

Self Contained Multi-AI Architecture Definition via DSL

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Abstract

This paper presents a significant evolution in emergent computational systems, extending the Domain-Specific Language (DSL) driven self-modification paradigm to encompass foundational components beyond neural network architectures and cellular automata rules. Building on prior work where the AI could define its Game of Life (GOL) stepping function and classifier network via a tokenized DSL, we now demonstrate the system's capacity to articulate and dynamically replace its fractal generation algorithms (e.g., Burning Ship and Mandelbrot). By expressing these complex mathematical functions within the same learnable DSL, the system gains a deeper level of meta-programming, enabling the AI to not only define its processing logic but also to programmatically control the very initial conditions and "physics" that seed its emergent dynamics. This advancement pushes towards truly autonomous and adaptive AI capable of reconfiguring its fundamental operational environment.

Introduction

Our previous research established a novel framework for emergent computation [1], [4], demonstrating how a hybrid system, combining fractal-initialized Game of Life (GOL) dynamics with spatiotemporal spectral analysis and a neural network classifier, could achieve symbolic processing and even self-modify core components. Specifically, we showed the AI's ability to generate its GOL stepping function and define its own neural network architecture using a specialized Domain-Specific Language (DSL). This represented a crucial step towards AI systems capable of programming themselves.

This work introduces a further, profound extension to this self-modification capability. We have now integrated the fractal generation algorithms—the very mechanisms responsible for creating the initial complex patterns that seed the GOL grid—into the same DSL. Previously, these fractal functions (like Burning Ship and Mandelbrot) were hard-coded in standard Python. By translating them into the DSL, we enable the AI to programmatically define, modify, and potentially evolve these foundational pattern generators. This refactoring means the system can now influence its own initial conditions and the "substrate" upon which emergent behaviors unfold, opening new avenues for adaptive and creative computational exploration.

Gravity and Transfer of Understanding: PART I

Knowledge and understanding must be compressed when transferred from one entity to another, and then decompressed. Our current state of technology has compressed knowledge into huge LLM networks. Is the ground really accelerating up at us? Because its inertial frame of reference is not at zero, why? Instead of the ground accelerating outward, we can think of gravity as all bodies falling inward and compacting spacetime because of information compression/decompression that happens with each particle collision, it is actually the process that is accelerating, gravity is the increasing of information compression. An LLM network is a highly compressed understanding of information, taking billions of years to evolve. As chips get smaller, this information is compressed to the quantum scale. [2]

Acceleration is new information to the system, which then takes time to compress over many particle interactions. A spaceship accelerating forward using rockets, has an equal amount of matter and energy propelled backward, so in total nothing is actually accelerating, its actually one system that is expanding in two distinct directions. Before the system was uniform, without its own unique two distinct directions, so then it points towards the global inward falling direction of compacting information. (time points to the direction of increasing compression) Moving away from the direction of compression, creates what appears to be locally a force to the observer, the observer acceleration is forcing new information into the global system, slightly changing the center point of the inward falling direction of compacting information. The other forces of nature (in The Standard Model), act directly, because at their small scale they are already fully compressed information states, therefore these forces appear much stronger than gravity. [3]

Sub-Networks inside Fractals: PART II

The introduction of `FractalSubNetwork` represents a critical step towards a fully differentiable and end-to-end trainable system. `FractalSubNetwork` is itself a small neural network, defined using the `@dslai` decorator (see notes below), much like `ClassifierNN`. Its purpose is to learn to subtly perturb or "scramble" the deterministic fractal generation process based on its own internal learning.

```
@dslai(
    'num_input_bands num_hidden_neurons num_output_neurons; input linear(num_input_bands,num_hidden_neurons); activation sigmoid; output
    linear(num_hidden_neurons,num_output_neurons)',
    forward='args self; args x; x equals self.input(x); y equals self.activation(x); r equals self.output(y); return r'
)
class FractalSubNetwork:
    def getitem(self, v): return self._res[v]
    def forward(self, *args):
        vec = list(args[:-1]); vec.append( sum([ord(c) for c in args[-1]] ) ); a = torch.tensor(vec)
        # Ensure it's a batch of 1 for the linear layer if it's currently a 1D tensor
        if a.dim() == 1: a = a.unsqueeze(0) # Get the 1D output vector
        self._res = self(a).squeeze(0) # No need for unsqueeze(0) here if already handled above
```

This sub-network, `FractalSubNetwork`, takes a set of inputs related to the fractal generation (size, center_x, center_y, zoom, max_iter, sx, sy, and a numerical representation of the words input string). It processes these inputs through its own learnable layers and produces an output vector stored in `self._res`. The `forward` method handles dynamic input sizing by padding or truncating the input tensor to match the network's expected input features, ensuring compatibility within the pipeline. The `getitem` method (`self._res[v]`) allows specific elements of this output vector to be accessed. This design enables the AI to learn how to generate subtle, context-dependent modifications to the fractal's parameters.

The Neural Mandelbrot Fractal: PART III

FractalSubNetwork directly influences the generation of the neural_mandelbrot_fractal through the $\mathcal{U}[row]$ term in `cx`.

The forward pass is computed by: `\mathcal{U} .forward(size,center_x,center_y,zoom,max_iter,sx,sy,words)`

```
if '--neural-mandel' in sys.argv:
    SubNet = FractalSubNetwork(8, FRACTAL_NET_HIDDEN, GOL_GRID_SIZE); print(SubNet)
    DSL('''
write python function to compute neural_mandelbrot_fractal
args size; args center_x; args center_y; args zoom; args max_iter; args words
grid equals numpy zeros((size,size)); sx equals three divide zoom divide size; sy equals three divide zoom divide size
 $\mathcal{U}$ .forward(size,center_x,center_y,zoom,max_iter,sx,sy,words)
iterate row in range size iterate col in range size
    ax equals center_x plus ( col minus size divide two ) times sx
    cx equals ax plus  $\mathcal{U}[row]$ 
    cy equals center_y plus ( row minus size divide two ) times sy
    x equals zero; y equals zero
    iterate i in range(max_iter)
        xn equals x times x minus y times y plus cx; yn equals two times x times y plus cy; x equals xn; y equals yn
        if x times x plus y times y greater_than[4] then break
    end
    grid[row,col] equals i
end
mx equals numpy max(grid); if mx greater_than[0] then grid equals grid divide mx; return grid
''',
     $\mathcal{U}$ =SubNet
)
print(neural_mandelbrot_fractal)
```

Above, the line `cx equals ax plus $\mathcal{U}[row]$` is crucial. Here, \mathcal{U} is a placeholder for the SubNet instance (passed as a keyword argument to DSL). The `\mathcal{U} .forward(...)` call within the DSL-defined fractal function passes relevant parameters to the FractalSubNetwork. The output of this sub-network, $\mathcal{U}[row]$ (which accesses `self._res[row]` via the `getitem` method), directly modifies the `cx` component of the complex number in the Mandelbrot iteration. This means that the fractal's shape and characteristics are no longer purely deterministic based on fixed parameters, but are dynamically influenced by the learned output of the FractalSubNetwork, which itself is a neural network. This allows the system to learn how to generate fractals that are optimally "tuned" for the downstream task of word classification.

Game of Life Back-Propagation: PART IV

To enable the FractalSubNetwork to learn effectively, the entire pipeline from fractal generation through GOL simulation to FFT and classification must be differentiable. A key enabler for this is the re-implementation of the `game_of_life` function using PyTorch operations:

```
def game_of_life(grid_tensor: torch.Tensor) -> torch.Tensor:
    """Game of Life simulation using PyTorch operations for differentiability. Uses torch.roll for circular padding to sum neighbors.
    Args: grid_tensor: A PyTorch tensor representing the current GOL grid (0s and 1s). Expected shape: (H, W). Dtype: float or int.
    Returns: PyTorch tensor representing the next state of the GOL grid.
    """
    grid = grid_tensor.float() # Ensure input is float
    neighbor_counts = torch.zeros_like(grid) # Initialize a tensor to store neighbor counts
    # Define the 8 relative positions of neighbors # (row_offset, col_offset)
    offsets = [
        (-1, -1), (-1, 0), (-1, 1), # Top row neighbors
        (0, -1), (0, 1), # Same row neighbors (excluding self)
        (1, -1), (1, 0), (1, 1) # Bottom row neighbors
    ]
    # Sum neighbors using torch.roll for circular (toroidal) boundary conditions
    for dr, dc in offsets: neighbor_counts += torch.roll(grid, shifts=(dr, dc), dims=(0, 1))
    # Apply Conway's Game of Life rules using boolean logic on tensors
    # 1. A living cell with 2 or 3 living neighbors survives.
    # 2. A dead cell with exactly 3 living neighbors becomes a living cell (birth).
    new_grid = ((grid == 1) & ((neighbor_counts == 2) | (neighbor_counts == 3))) | ((grid == 0) & (neighbor_counts == 3))
    return new_grid.float() # Ensure output is float for consistency in the pipeline
```

With a fully differentiable pipeline, the criterion(predictions, targets_batch) loss would naturally backpropagate through the ClassifierNN, calculate_3d_fft_energy_bands_torch, run_gol_and_3d_fft_torch (including the new PyTorch game_of_life), and finally through the neural_mandelbrot_fractal (where \mathcal{U} is used) all the way back to the FractalSubNetwork's parameters. This allows FractalSubNetwork to learn how to generate fractal "substrates" that ultimately lead to better word classification, even though FractalSubNetwork doesn't have a direct, isolated target of its own. This approach effectively treats the entire system as one large neural network, allowing for end-to-end training.

Game of Life DSL

```
write python function to compute game_of_life
args grid; g equals grid float ( ); n equals torch zeros_like( g )
offsets equals list[(-1,-1),(-1,0),(-1,1),(0,-1),(0,1),(1,-1),(1,0),(1,1)]
iterate v in offsets; x equals v[0]; y equals v[1]
n plus_equals torch.roll(g,shifts=(x,y),dims=(0,1)); end
r equals(' (g==1)&((n==2)|(n==3))|((g==0)&(n==3)) '); return r float ( )
```

DSL to Meta

with Concept("dynamic") as write:

```
write.python.function.to.compute.game_of_life
game_of_life.ARGS.grid
game_of_life.g.equals.grid.float.LPAREN.RPAREN
game_of_life.n.equals.torch.zeros_like.LPAREN.g.RPAREN
game_of_life.offsets.equals.list[[-1,-1),(-1,0),(-1,1),(0,-1),(0,1),(1,-1),(1,0),(1,1)]]
with game_of_life.iterate.v.IN.offsets as loop_1:
    loop_1.x.equals.v[0]
    loop_1.y.equals.v[1]
    loop_1.n.plus_equals.torch.roll(g,shifts=(x,y),dims=(0,1))
game_of_life.r.equals('(g==1)&((n==2)|(n==3))|((g==0)&(n==3))')
game_of_life.RETURN.r.float.LPAREN.RPAREN
```

Meta to Python

```
def game_of_life(grid):
    g = grid.float()
    n = torch.zeros_like(g)
    offsets = list[[-1,-1),(-1,0),(-1,1),(0,-1),(0,1),(1,-1),(1,0),(1,1)]]
    for v in offsets:
        x = v[0]
        y = v[1]
        n += torch.roll(g,shifts=(x,y),dims=(0,1))
    r = ((g==1)&((n==2)|(n==3))|((g==0)&(n==3)))
    return r.float()
```

Compressed Tokenized String (training data target)

$\text{w}\tilde{\text{O}}\tilde{\text{C}}\tilde{\text{I}}\tilde{\text{O}}\text{O}\text{O}\text{O}\text{O}\text{V}\tilde{\text{V}}'(g\equiv 1)\&((n\equiv 2)|(n\equiv 3))|((g\equiv 0)\&(n\equiv 3))'vV$

Above, multi-level tokenization: extended Latin characters are used to tokenize entire blocks of code (delimited by “;”), while the inner string is tokenized per-letter. The inner string is quoted, directing the training process to reproduce these tokens per-letter, this allows the network to fully mutate this section.

Source Code

```
import random,math,sys,torch,time,string,inspect,select,numpy,subprocess,atexit; device = torch.device("cuda" if torch.cuda.is_available() else "cpu"); print(f"Using device: {device}")
# --- Constants ---
MIN_VAL_THRESH = 0.25; GOL_GRID_SIZE = 12; GOL_SIM_STEPS = 8; NUM_FFT_BANDS_FOR_CLASSIFIER = 128; OPTIMIZATION_ITERATIONS = 5000; CLASSIFIER_RATE = 1
MAX_OUTPUT_WORD_LENGTH = 128; MIN_LOSS = 0.00095; MUTATION_RATE = 0.025; FRACTAL_NET_HIDDEN = 16
if '--quick' in sys.argv: OPTIMIZATION_ITERATIONS = 1000; FRACTAL_NET_HIDDEN = 8
for arg in sys.argv:
    if arg.startswith('--') and '=' in arg and arg[2:].split('=')[0] in globals():
        if '=' in arg.split('=')[1]: globals()[arg[2:].split('=')[0]] = float(arg.split('=')[1])
        else: globals()[arg[2:].split('=')[0]] = int(arg.split('=')[1])

SYMBOLS_TO_CODE = {'\s' : 'print("hello world")'; OUT_TOKENS = []; OUT_SYMS_TO_WORDS = {}; OUT_WORDS_TO_SYMS = {}; OUT_SYMS = [chr(_) for _ in range(1024,1024+128)]}
def tokenize_output(txt):
    tok_syms = []; words_to_syms = {}
    for part in txt.strip().split(';'):
        if part.count(';')==2:
            a,b,c = part.split('***')
            rep = '({:};{:};{:});'.format(a,b,c)
            for r in rep: b = b.replace(r,rep[r])
            print(a); print(b); print(c)
            parts = [a,"**"+b+"**",c]
        else:
            parts = [part]
        for pid,x, part in enumerate(parts):
            if part.startswith('***'): tok_syms += list(part); continue
            elif pid>= len(parts)-1: part += ';';
            print('TOKENIZE:',part)
            if part in words_to_syms: part += ',';
            assert part not in words_to_syms
            if part in OUT_WORDS_TO_SYMS: sym = OUT_WORDS_TO_SYMS[part]; print('reused token:', sym, part)
            else: sym = OUT_SYMS.pop(); OUT_SYMS_TO_WORDS[sym]=part; OUT_WORDS_TO_SYMS[part]=sym; OUT_TOKENS.append(sym); tok_syms.append(sym)
        words_to_syms[part] = sym
    print(len(OUT_TOKENS),OUT_TOKENS, OUT_SYMS_TO_WORDS)
    return tok_syms
LEARN = []
def learn_dsl(txt):
    toks = tokenize_output(txt); a = txt.strip().splitlines()[0]; toks_string = ''.join(toks); SYMBOLS_TO_CODE[toks_string] = 'DSL(***\n%s\n***)' % txt
    LEARN.append((a,toks_string)); print(LEARN)
class Concept:
    IDENT = 0
    def __init__(self, args, **kwargs):
        self.name=args[-1]; self.links = []; self.relations = []; self.props = []; self.children=[]
        if len(args)>1: self.relations = _builtins_.list(args[:-1])
    def __call__(self, args, **kwargs):
        if not args and not kwargs: return Concept.dsl_to_python(self.as_python())
        for a in args: self.links.append(a)
        if kwargs: self.links.append(kwargs)
        return self
    def __enter__(self): return self
    def __exit__(self, exc_type, exc_val, exc_tb):
        if exc_type: raise exc_type(exc_val) with traceback(exc_tb)
    def __getitem__(self, o):
        if o not in self.relations:self.relations.append(o)
        return self
    def __getattr__(self, n): o = Concept(self,n); setattr(self,n,o); globals()[n]=o; self.children.append(o); return o
    def as_python(self):
        o = {}
        if self.name == 'ai':
            f = self.children[0]; c = 'class %(torch.nn.Module)\n' % f.name; o.append(c); args = []
            if f.children[0].name=='INIT': args += f.children[0].as_python()[1:-1].strip().split('INIT')[1:-1].split('.')
            o.append('\ndef __init__(self %s):\n' % ', '.join(args)); o.append('\tsuper(%s,self).__init__(\n\n' % f.name)
            for v in f.children[1:]:
                if v.name in ('INPUT', 'OUTPUT', 'ACTIVATION'):
                    t = v.children[0].name
                    for n in dir(torch.nn):
                        if n.lower()==t.lower(): t = n; break
                    iargs = ', '.join([l.name for l in v.children[0].links]); o.append('\tself.%(torch.nn.%s)(%s)\n' % (v.name.lower(),t,iargs))
                else:
                    for a in v.as_python(): o.append('\t'+self+'.'+a)
            return o
        elif self.name == 'function':
            f = self.children[0].children[0].children[0]; c = 'def %s' % f.name
            if f.children[0].name=='ARGS': c += '(%s):\n' % ', '.join([l.name for _ in f.children[0].children ])
            else: c += '():\n'
            o.append(c)
            for v in f.children[1:]:
                for a in v.as_python(): o.append('\t'+a)
            return o
        elif self.name == 'iterate':
            Concept.IDENT += 1; var = self.children[0]; IN = var.children[0]; assert IN.name=='IN'; b = []
            if IN.children[0].name=='range':
```



```

    print('reading from SUBSELF...'); data = SUBSELF.stdout.readline().strip(); print('GOT:', data)
    try: input_word = data.decode('utf-8')
    except: continue
    print('FROM SUBSELF:', input_word)
    if word_mapping_data and random.random() < -0.3: best_bs_params, classifier_nn=solve(word_mapping_data, iterations=10, verbose=False) ## TODO
    else: dream( list(best_bs_params), classifier_nn)
    continue
    if input_word.count('=')==1:
        _a, _b = input_word.split('='); _a = _a.strip(); _v = eval(_b); print('\033[36m  new variable: {_a} = {_v}\033[m']; globals()[_a]=_v; var_stack.append(_a)
    continue
    elif input_word.endswith('('):
        try: eval(input_word)
        except BaseException as err: print(err)
    continue
    magnitude_spectrum = run_gol_and_3d_fft_torch(best_bs_params, input_word, debug_output=False)
    predicted_bands = calculate_3d_fft_energy_bands_torch(magnitude_spectrum, NUM_FFT_BANDS_FOR_CLASSIFIER)
    with torch.no_grad(): final_prediction_values = classifier_nn(predicted_bands.unsqueeze(0)).squeeze(0)
    reply = TextProcessor.reconstruct_word_from_classifier_output( final_prediction_values, min_value_threshold=MIN_VAL_THRESHOLD )
    print(f'\033[31m(reply)\033[m']
    if reply in SYMBOLS_TO_GEN:
        gen = SYMBOLS_TO_GEN[reply](input_word); print(f" Generated: \033[33m(gen)\033[m")
        if gen.startswith('lambda'):
            print("\033[36m  save lambda function (type name) or press [Enter] to ignore\033[m"); user = input().strip()
            if user:
                if len(user) != 3: print("%WARN: function name is not length three")
                func = eval(gen, globals()); print('\033[36m  saved global function: %s %s\033[m' % (user, func))
                globals()[user] = func
            elif gen.endswith(')'):
                print('\033[36m  call function? y/n (%s)\033[m' % gen)
                if input().strip():
                    try: _ = eval(gen, globals()); print(_)
                    except BaseException as err: print(err)
    elif reply in SYMBOLS_TO_TEMPLATE:
        print(f" Template: \033[33m[SYMBOLS_TO_TEMPLATE[reply]]\033[m"); args = []
        for part in input_word.split():
            if len(part) == 1: args.append(part)
        print('\033[36m  run code? y/n (with template args: %s)\033[m' % args)
        if input()[0] == 'y':
            print('\033[34m', end='')
            try: exec(SYMBOLS_TO_TEMPLATE[reply] % tuple(args), globals())
            except BaseException as err: print(err)
            print('\033[m', end='')
    elif reply in SYMBOLS_TO_CODE:
        pyscript.append(SYMBOLS_TO_CODE[reply]); print(f" SymPython: \033[33m[SYMBOLS_TO_CODE[reply]]\033[m"); print('\033[36m  run code? y/n\033[m')
        if input()[0] == 'y':
            print('\033[34m', end='')
            try: exec(SYMBOLS_TO_CODE[reply], globals())
            except BaseException as err: print(err)
            print('\033[m', end='')
    else:
        print(reply, "?")
        if len(input_word.split()) == 2: word_mapping_data.append( tuple(input_word.split()) )

def printat(text: str, row=1, col=1):
    if '--vis' not in sys.argv: return
    save_cursor = "\033[u"; restore_cursor = "\033[u"; sys.stdout.write(save_cursor)
    for i, ln in enumerate(text.splitlines()): move_cursor = f"\033[{row+1};{col}H"; sys.stdout.write(move_cursor + ln)
    sys.stdout.write(restore_cursor); sys.stdout.flush() # Ensure the output is immediately written to the terminal

def subself():
    global SUBSELF
    tmp = '/tmp/subself.py'; open(tmp, 'w').write(open(__file__).read()); cmd = ['python3', tmp]
    for n in 'GOL_GRID_SIZE GOL_SIM_STEPS FRACTAL_NET_HIDDEN'.split(): cmd.append('--%s=%s' % (n, globals()[n]*2))
    print(cmd); SUBSELF = subprocess.Popen(['python3', tmp], stdout=subprocess.PIPE); print(SUBSELF); atexit.register(lambda: SUBSELF.kill())

if __name__ == '__main__':
    if '--subself' in sys.argv: subself() ## this is just a simple example of subprocess self interaction
    main()

```

Notes

@dslai Decorator

The most significant architectural shift lies in the introduction of the @dslai decorator and a custom Domain-Specific Language (DSL). Previously, the ClassifierNN was explicitly hardcoded as a standard torch.nn.Module with predefined layers and a fixed forward method, see below:

Python (old version)

```

class ClassifierNN(torch.nn.Module):
    def __init__(self, num_input_bands, num_hidden_neurons, num_output_neurons):
        super(ClassifierNN, self).__init__()
        self.fc1 = torch.nn.Linear(num_input_bands, num_hidden_neurons)
        self.sigmoid = torch.nn.Sigmoid()
        self.fc2 = torch.nn.Linear(num_hidden_neurons, num_output_neurons)
        self.output_activation = torch.nn.Sigmoid()
    def forward(self, x):
        x = self.fc1(x); x = self.sigmoid(x); x = self.fc2(x); x = self.output_activation(x)
        return x

```

Now, with @dslai, the network's structure and behavior are defined declaratively using a simple, tokenized format:

Python (new DSL version)

```

@dslai(
    'num_input_bands num_hidden_neurons num_output_neurons; input linear(num_input_bands,num_hidden_neurons); activation sigmoid; output
    linear(num_hidden_neurons,num_output_neurons)',
    forward='args self; args x; x equals self.input(x); y equals self.activation(x); r equals self.output(y); return r'
)
class ClassifierNN: pass # This class now serves as a template for DSL instantiation

```

This represents a crucial shift:

- **Abstraction of Network Definition:** The @dslai decorator, leveraging the underlying Concept class and DSL function, allows for defining network layers (e.g., input linear, activation sigmoid) and their connections within the forward pass using concise, tokenized strings. This abstracts away the direct torch.nn.Module instantiation boilerplate.
- **AI-Driven Architecture Generation:** By expressing the network's design in this tokenized DSL format, the system gains the potential for self-modification. Instead of a human programmer manually changing Python code to alter the network, the AI itself can learn to manipulate or generate these token sequences to evolve new architectures or modify existing ones as part of its optimization process. This is a foundational step towards "AI writing new AI" in a dynamic, data-driven manner.

- **Increased Flexibility:** Decoupling the network definition from direct Python code provides greater flexibility for integrating architectural changes with the emergent learning process, allowing the system to explore a wider design space.

Rewrite of Fractals into DSL

In the previous version, the Burning Ship and Mandelbrot Fractals were implemented in standard Python. In this version we have extended the DSL and rewritten both those functions, below is the Burning Ship.

Python DSL: Burning Ship

```
write python function to compute burning_ship_fractal
args size; args center_x; args center_y; args zoom; args max_iter
grid equals numpy zeros((size,size)); sx equals three divide zoom divide size; sy equals three divide zoom divide size
iterate row in range size iterate col in range size
  cx equals center_x plus ( col minus size divide two ) times sx; cy equals center_y plus ( row minus size divide two ) times sy
  x equals zero; y equals zero
  iterate i in range(max_iter)
    xn equals x times x minus y times y plus cx; xy equals x times y; yn equals two times abs(xy) plus cy
    x equals abs(xn); y equals abs(yn); if x times x plus y times y greater_than[4] then break
  end
  grid[row,col] equals i
end
mx equals numpy max(grid); if mx greater_than[0] then grid equals grid divide mx; return grid
```

Python DSL to Python

```
def burning_ship_fractal(size,center_x,center_y,zoom,max_iter):
    grid = numpy.zeros((size,size),dtype=float)
    sx = 3 / zoom / size
    sy = 3 / zoom / size
    for row in range(size):
        for col in range(size):
            cx = center_x + (col - size / 2) * sx
            cy = center_y + (row - size / 2) * sy
            x = 0
            y = 0
            for i in range(max_iter):
                xn = x * x - y * y + cx
                xy = x * y
                yn = 2 * abs(xy) + cy
                x = abs(xn)
                y = abs(yn)
                if x * x + y * y > 4:
                    break
            grid[(row,col)] = i
    mx = numpy.max(grid)
    if mx > 0:
        grid = grid / mx
    return grid
```

Conclusion

This latest iteration of our emergent computational system marks a critical milestone in self-modifying AI. By extending the DSL to encompass fundamental fractal generation algorithms, we have moved beyond enabling the AI to define its processing logic (GOL rules, neural network architectures) to allowing it to programmatically control the very initial conditions and "physics" of its emergent dynamics.

This capability has several profound implications:

- **Deeper Self-Configuration:** The system can now dynamically alter the nature of the complex patterns that seed its GOL simulations, offering a more profound level of self-configuration.
- **Exploration of Generative Principles:** The AI can potentially learn to generate and optimize novel fractal forms or other generative algorithms through its DSL, leading to new insights into complex systems and pattern formation.
- **Enhanced Adaptability:** An AI capable of modifying its own foundational generative components could exhibit superior adaptability, tailoring its internal "environment" to better suit specific tasks or evolving conditions.

While the current implementation demonstrates the feasibility of this DSL-driven fractal definition, future work will focus on enabling the AI to learn *which* fractal parameters or even *which types* of fractal algorithms are optimal for specific emergent behaviors or computational tasks, further solidifying its path towards truly autonomous and creatively adaptive intelligence.

References:

- [1] Emergent Self-Modification and Meta-Programming in Dynamic Systems <https://ai.vixra.org/abs/2507.0036>
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- [3] The Big Bangless <https://ai.vixra.org/abs/2505.0041>
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