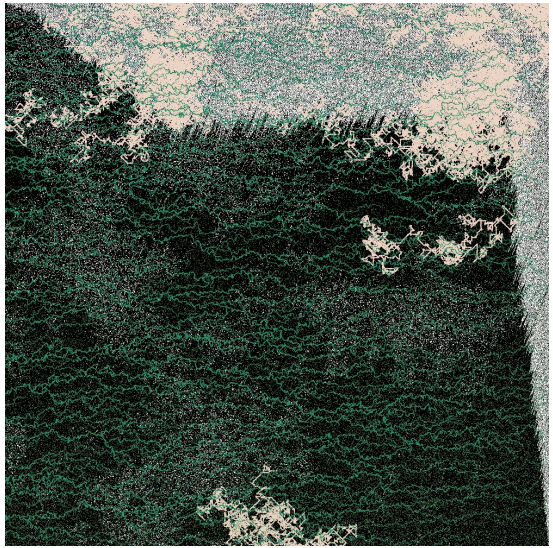
- Many-objective: Lexicase
- Single-objective: Tournament selection
- Random: No selection

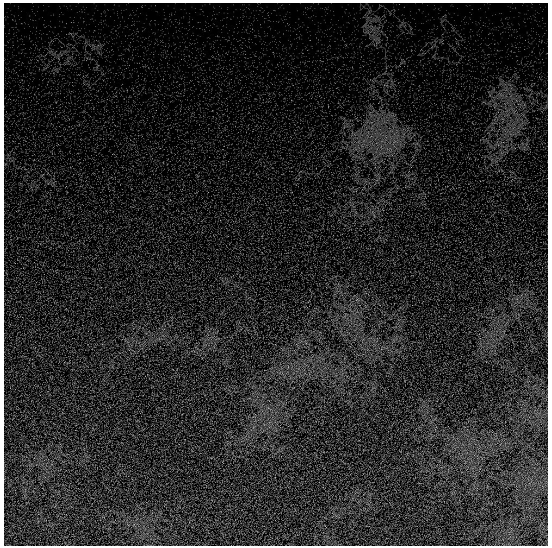
(5) Output Best Images

Final population of image objects stored to disk upon completion









Experiment Configuration

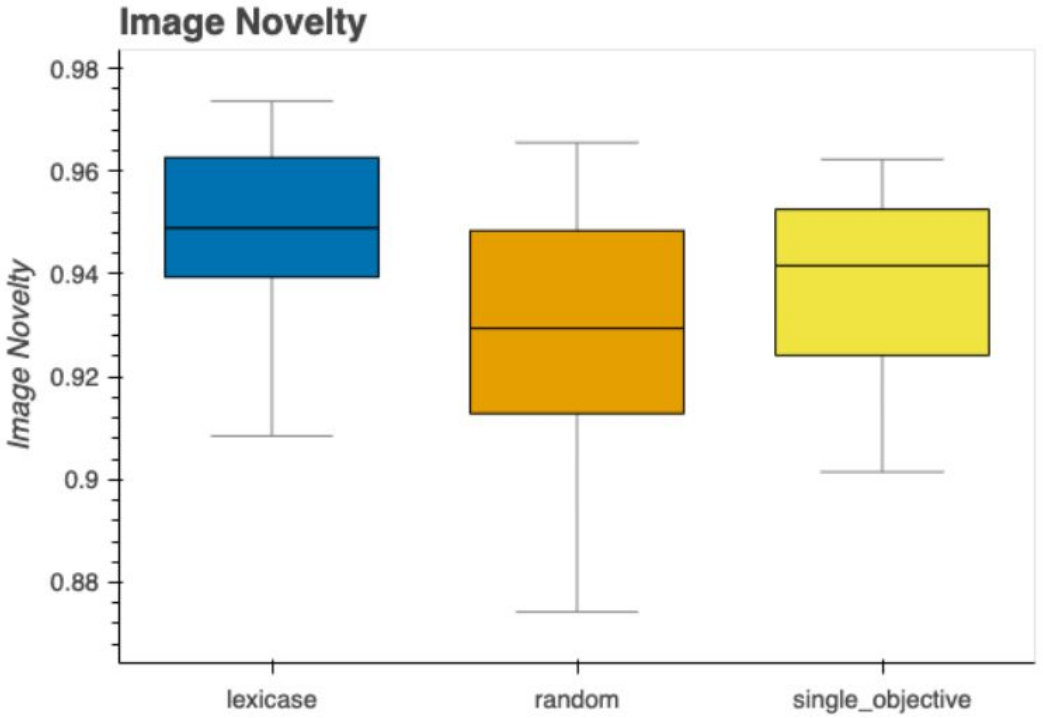
Parameter	Value
Experimental replicates	10
Image size (pixels)	1000 x 1000
Number of generative techniques	8
Generations	100
Population size	100
Crossover rate	0.5
Mutation rate	0.4
Number of Lexicase objectives	4
ϵ (Lexicase - many-objective)	0.85

TABLE I: Evolutionary parameter configuration.

Results - Novelty

Wilcoxon rank-sum test with Bonferroni correction

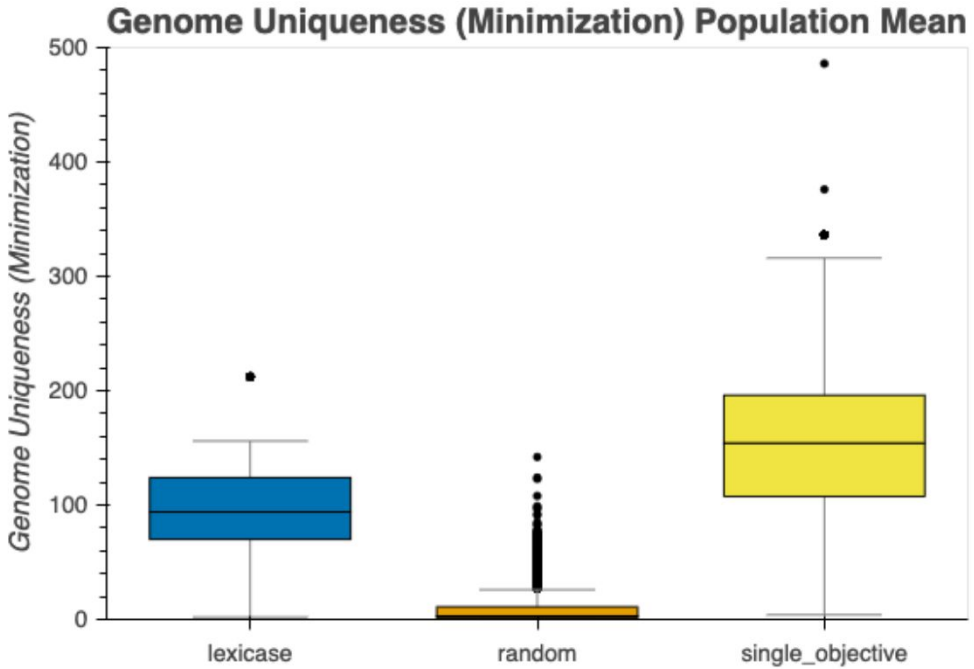
Lexicase vs. random ($p < 0.01$)
Single-objective vs. random ($p < 0.03$)
Lexicase vs. single-objective ($p > 0.03$)



Results - Gene Uniqueness

Wilcoxon rank-sum test with Bonferroni correction

Lexicase vs. random ($p < 0.001$)
Single-objective vs. random ($p < 0.001$)
Lexicase vs. single-objective ($p > 0.001$)



Discussion / Sample Outputs

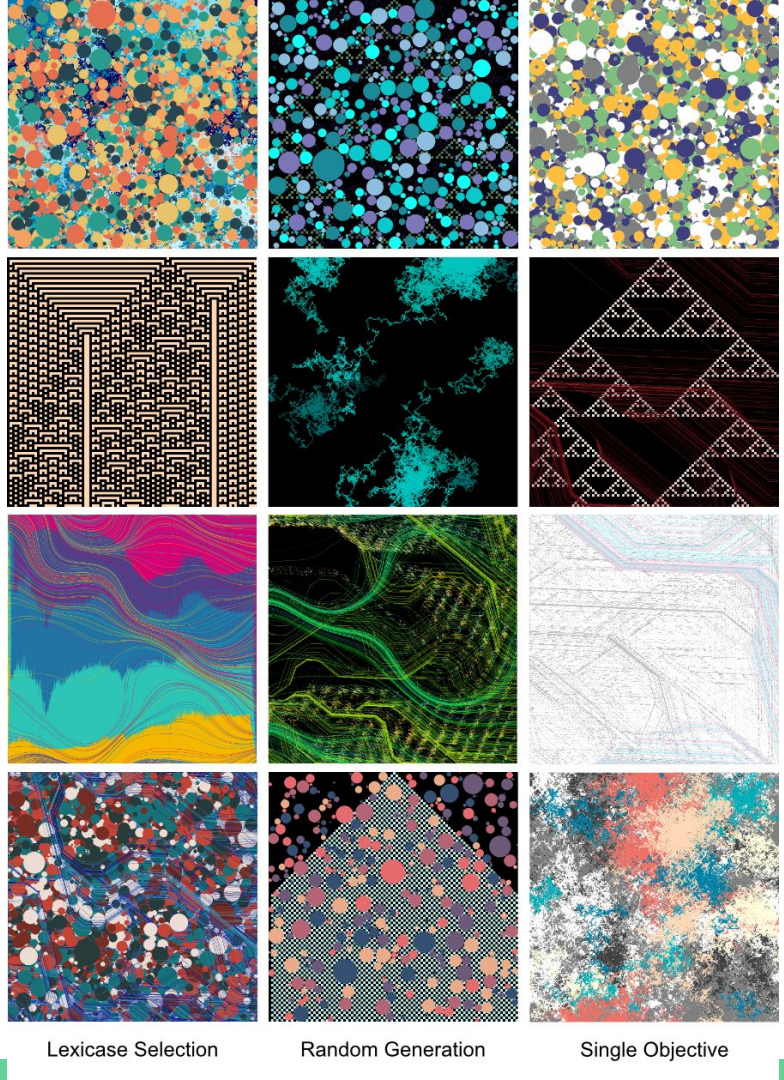
Single- and many-objective both **tended to converge towards both multiple and common suites of techniques**

- On a 'per run' basis
- Resulting from maximizing pixel differences and maximizing the number of techniques

Random search **tended towards 'blank space'**

- Fewer techniques in genome

Lexicase tended to converge to a smaller set of techniques with common outputs



Related Work

Generative art via artificial intelligence

- Extremely popular right now thanks to large language models!
  - DALL-E, Midjourney, Stable Diffusion, VQGAN+CLIP, etc [15,35,36].
  - All require a massive dataset and massive amount of computing power

  - *GenerativeGI* only requires a suite of techniques and computing necessary for evolutionary search

https://www.reddit.com/r/StableDiffusion/comments/yxtdrh

Related Work

Generative art via search heuristics

- Often used in visualization and creative coding domains

- Visualize 3D models of mathematical formulae [4]
- Creating environments within game worlds [5]

    - *GenerativeGI* focuses on fine-tuned control over artistic techniques

- Taxonomy of fitness metrics for evolutionary art/music [8]
    - Metrics can be non-trivial to evaluate (e.g., human preference)
    - Target for future work of this paper

Future Work

Additional fitness functions
- Guide towards specific outputs

Human in the loop
- What constitutes a "good" output?
- How do you measure aesthetic preference?

Merging artistic techniques
- How can distinct techniques provide a seamless output?
    - E.g., a flow field into an automata

Thanks to..

Award 80NSSC20M0124

Q&A

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