Bespoke Physics for Living Technology

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Abstract In the physics of the natural world, basic tasks of life, such as homeostasis and reproduction, are extremely complex operations, requiring the coordination of billions of atoms even in simple cases. By contrast, artificial living organisms can be implemented in computers using relatively few bits, and copying a data structure is trivial. Of course, the physical overheads of the computers themselves are huge, but since their programmability allows digital "laws of physics" to be tailored like a custom suit, deploying living technology atop an engineered computational substrate might be as or more effective than building directly on the natural laws of physics, for a substantial range of desirable purposes. This article suggests basic criteria and metrics for *bespoke physics* computing architectures, describes one such architecture, and offers data and illustrations of custom living technology competing to reproduce while collaborating on an externally useful computation.

1 Living Technology and Big Computing

In some ways, indeed, life is hard. Certainly, in the natural world, making a self-sustaining and reproducing creature is a messy and complex affair. Even the tiny *Pelagibacter ubique* bacterium [30], for example, known as one the smallest of free-living creatures, involves hundreds of millions of atoms, and its reproduction involves intricate choreography, for over a day, of that many more. Natural life is an amazing, obstinate process, but—at least from the viewpoint of an atom, say—it isn't easy.

In exploring life as it could be, artificial life researchers deploy technologies—from robotic hardware, to pure software, to biochemical preparations—that implement the organisms and operations of life in many ways, sometimes quite differently from traditional life as we know it. The primary purpose of such research has often been scientific, but—as introduced and discussed in [5]—there is also growing interest in *living technology*: engineered systems that make essential use of lifelike components or principles. A recent focus (see, e.g., many of the articles in [31]) is *wet* living technology, which uses atoms and small molecules as basic units and builds from there toward basic living mechanisms like metabolism and reproduction. Such efforts have tremendous potential because they build on the same low-level, widely available ingredients and conditions as natural life, and can deploy similar structures and mechanisms for similar jobs—but by the same token, many aspects of their design are prefigured by their relatively traditional atomic units and chemical interactions.

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Choosing atoms, say, as the basic units for an approach to living technology is just one possibility—as discussed for example by Pattee [29], it is ultimately a definitional question how we categorize phenomena as "physical law" versus "initial condition." Like nesting *virtual machines* in computer science—one machine simulating another, which may be simulating a third, and so on—one theory's initial condition can be another's physical law. As a practical matter, for basic units we can choose almost anything in reality that can be found or fabricated in sufficient numbers, and manipulated as needed, for our living technology to be productive. A simple-minded approach to viruses, for example, might treat complete cells or complex cellular components as "atomic" entities. Similarly, adopting initial conditions like "clean white sand, air, falling water, and sunlight" [32] makes scientific sense when exploring the origins of natural life, but for systems engineering all such decisions are for the living technology designer to make, given the tasks and resources at hand.

Compared to low-level wet approaches, living technologies built on digital software and hardware require extensive computing machinery before we can even begin to design—but that looks increasingly reasonable, given the proliferation of inexpensive computing devices in our environment. Relatively low-cost processor and memory chips are now being produced by the million, creating a potential "complexity sweet spot" for digital living technologies based on such machinery. And building living technology atop digital hardware offers an extreme level of freedom to the designer. General-purpose programmability allows bits and Boolean operations to combine in a staggering panoply of possible "atomic" units and "chemical" mechanisms to underpin a living technology. Computer-based models of *artificial chemistries* ([13] is an early review) vary widely, in everything from their size and level of detail to their spatial dimensionality and treatment of time. Such diversity in laws of digital physics is understandable given the design freedom of the approach and the range of the scientific and theoretical purposes of the models. At the same time, such variety makes it challenging to compare models or have much confidence that results from one may apply in another.

My primary purpose in writing this article is to highlight potential connections between computer architecture and engineering on the one hand, and artificial life, artificial chemistry, and artificial physics on the other. Section 2 offers possible requirements and quality principles, or *metalaws*, for custom laws of physics in computer systems, motivated primarily by engineering concerns, and suggests some rough and ready metrics for comparing approaches. Section 3 provides an overview for the artificial life community of our work with the Movable Feast Machine, a metalaw-compliant architecture for bespoke physics processing. Section 4 relates this work to some existing research efforts, and finally, Section 5 offers a brief conclusion.

2 Bespoke Physics as Interface

In traditional scientific use, laws of physics are descriptive—representing more or less accurate or predictive abstractions of reality—and, in effect, they are judged by their *leverage*: the simplicity or cleanliness of the laws themselves versus the range of initial conditions over which the laws make useful predictions. For engineering use, here our purpose is prescriptive: laws of physics as specifications for the structure and behavior of machinery. A law like $F = ma$, for example, can be at once a scientific description of a wide range of physical phenomena, and an engineering prescription for a computer game or physical simulation.

In computer and software engineering, an *interface specification* defines the legal interactions between some system components. As in laws of physics, in interface specification quality derives largely from simplicity and clarity versus completeness and utility—which all vary widely, depending on the scope and maturity of the interface, as well as the underlying wisdom of its design. The Unix `yes` program—which endlessly prints lines containing 'y' or another given string—fills only a small niche, but its interface specification is just a few lines of text [28]. The IA32/64 architecture, by contrast—a widely used interface between computer hardware and software—is specified by a software developer's manual [18] that, currently, spans some 3,000 pages in seven volumes.

The vast gap between such a complex specification and the simple power of, say, Newtonian mechanics mostly reflects different divisions of labor between "law" and "initial condition," as discussed earlier. The same physical laws describe basically all mechanical devices; the additional details needed to describe any particular machine are relegated to the initial conditions. By contrast, an IA32 machine remains distinctly a *computer*—though perhaps operating only briefly or uselessly—no matter what the initial contents of its memory.

The very notion of a bespoke physics may seem a pointless contrivance, because any bespoke-physics-plus-implementation can always be viewed as a single undifferentiated system in the "real" laws of physics of the natural world. But the same is true of interfaces in computing—any collection of interfaces-plus-implementations can also be viewed as a single monolithic computation—and yet good interfaces are crucial to manage complexity throughout hardware, software, and systems engineering.

At root, my goal for the concept of bespoke physics is to pull the concepts of interface specifications and laws of physics toward each other. Bespoke physics asks us to frame laws of physics that are somewhat constrained and task-specific—as is typical for interface specifications—while also defining computing interfaces and architectures that are simple and indefinitely scalable—as is typical for laws of physics.

2.1 Definitions and Design Principles

In this section we use the key words MUST and SHOULD (similarly SHOULD NOT)—as described in RFC2119 [7]—to introduce passages constituting requirements and strong expectations, respectively, of a specification.[1] Let a *bespoke physics* be composed of a definition of a *basic unit*, which may have any set of ascribed properties representable in finite state, plus a finite set of *dynamical laws* determining how the basic units move and interact. Depending on the purpose, a basic unit might be akin to an atom or a subatomic particle, or a molecule or a cell, or a billiard ball or a bit or a widget; ascribed properties might include atomic number or charge, valence or cell type, solid or striped, or some wild pastiche never before seen in one entity.

A bespoke physics, plus an *initial condition*—some arrangement of basic units—defines a *computation*. A *computational system*, in turn, is a physical realization or implementation of a computation. And finally, a bespoke physics for computation can also be called a *hosted physics* relative to such an implementation, which may also be called a *host physics*.

Those definitions are meant to be agnostic about whether the basic units and dynamical laws are more or less analog or digital in character—but, minding the complexity sweet spot discussed above, this article considers only implementations based on widely available digital circuitry. Note also that in a digital bespoke physics, a single bit may or may not be a basic unit—some larger data structure involving multiple bits may be more useful. For example, the basic units in the physics described in Section 3 have ascribed properties specified by 64 bits each.

As in the scientific usage, for our engineering use we also wish to maximize the leverage of our custom physics—on the one hand by keeping the laws as manageable and affordably implementable as possible, while on the other hand ensuring their widest applicability to possible initial conditions. To that end, first, there is the *implementability requirement*: A bespoke physics for a computational system MUST be implementable, somehow, in conventional physical reality as we understand it. Such implementations—in principle or (preferably) in actual practice—provide one more or less quantitative basis for comparing the capabilities and costs of different bespoke laws of physics, as discussed in Section 2.3.

1 Applying a term like "should" to the laws of physics seems utterly teleological and mystical—suggesting they have a creator capable of purpose and expectation—but of course that is precisely what bespoke laws of physics do have. And despite the lure of purely formal specifications, in practice, adopting an intentional stance is often essential to the effective use of complex systems of interfaces.

Second, we offer four *quality principles*, or *metalaws*, aimed at increasing the compactness or usability of the laws themselves, or increasing the set of possible initial conditions, or both:

1. *Indefinite scalability*: The laws themselves SHOULD NOT have internal restrictions or limits; they SHOULD apply to arbitrary and arbitrarily large initial conditions—at least in principle and for analysis, even if such initial conditions may not be practically constructible.
2. *Spatiotemporal isotropy at scale*: There may be some fine structure or granularity to the laws, but, at least above some length and duration accessible to the artificial life organisms, the laws SHOULD apply uniformly, regardless of specific disposition in space or moment in time.
3. *Limited causality*: The laws SHOULD NOT (and arguably cannot) require globally deterministic evolution from the initial conditions, but there SHOULD be generally reliable causal regularities, at space and time scales locally exploitable by the artificial life organisms.
4. *Strong level isolation*: It SHOULD be as difficult as possible to affect the bespoke laws of physics from within the computation itself. Hardware designed to implement just one bespoke physics would be perfect, but for economies of scale, or research and development, programmable hardware may be used, meaning the bespoke physics *can*, somehow, be modified without manufacturing, so this possibility must be treated carefully.

In descriptive contexts, principle 1 usually goes without saying—at least until it is violated, as when classical mechanics breaks down around a black hole. In computer engineering, though, the widespread use of techniques that are only finitely scalable—such as global synchronous clocking, fixed-width memory addressing, or globally unique network addresses—mean that very few existing computing mechanisms *don't* violate principle 1 (see [2] for further discussion).

In his 1963 Nobel Lecture [37], Wigner discussed basic *superprinciples* that physical laws should possess even to be recognizable as such—including invariance under Euclidean geometric transformations and time displacements, which he called "Category (a) and (b) invariance transformations." Principle 2 is a rendering of that same intent, though weakened to add engineering "wiggle room" at the bottom.

Principle 3, similarly, is an explicit weakening of the notion of global determinism or causality. Though physical and philosophical theories differ on the degree and nature of determinism presumed to exist in reality, nearly all current computers are deterministic in the sense that they are designed to produce exactly the same outputs given the same inputs, with very high probability. This can ease debugging and logical analysis, but means any randomness needed by the computation must be simulated.[2] Furthermore, such determinism is increasingly unaffordable as systems grow under principle 1, due to synchronization costs and the need for large systems to handle errors and local failures gracefully. Some researchers [9] in high-performance computing, for example, discuss limited ways to move beyond determinism in the move to exascale computing (machines performing 10^{18} operations per second). Principle 3 countenances that and even more radical departures from traditional computational determinism, but does ask—albeit rather informally—that bespoke physics provide *enough* stability and repeatability to make locally reliable computation possible.

Principle 4 also usually goes without saying; in the natural world, violations of it—known as *magic*—are considered rare. Here it is an explicit quality principle, in large part, to call out the dismal state of security and trustworthiness in computing today. It is said one *shouldn't* violate the laws of man while one *can't* violate the laws of physics—but far too often, programmed "laws" for computer security and privacy have proven merely the former when we needed the latter. Principle 4 asks the computer architect and living technology designer to recognize and manage the liabilities, and not just the benefits, of general-purpose programmability.

2 Computer designers are increasingly augmenting traditional deterministic machines with hardware devices providing "true randomness"—or call it "external unpredictability"—primarily to facilitate encryption.

2.2 Natural versus Bespoke Physics

A bespoke physics can call its basic unit an "atom," but it's unlikely that that basic unit can or will be implemented using a single physical atom. This article focuses on using stored digital bits to represent a basic unit, with the bit values specifying the unit's ascribed properties. At a minimum, therefore, one bespoke atom requires however many real atoms it takes to store those bits. That hosting overhead—the number of host atoms per hosted atom, overall—is the huge elephant in the bespoke physics room, in contrast with the direct "an atom is an atom" physics of reality itself.

How bad does that ratio need to be? A MicroSD card, for example, weighing perhaps half a gram, can today store 64 GB; if we imagine our basic units are 64 bits each, that amounts to perhaps 10^{-10} g per bespoke atom, compared to around 10^{-23} g for say a carbon atom. Thirteen orders of magnitude of hosting overhead goes well beyond the perhaps billions of atoms tied up in a *P. ubique*, for example, and additional hosting resources are needed—processors and program memory, for example—that only make it worse. At least in the nearer term, hosting overheads are likely to be substantial, raising concerns about cost-effective scalability. Half a century ago, Feynman [14] discussed the vast "room at the bottom"—at the fine-grained end of natural physics—for increased information storage and processing density. From *within* a bespoke physics, there is no explicit structure below the level of its basic unit properties—although implementation details may be detectable by the hosted physics, despite principle 4—but Feynman's arguments do suggest that clever implementations might reduce hosting overhead significantly.

Even without such optimizations, though, there are at least two considerable benefits to bespoke physics over natural physics. First, and most important for the present purposes, a bespoke physics gains the same advantage held by any programmable machine over a special-purpose one: Deferring functional commitment from manufacturing time to programming time creates flexibility, allowing us to change the laws of bespoke physics as needed, for research or upgrades or custom computation. Basic tasks such as active transport faster than diffusion, for example, which involve considerable complexity in direct biology (e.g., [33]), can be programmed directly in a bespoke physics (see Section 3.4 for an example). In effect, having spent an order of magnitude of orders of magnitude to buy the flexibility of bespoke physics, we do get to choose some rebates while furnishing the place.

A second advantage is less immediately useful, but should be noted because it may ultimately prove overwhelming. In principle, bespoke matter could move within a bespoke universe more quickly and nimbly than actual matter in the spatially coextensive direct physics, because the motion is performed by digital copying mediated by electromagnetic wave propagation at a substantial fraction of light speed, rather than by actual movement of massive, inertial nuclei in the direct physics. It is pure science fiction at present [35], but it is possible that digital technologies based on biological components (e.g., [8, 34]) could ultimately be outcompeted by living technologies based on electronic components.

Long before such concerns can be taken seriously, however, we need ways to compare bespoke physics systems with each other and with natural physics systems, and that is our next topic.

2.3 Scalable Metrics of Computation

Any individual computing device is a *finite* machine, both in physical size and in computational capacity; as a platform for bespoke physics it would violate principle 1 of Section 2.1. But "finite" doesn't mean "isolated": To be useful, a finite machine has to have external connections, at least for power and communications. We define an *indefinitely scalable machine* to be any procedure for tiling space with finite machines, with no a priori requirements that such a tiling have any particular properties—like aligning tile outputs with adjacent inputs. So tiling space by, say, laying HP65 pocket calculators out in a grid is admissible as an indefinitely scalable machine.

Given such a tiling procedure, Table 1 defines some *indefinitely scalable machine metrics*, which—though incomplete and underdetermined—suffice to show why a tiling of HP65s would not be a *good* indefinitely scalable machine. The symbols are subscripted with "*s*" to stress they require a *scalable*

Table 1. Tile-based performance metrics for indefinitely scalable machines. Here g, s, j, and m are grams, seconds, joules, and meters, while N_i, N_e, and N_s are counts of instructions, events, and sites, respectively. See text.

Quantity	Code	Symbol	Value	Unit
Peak computational density	PCD	ρ_s	$\frac{\text{tile computation speed}}{\text{tile mass}}$	$N_i \cdot s^{-1} \cdot g^{-1}$
Peak power efficiency	PPE	η_s	$\frac{\rho_s}{\text{dissipated power}}$	$N_i \cdot g^{-1} \cdot J^{-1}$
Peak communications velocity	PCV	v_s	$\frac{\text{max tile pitch}}{\text{hosted bit latency}}$	$m \cdot s^{-1}$
Average event rate	AER	α_s	$\frac{\text{events per tile per second}}{\text{sites per tile}}$	$N_e \cdot N_s^{-1} \cdot s^{-1}$

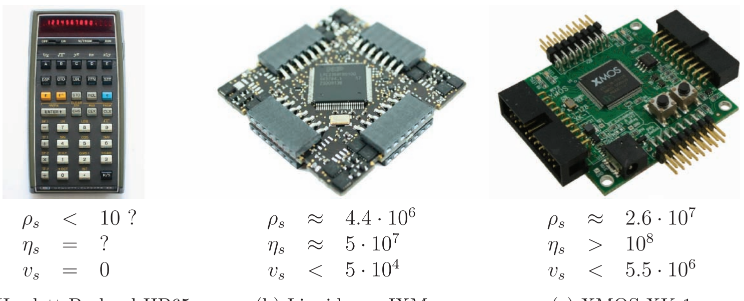
basis; until a tiling procedure is understood, all the Table 1 metrics are undefined, no matter how capable some finite machine may be.

We can construct an indefinitely scalable machine that is as large as we need, so long as we have sufficient materials, energy, room, and time; the desire to minimize those resources, while somehow maximizing computational power, motivates the metrics of Table 1. Dehon's [11] early and influential "ALU bit ops/area-time" metric for *computational density* is a similar approach, although that was applied just to components rather than a whole tile, and was measured in process-specific units rather than as absolute physical values, hindering comparisons between technologies.

The indefinitely scalable *peak computational density* (PCD for code, ρ_s for math) is defined as the number of instructions per second per tile divided by tile mass, where the tile itself drops out of the equation but determines the granularity of the measurement. One instruction per second per gram of mass hopefully will prove to be a rather small unit; recognizing Stross [35], who popularized the phrase "MIPS per milligram," I sometimes informally refer to a PCD of 10^9 as 1 *stross*. The PCD's use of "instructions" inherits all the notorious ambiguities that plague the notion of MIPS, but captures well the whole-system perspective we are advocating.

An HP65 calculator (Figure 1a, [17]) weighs 312 g and as a guess might deliver a few thousand instructions per second, so a spatial tiling of HP65s might have a PCD in single digits. The IXM hardware tile in Figure 1b—our first indefinitely scalable prototype, developed in collaboration with liquidware.com [21]—masses about 16.5 g per tile (including two intertile connectors, not shown) and peaks at 72 MIPS, for a PCD of about 4.4 million, or 4.4 millistross. At 19 g with a 400-MHz processor, the XMOS XK1 (Figure 1c, [38]) might offer over 26 millistross.

An obvious measure of *peak power efficiency* (PPE, η_s) is PCD per watt of dissipated power, or instructions per gram-joule as in Table 1. But of course, no matter how dense or efficient, without communications a tiling is effectively worthless. We define the indefinitely scalable *peak communications velocity* (PCV, v_s) as the *tile pitch*—the distance between adjacent tile centers—divided by the time for one hosted bit to travel from tile to tile (taking maxima of both quantities if it matters). Here


$\rho_s < 10$? $\quad \eta_s = $? $\quad v_s = 0$

(a) Hewlett-Packard HP65

$\rho_s \approx 4.4 \cdot 10^6 \quad \eta_s \approx 5 \cdot 10^7 \quad v_s < 5 \cdot 10^4$

(b) Liquidware IXM

$\rho_s \approx 2.6 \cdot 10^7 \quad \eta_s > 10^8 \quad v_s < 5.5 \cdot 10^6$

(c) XMOS XK-1

Figure 1. Estimated indefinitely scalable performance metrics for sample hardware tiles.

the unconnected HP65s manifestly score zero; the v_s upper bounds shown in Figure 1 for IXM and XK-1 are based on their typical channel speeds, without including the latencies of hosted physics processing. (Note that the XK1 natively supports communications in only one scalable dimension, despite its visual similarities to the 2D-scalable IXM.)

Such peak performance values are *host physics* implementation properties that hardware and marketing people can love, but more important to programmers and users is how fast events are likely to unfold within the *hosted physics*. In that context, the key implementation parameter is the indefinitely scalable *average event rate* (AER, α_s), where again the tile drops out, but the averaging is over both isolated intratile events and intertile events requiring communications, in whatever proportion is implied by the hosted physics. We currently lack any satisfactory bespoke physics implementation on indefinitely scalable hardware—so no α_s values are reported in Figure 1, for example—but hope to establish an initial benchmark at $\alpha_s = 1$ for DReg physics (see Section 3.2) on our next-generation hardware now in development.

For a bespoke physics independent of any implementation, there is no inherent unit of time; instead we measure duration and scalable computational effort in terms of *average events per site* (AEPS). In one AEPS, on average each site will perform one event, which would take 1 s on an indefinitely scalable implementation that delivered one AER.

2.4 Interdimensional Comparative Metaphysics

The measures in the previous section are fundamental but far from exhaustive; other metrics could be as or more useful, depending on the goals and specifics of a bespoke physics and the needs and capabilities of any given implementation strategy. For example, a volume density of computation would emphasize spatial compactness, compared to the mass density ρ_s. And for effective parallelism, the scalable communications bandwidth, expressed as a hosted bit current density, would likely be a key parameter.

Beyond the specific choices, however, a larger goal for such metrics is to create a common physical framework for computational machinery, allowing quantitative comparisons between bespoke laws of physics that may differ on matters as fundamental as their basic granularity and global dimensionality. Together, the implementability requirement and the quality principles all but force bespoke physics to employ no more than three scalable dimensions,[3] but finite-sized *compact* dimensions can be added as desired. For example, a "thin film" of one finite and two scalable dimensions could offer locally three-dimensional bespoke physics on top of an essentially two-dimensional implementation, facilitating construction and maintenance and the routing of energy and heat. As another perspective, the bespoke physics presented in the next section is purely two-dimensional and differs from traditional 3D physics in many ways—but those differences may be problematic, irrelevant, or advantageous, depending on the computational purposes and techniques involved.

3 Living Technology in the Movable Feast Machine

Traditional deterministic and synchronous computer architectures, viewed as bespoke physics, are blatantly incompatible with the principles of the previous section—so much so it may be unclear what a conforming architecture might look like. This section highlights one concrete approach, illustrating how robust and indefinitely scalable computation—perhaps inevitably—will look far more lifelike than most computation has to date. We expect that mature computer architectures will necessarily manifest ongoing concerns with distributed agents building, preserving, and growing

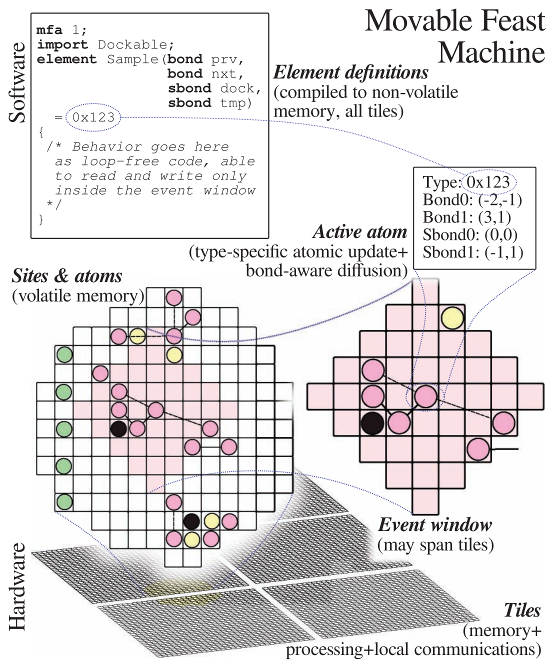
3 At least, simple-minded approaches to encoding multiple scalable dimensions into fewer ultimately run afoul of principle 2. Time, arguably, could provide a fourth scalable dimension, if it is acceptable to impose some fixed time limit on individual computations occurring within the physics.

their own mechanisms and relationships, rather than presuming a computation can be set up once and for all in the finite style.

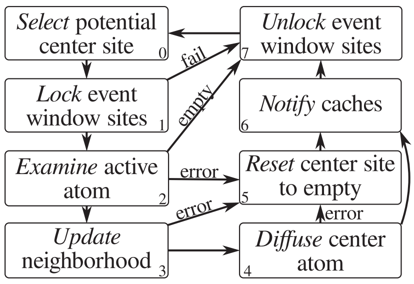
We have previously reported [2, 3] on the Movable Feast Machine (MFM), a computer architecture for an indefinitely scalable machine. Here we give a high-level introduction and then briefly step through three connected examples of building a living technology "ecosystem" using custom laws of physics, with simulation-based data and observations illustrating both more obvious and more surprising aspects of MFM-style living technology.

Figure 2a is an overview of the MFM. The hardware structure is a spatially distributed, two-dimensional parallel processing array, designed with the Section 2 principles first and foremost:

1. *Indefinite scalability*: Each tile is internally clocked; direct communications are asynchronous and to adjacent tiles only; there is no global clocking or long-range routing fabric.
2. *Isotropy*: Uniform scalability in two symmetric spatial dimensions (see Figure 2a) with relative coordinates only; there is no global coordinate origin. Tiles are completely fungible, with no hardware-defined unique identifiers. Time is structured as an open-ended sequence of brief atomic events (see Figure 2b).
3. *Limited causality*: Hosted physics processing has no inherent global sequential structure. A single atomic event runs sequentially to completion, providing a bounded event window of causality to ease local programming and analysis, but interevent scheduling is randomized and subject to acquiring any necessary intertile locks. Tiles are hot-pluggable without requiring a global restart.
4. *Level isolation*: Strict Harvard architecture separating code and data; the code implementing the laws of hosted physics is treated as firmware and is stored, accessed, and updated separately from all bespoke physics processing.


```
mfa 1;
import Dockable;
element Sample(bond prv,
               bond nxt,
               sbond dock,
               sbond tmp)
  = 0x123
{
 /* Behavior goes here
   as loop-free code, able
   to read and write only
   inside the event window
 */
}
```

(a) Architectural overview of the Movable Feast Machine.


Select potential center site 0
Lock event window sites 1
Examine active atom 2
Update neighborhood 3
Diffuse center atom 4
Reset center site to empty 5
Notify caches 6
Unlock event window sites 7
fail
empty
error
error
error

(b) Internal temporal structure of an MFM event.

Figure 2. Architectural overview and event details.

3.1 Model Details

In the current version of the MFM (using the P1 parameter set [3]), data is stored in structured form within atoms each containing 64 bits. Sixteen of those bits specify the atomic format, which in turn specifies the interpretation of the remaining 48 bits and determines the dynamics of events centered on an atom of this type. Each tile contains an array of sites, each of which may hold one atom. Figure 2b illustrates the event window processing cycle as seen from the MFM programmer's point of view. Steps 1 through 7 are a critical section—so although the sequencing *between* events is unpredictable, the bespoke element programmer does not have to worry about race conditions *within* a single space-time event window.

An atomic *bond* denotes a linkage between two atoms, and is offered in two types: *Long bonds* can connect atoms up to a Manhattan distance of four, while *short bonds* reach distance two. When an atom diffuses (step 4 in Figure 2b), bond length limits are respected and all involved bond coordinates are updated automatically.

Behavior in the MFM is determined by the set of custom elements defined by the programmer, plus initial conditions[4] including the size and shape of the available computational space and the distribution of elements within that space. Unlike much work in artificial life, in the MFM there are no a priori mechanisms forcing computations to display adaptive or evolutionary or indeed any particular behaviors, though, as we will see, lifelike behaviors such as homeostasis and reproduction can readily be programmed as bespoke physics.

The MFM exposes a flexible and reasonably familiar sequential programming model at the level of elements, providing significant power and expressiveness for creating sets of hosted physical laws. Here we present three sample case studies, illustrating simple living technologies and how such low-level mechanisms can interact and coexist with each other and with larger computational goals, using space sharing within a grid.

For reference throughout the following subsections, Figure 3 presents a partial "table of elements" for the examples we consider; Figure 3a in particular illustrates the basic structural properties shared by MFM atoms. The 48 user-programmable bits of an atom are divided on a per-element basis among four uses: type bits to represent the unique type number of this element, long bonds connecting atoms up to four sites apart, short bonds stretching up to two sites, and state bits to record miscellaneous information as needed.

3.2 Regulating Occupied Site Density

The ability of atoms to move within the grid is critical for reactions, and thus computations, to occur, and atomic mobility is strongly affected by how crowded the grid is, as measured, for example, by the occupied-site density (OSD) expressed as a percentage of occupied sites over some region of interest.

We have explored managing the OSD using a simple dynamic regulator element we call `DReg`, whose dynamical law is depicted[5] in Figure 4: A random nearby location is selected (at Manhattan distance 1, i.e., the Moore neighborhood) and examined. If it is empty, there is a low probability of creating another `DReg`; otherwise there is a somewhat higher probability of creating a `Res`, a basic resource element designed to be transmuted into more useful forms by other elements in a more complex system. On the other hand, if the chosen location is occupied by a `DReg`, there is a significant chance of destroying it, while anything else has a lower probability of being destroyed.

Recasting that dynamical law in the style of an artificial chemistry, Figure 5 summarizes the possible `DReg` reactions. Unlike traditional chemical notation, here there is explicit accounting of empty space in the reaction diagrams, because the MFM physics allows creation of an atom on the fly—but only if there is a place to put it. The reaction rates shown in Figure 5—which restate the `odds`

4 Since indefinitely scalability offers no guarantee of a single global starting time, these are probably better described as "boundary conditions."

5 In pseudocode for now; an actual Movable Feast Assembler is currently under development.

ElementName=*typeNumber*[*typeBits*]

long bond names	*short bond names*
state names: bits and fields[*size*]	

(a) An "element information box."

DReg=0xdba[12]

–	–
–	

(b) DReg: Dynamic regulator.

Res=0xa11ce11[28]

–	–
–	

(c) Res: Resource atom.

BaseChain=0xbc[8]

left, right	dock
state[2], data[16]	

(d) BC: Base chain.

BaseChainPolymerase=0x2bc[10]

copyEnd	sourceDock, nextBC
–	

(e) BCP: Base chain polymerase.

BaseChainInterpreter=0xbc1[12]

–	pcDock, arDock, brDock
pc[2], ir[2], r0[12], arb[2], brb[2], state[2]	

(f) BCI: Base chain interpreter.

Datum=0xdada[16]

–	–
value[32]	

(g) Datum: Sortable data.

Sorter=0xab[8]

–	–
init[1], threshold[32]	

(h) Sorter: Comparator.

Figure 3. Sample bespoke elements: (a) illustrates the notational structure; (b) and (c) are discussed in Section 3.2; (d), (e), and (f) are discussed in Section 3.3; (g) and (h) are discussed in Section 3.4.

parameters in Figure 4—are inexact, because the sequential checking in the DReg dynamical law causes some reactions to interact. For example, the create/other reaction that produces Res will actually occur in less than 0.5% of its opportunities, because sometimes a DReg will be created instead.

A grid initialized with such a DReg gradually fills with Res and DReg atoms, until their concentrations—and the overall OSD—equilibrate at a level determined by the reaction rates. With the create/other reaction running about half the rate of destroy/other, as shown, the OSD settles somewhat above 33%, including about a percent of DReg. The OSD is higher than might be expected, despite the reduced create/other reaction rate, because absent stirring, a DReg has a higher than average chance of reencountering the results of its own actions, producing a bias toward 50% OSD.

Figure 6 illustrates dynamic regulation at work, showing approaches to equilibrium from various initial concentrations of DReg and Res. The data shows that, as intended, the high destroy/self reaction rate causes excess DReg to be eliminated quickly (Figure 6b and 6c); a surprise was the significant DReg undershoot and slow recovery visible in Figure 6d, leading to its incomplete convergence even after 25K AEPS. The reason, again, is local deviations induced by the computation itself: With initial OSD so very high, the few existing DReg end up migrating to or being created in small pockets within dense fields of Res, causing much higher rates of destroy/self than the global concentrations would predict. Still, the Figure 6d initial OSD is so far above typical system operations that this pathology seems mostly a minor concern.

```
/* DReg: Dynamic Regulator.  This version hardcoded for 33+% OSD */
element DReg() = 0xdba {  // The ''Death / Birth Agent''
  if n:anyAt(1), n is Empty, odds(1,1000) then n = DReg; // Rare DReg
  else if n is Empty, odds(1,200) then n = Res;  // p=.005, make Res
  else if n is DReg, odds(1,10) then n = Empty;  // Limit DRegs
  else if odds(1,100) then n = Empty;            // p=.01, nuke it
}
```

Figure 4. Movable Feast Assembler pseudocode of a dynamic regulator element. See text.

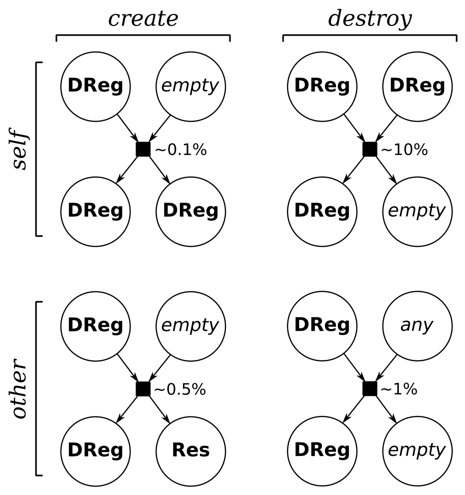


Figure 5. Dreg reactions.

DReg and Res are a simple *autocatalytic set* [20] driving a basic metabolic cycle, creating new bottom-of-the-food-chain Res, and randomly destroying arbitrary atoms to maintain the OSD—while controlling DReg levels to preserve the reaction system itself. Such autocatalytic regulation—involving "birth" and "death" at the lowest level—is a durable and basic living technology mechanism for robust, indefinitely scalable computing. In addition to managing grid liquidity, DReg creates an environment of continuous training, forcing the other elements to handle a basic class of attacks on an ongoing basis, long before any power failure, cosmic ray, or malicious intruder must be confronted.

3.3 Base Chains, Polymerization, and Interpretation

DReg specifically creates Res and DReg and nothing else—it is robust, but not flexible. Shifting to the other direction, we have drawn inspiration from natural information carriers such as RNA and DNA, and developed a simple molecular carrier of arbitrary digital information that we call a *base chain* (BC, Figure 3d). It possesses left and right long bonds to chain BCs together, a dock short bond allowing other elements to grab hold, and a data field that carries 16 bits of arbitrary data.

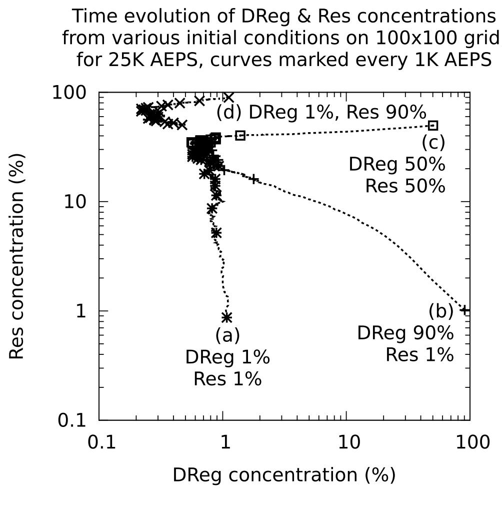


Figure 6. Typical approaches to equilibrium to DReg and Res systems. Four separate runs shown in (a)–(d); in each run all grid sites are initialized at random with given odds.

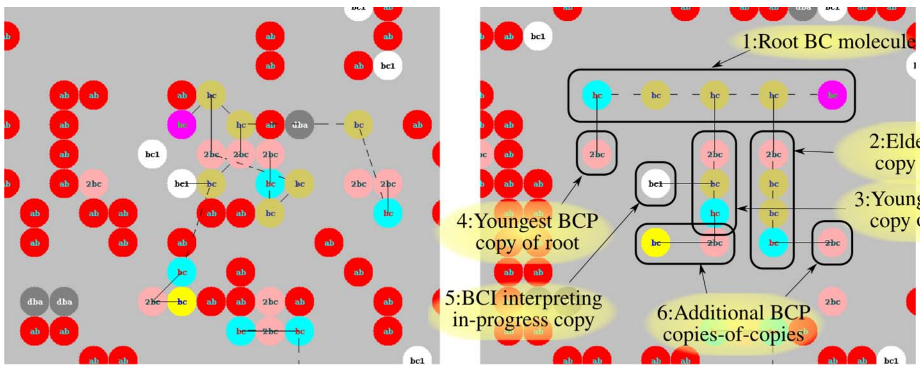

1:Root BC molecule
2:Eldest BCP copy of root
3:Younger BCP copy of root
4:Youngest BCP copy of root
5:BCI interpreting in-progress copy
6:Additional BCP copies-of-copies

Figure 7. A base chain molecule complex as found in the wild (*left*), and the same manually "denatured" and annotated (*right*). See text.

We made a *base chain polymerase* (`BCP`, Figure 3e) atom that—over the course of many events, if not disrupted—is capable of copying any preexisting, well-formed `BC` chain, by capturing `Res` atoms from the environment and transmuting them into copied `BC`s as it works from left to right. And finally, to put it all together, we made a simple *base chain interpreter* (`BCI`, Figure 3e) element that incrementally executes the data contained in a chain of `BC` molecules, treating each four bits as an opcode for one of various operations: Shift a value into a register (field `r0` of `BCI`), wait for a `Res` and capture it, transmute a captured atom into an atom whose type is specified by `r0`, and so forth.

Given an initial configuration containing a `DReg`, some `BCI`, and a `BC`-encoded program that specifies making a `BCI` and a `BCP` (and perhaps other things), an entire autocatalytically sustained population of reproducing and executing programs usually develops, except for rare "infant mortalities" in which `DReg` erases all the `BCI`s or breaks the primordial `BC` chain before copies proliferate. Figure 7, drawn from a program discussed in the next section, illustrates some of the surprising complexity that is generated.

These first two examples suggest some of the low-level mechanisms and techniques we are exploring: `DReg` provides resilient grid density management, while `BC`, `BCP`, and `BCI`s provide a measure of robust programmability within the grid. But those tasks are only living technology support mechanisms—they establish, preserve, and regulate themselves, which is indeed crucial, but they accomplish nothing else.

3.4 Demon Horde Sort

Our final example shows how these living technology pieces can be put together to perform an externally facing computation—a simple stream-sorting task, in which an endless stream of numbers are injected near the right edge of a 128 × 64 rectangular grid, with each 32-bit number encoded in a `Datum` atom (Figure 3g). The stream of `Datums` are to be sorted on the fly so that by the time they are absorbed at the left edge of the grid, the smaller numbers have risen to the top, and the larger are farther down.

Our sorting strategy, inspired by Maxwell's demon, is based on the `Sorter` element depicted in Figure 8—a whole horde of such `Sorters`, generated by a `BC` program designed to produce two `Sorters` as a payload before producing the `BCP` and `BCI` that keep the population robust.[6] Each `Sorter`'s threshold is just the value of the last `Datum` that it moved.

Figure 9 is a typical illustration of how the demon horde performs in simulation, both when the system is peaceful, and when it is subjected to a series of shocks to test robustness. The y axis is the sorting performance on the left and the data throughout on the right, while the x axis is

6 In the online version, all of the red atoms marked with type ab in Figure 7 are `Sorters`. Note also that the demon horde sort discussed and demonstrated in [3, 1] is simplified compared to this approach.

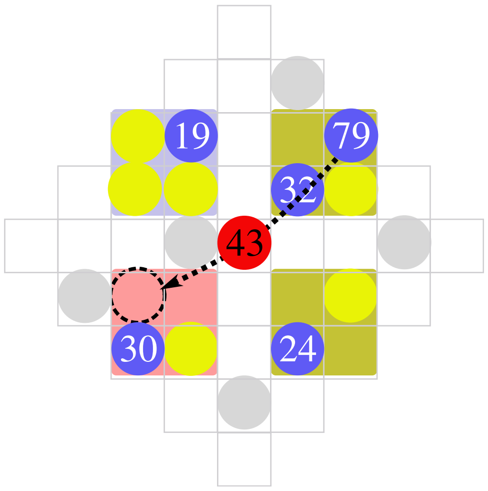


Figure 8. A right-to-left sorting demon (*center*) discovers that datum 79 in its upper right region is larger than its current threshold (43), and it moves to an empty location in the left lower. The demon would be willing to move 24 to the upper left, but no empty locations are currently available.

abstract time in units of 1,000 AEPS (see the end of Section 2.3). The grid has 32 `Datum` sources near the right edge, each of which probabilistically emits uniform random numbers from 0 to 999,999, and 32 `Datum` sinks at the left edge, each of which absorbs (and scores for statistical purposes) any `Datums` that appear within its short bond range. We measure performance by computing an average bucket error (dashed, green curve in the online version) based on how far each absorbed `Datum` is from its "perfect" bucket (derived using our experimenter's knowledge of the input data distribution). We also compute the *categorization error rate* (dotted, blue curve in the online version), which is the percentage of `Datums` that are absorbed by a sink more than a third of the total number of sinks away from the correct bucket, approximating just a high-medium-low categorization. Finally, we also compute the *data throughput* (solid, red curve in the online version) as the ratio of data absorbed to data emitted per unit time (which can be greater than 100%, due to variable buffering in the grid).

The program initial configuration contains simply data sources and sinks and small blocks of `DRegs`, `Res`, `BCIs`, and preprogrammed `BCs`. At first we see the system warming up as the elements gradually approach equilibrium concentrations; it will "boot" much more rapidly if initialized to a near-equilibrium state by about 15K AEPS, the average error is a little over two buckets out of 32, the categorization error is perhaps a percent or two, and the data throughout hovers right around 100%.

At equilibrium we observe about 40–50 complete BC chains in the grid at any given time, typically in large complexes as exemplified by Figure 7. That count is an important measure of system resilience, as became evident when we began to stress the system. First we hit it with five "cosmic ray blasts" from 20K to 22K AEPS, each blast flipping about 0.1% of the grid bits—hundreds of bits per blast—and then a flash "power outrage" at 30K AEPS that reset two-thirds of the grid sites.[7] The system recovers from both of those events, more or less quickly, but then at 50K AEPS, 25 more closely spaced "cosmis ray blasts" occur, ultimately disrupting the last of the BC chains containing the master program, after which the system degrades and fails.

Though we managed to kill the demon horde in that demonstration, it is indeed strikingly robust—sometimes in ways we had not anticipated. We initially picked a data input probability that seemed high enough that the system had to actively transport the `Datums` from right to left, faster than diffusion, or

7 Though the data sources and sinks do not diffuse, they are also vulnerable to these events; they employ custom autocatalysis to repopulate themselves at their designed spacing.

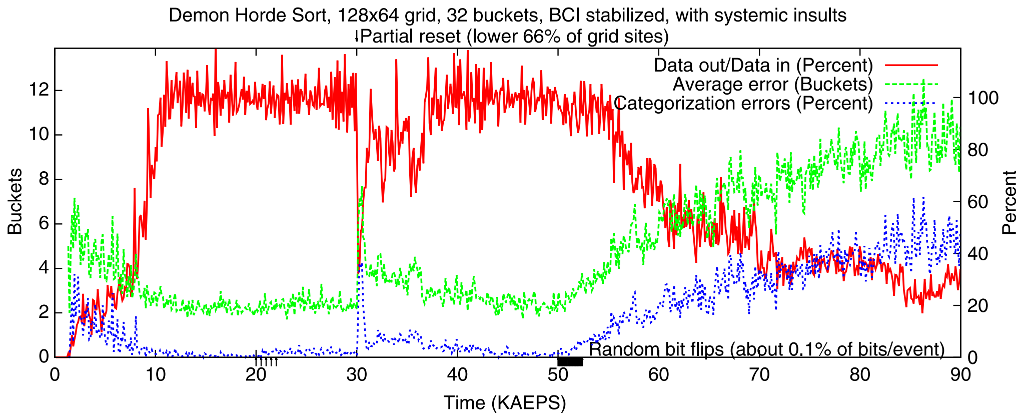


Figure 9. The demon horde continues to sort in the face of transient hardware failures—until it doesn't. See text for details.

else the array of data sources would get clogged and data injections would begin failing, punishing the throughput.

Later on, seeking an additional system stressor, we thought of increasing the data input rate, but were surprised to find (see Figure 10) that this MFM program's performance improved with increasing data rate over a fairly wide range, before it was ultimately unable to avoid input grid clogging. In retrospect, at least this behavior is understandable. Higher data rates both help the in-grid data better match the distribution used for scoring, and also cause the sorters to move data more frequently compared to their diffusion rate, tending to keep their thresholds more appropriate to their grid positions.

This is adaptation of a rather fundamental and inherent and, we think, satisfying variety: a programmed computation that naturally improves when worked harder, while deteriorating with idleness—a sorting muscle.

4 Related Work

The present work is perhaps unusual in its use of living technology for robustness and scalability in computer architecture and computer engineering, but its approach and mechanisms are related to existing work in several areas; here we briefly touch on three.

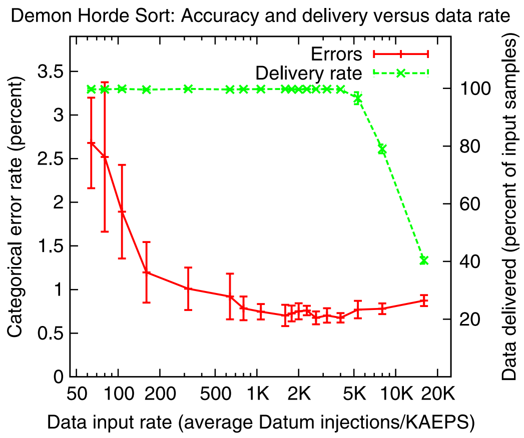


Figure 10. The demon horde's sorting performance improves with increased workload, until capacity is reached, causing throughput to decline. See text for discussion.

4.1 Cellular Automata

Cellular automata (CAs) are a typically fine-grained and spatiotemporally isotropic model of computation. They have been extensively studied in many variations [16], some of which can satisfy all the quality principles of Section 2. The MFM can be viewed as an asynchronous, stochastic CA [24], using the random independent updates [10] strategy.[8] But while CA models often focus on theoretical parsimony and existence proofs, the MFM focuses instead on resilient programming expressiveness for scalable hardware. Consequently, instead of minimizing the automata alphabet or neighborhood size on a problem-specific basis, we establish those parameters once, based on hardware and software engineering concerns.

As a result, the MFM atom size and event window size—though minuscule in comparison with the addressable random access memory of a von Neumann machine—is also gargantuan in CA terms. The "P1 parameters" mentioned in Section 3.1 specify 64 bits in a site, and 41 sites in a (Manhattan distance 4) neighborhood. That would imply a hopelessly infeasible CA state table with about 10^{800} rows, so the formal equivalence between the MFM and a CA, in practical terms, may rarely be of great use. But computer science and software engineering have learned much about how to express contingent behavior in compact and expressive programming language forms; the MFM applies that knowledge to CA-style state transition programming, while shedding the global determinism that traditionally accompanied it.

4.2 Artificial Chemistry

Artificial chemistries (ACs) are models inspired in some way by chemical systems (see [13] for a review), and, like CAs, vary widely in the intent and in the broad mechanisms and fine details of their presumed physics. Early influential AC work such as λ-chemistry [15] used explicit molecules in a "flow reactor" physics that was finite, non-spatialized, and globally randomized—which was wise for its scientific purposes, but is not indefinitely scalable; many other ACs are similar. Graph-based models such as random reaction networks (e.g., [19]) are even more abstract and inherently descriptive, explicitly representing not individual molecules but potential chemical reactions.

Among ACs, lattice molecular systems [13] are sometimes designed with explicit sensitivity to computer engineering concerns (e.g., [25]), and often postulate physics that comes close to satisfying the Section 2.1 metalaws—although presumptions of global clocking and deterministic operation remain common. The MFM is a lattice molecular system, and its physics is clearly related to influential early lattice models such as the autopoiesis model [36] (with its important later corrections [26]). To date we have explored a few bespoke physics programs that support membranes to create spatial boundaries (see [3])—rather than for variable-length information-carrying as in Section 3.3—and it would be interesting to develop a more fully autopoietic cell template in the MFM.

4.3 Spatial Computing

Though aspects of space—geometry and location, distance, and direction—are central to particular tasks like mapping, the inherently spatial properties of a physical computing system are abstracted from and ignored by most of computer science. However, as clock speed growth stalls, and distributed computer networks proliferate at multiple spatial scales, continuing to marginalize space becomes increasingly myopic. Primarily in the last decade, an increasing number of researchers have begun to focus on spatial computing models that retain space as a first-class concern ([12] is an introduction). Diverse avenues have been explored, from continuous spatial models (e.g., [4, 22]), to models aimed at wireless and mobile computing (e.g., [6, 23]), to fine-grained spatially organized machines such as FPGAs (e.g., [11]).

Compared to many spatial computing approaches, a primary distinguishing feature of the MFM is its focus on inherent resilience, employing stochastic execution and emphasizing autocatalytic and

8 At least in the current simulator; our hardware implementations may vary.

concentration-based reliability—much in the spirit of [27], except with reified agents in extended space, rather than a well-stirred reactor.

5 Call to Action

Living technologies based on robotic hardware or biochemical wetware have the potential for huge applications across society, but are mostly in the early stages of research and development. Computer-based soft ALife research has explored many models, but its influence on computer science and engineering has been limited. It is distressing that the highest-impact lifelike computational objects today—though not springing from overtly ALife research—are the computer viruses and other digital vermin of the Internet.

Life is the most practically scalable semiprogrammable behavior generation system we have encountered—and that is why artificial life can and should play a central role in the design of post-von Neumann architectures and computations capable of open-ended growth. To date, though, typically each ALife model specifies its own co-designed custom physics as an integral component, creating a "universe of Babel" problem among models that hampers scientific generalization and engineering interoperability.

A common physics could offer tremendous leverage for building and combining ALife models and mechanisms, but what type of physics should that be? Design decisions like global synchronous clocking and deterministic error-free operation can be tempting, to simplify logical and combinatoric reasoning, and they may seem like harmless conveniences—especially for computations offered only as existence proofs anyway, as many artificial life models have been, explicitly or implicitly. But to the contrary, although ALife models built on unscalable physics have inspired and informed us, they have also importantly deluded and misled us—both generally about how much of the problem we have solved, and specifically about what architectural directions to pursue for enduring progress.

For artificial life to advance future computing and contribute powerfully to the emergence of living technologies, we must ground our physics in something other than the needs of any particular ALife model. As an affirmative effort to help stiffen our spines to do better, the Section 2 principles of bespoke physics offer one such grounding. Moving beyond synchronous and error-free determinism is not a small matter; the imperatives of robustness and indefinite scalability influence computational design from top to bottom and back again. Compare Figure 7 with Figure 11. Both depict implementations of programmed reproduction in a discrete two-dimensional environment—and yet

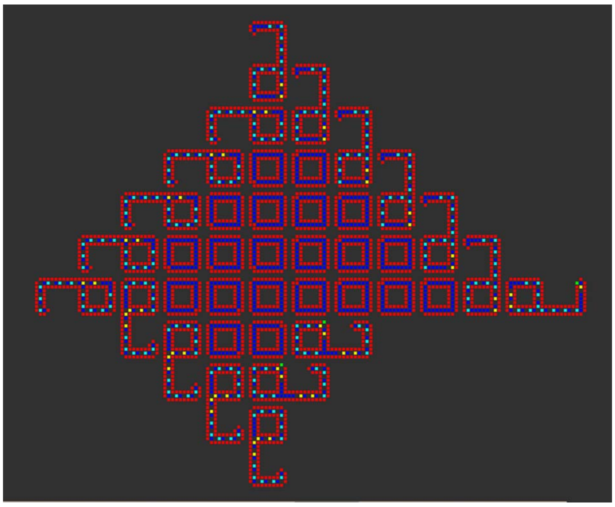


Figure 11. The Langton loop: Programmed reproduction in a synchronous deterministic physics (cf. Figure 7).

they are utterly different in character. And, I suggest, the former is far more suggestive of life in the wild.

Architecture is destiny.

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