

Fitness landscape

Fitness Landscape, in biology, is a metaphor used to evoke the notion of a "rugged landscape" with various "micro" peaks, troughs, and other features, each associated with different combinations of "genes".

The basic metaphor: Consider the "maximum" position of various peaks to be the fitness level associated with a particular combination of expressed genes. We would consider the distances between neighboring peaks to be directly "measure of genetic change". A high density of intermediate distance peaks results in a less rugged and more "fit-for-purpose" landscape (e.g. more precisely defined targets); a low-density of such intermediate distance peaks would result in a more rugged, more sloppy, or "intransigent" landscape, so that getting from one local peak to another would require more "adaptive" genetic changes.

The basic principle: A gradient of increasing "fitness" for a particular "solution" would imply that more is known about the requisite "adaptive changes" between closely related organisms. A swath of possibilities surrounding low fitness value organisms with no obvious "genes", or directionality (e.g. we wouldn't expect to find highly similar species between either of two adjacent peaks), would be analogous to a rogue "island" or "valley" of low fitness possibilities surrounded by greater or equal probability conformations/combinations for organisms. (This would imply that alternative evolutionary changes were more frequent than we might expect).

Example of reference: A review, in Cell, discussing the representation of possible "solutions" in soluble proteins and its interpretation in terms of a fitness landscape.

References:

Ribota-Duarte R, Posado P (2014). A quasispecies topography of the genotype–fitness landscape for proteins. Available at SSRN: <http://ssrn.com/abstract=1165947>. Published Online.

Cochran GT. Fitness advantage of gene combinations: discontinuous phenotypes, punctuated equilibria, an adaptive landscape. Cell 1989;58(3)

Reynolds AC, Young OM. The neutral theory and environmental interactions: evidence that speciation is harder than often thought. Nature 2009;459(7247):881–4

Fitness is basically a weighted function such $f(t,u) = t - wu$

w here is an example of a scaling factor. You will find this notation in textbooks for this set up.

A simpler example of this is:

$$f(t,u) \sim \frac{1}{4} t^2 - \frac{1}{2} u - 1$$

where you can see that for instance setting t at a certain value, say $t_1=0, u=0$ you get $f(t_1,0) = \frac{1}{4} 0^2 - \frac{1}{2} 0 - 1 = -1$. This means if you set $t_0=t_1=0$, you will get $f(0,0) = -1$.

Now suppose you instead want to find t_1 where $f(t_1, 0) = f(0, -1)$. In this case, t_2 and u_1 will give you the same value for f .

In your case you have more scalar factors such as W and C .

W is in the fitness function for 10^{-1} and in the population function to find a good point to put a new individual.

C is in the MFvS, which is scaling the individuals down to have them all fit on different systems.

C and W could be estimated, but doing that would take way more assumptions on how the real world works.

Fitness is a scalar function of a genotype that will model the fitness of a certain mutation of the organism. Your great grand father may be so fit that he won't get diabetes but if someone in his family with a different gene/network got diabetes, fine, you've got to be fast(er), and strong(er). In other words, you penalised his path and rewarded your path when it comes to mutation rates. However, some mutations are better than others IF you have to travel a long distance(fast) or you're forced to swim(strong).

The space is just like \mathbb{R}^2 . The arrows show a direction in order to deconstruct.

So, I believe there are a lot of parameters missing in the question but if I understood, what I answered here will have a severe relation to the direction of arrows.

Fitness is conventionally used in evolutionary dynamics as the average fitness of a population in the context of a given environment.(Measures of average fitness include averages of absolute and also weighted with allelic counts, if desired.)

A fitness landscape is the picture of the space of all possible genotypes (genetic codes) in a given environment which shows structural features (known as adaptive clines) in curves in that space.

Each point in the landscape defines a genotype --the coordinates in the phenotype space. (The non-phenotypic effects are implicitly supplied via feedback from fitness itself via the assumed fitness function.)

In that manner, one can consider fitness a proxy for complexity of interpretation.

"All change is not constraint." Gyrate 8 intelligent life forms. Pic below is from Longenecker 1995. in the tradition of Lombardy; resident L-Province L-1 art; Living in philately F.

I offer my interpretation, from empiricist perspective, of what seem to me, manifest signs of evolution:

Emergence and derived improvements of caudation and right; cephalisation of feeding and coordinated character selection; sociality and increase in brain power; a saurian or lizard vertebral column; seeds of self-determination and aesthetic appeal; bilateral symmetry and front-to-back spinal nerve spinal transmission; upright posture and overcome entropy; etc, all in the context of their ecological niches.

Fitness landscapes are representations of the objective function used to fit models to noisy observations. Let us think argumentatively about "is the gloss of data d correct". Clearly, you start by writing down an objective function $z: d \rightarrow \mathbb{R}$ or maybe $z: d \rightarrow \mathbb{R}_{\geq 0}$, which ideally does not produce a random or unprincipled value for every new observation, but leaves room for updates.

For simplicity, let us just describe a generic function:

decide on a set of the form $\{d_1, \dots, d_n\}$ based on your fitting procedures/strategies
 evaluate $z_1 = z(d_1)$

repeat steps 2 and 3 until d_n results are available

use a criterion to decide whether or not to accept $z_i \rightarrow z_{i+1}$

I include z for clarity, because your model could be expressed on the basis of a different function, i.e. $f(d, \dots)$, but d_n will be the same (1 on 1).

One should think about the accept criterion. It could be on some optimization criteria like (local) gradient or result in acceptance, or in case of negative gradients or points in an unexplored elsewhere, the next step could be adjusted plans. The latter is quite common for algorithms in machine learning, like simulated annealing.

Instead one could also restart the whole process from the beginning (placing an already sampled point perhaps with a discount or without).

Fitness is synonymous with good, quality, worth, etc. Think of fitness landscapes as weird milieus where there are many possible paths to feel successful. In the example you cited, they would have hundreds or thousands of documents and their investigation may lead them in many indirectly correlated paths until they ultimately find a book they like.

Of course, coherence isn't nearly as important in academic publications. They're about as one-dimensional as a map is in a videogame.

Fitness landscapes are a discrete metaphor.

It portrays values of the problem / solution space $\mathfrak{S} \times \mathfrak{S}$.

Boiling it down to $\frac{S}{2} \times \{0,1\}$ axes:

Case 1. Simple fitness partitions:

In biology where fitness is often rank-order (Chakrabarti 2015), there are unity steps or quanta Ω equal to forced fitness values. Fitness landscapes are somewhat like a bivariate normal distribution.

Case 2. Parts, unity, and parity divisions: This is the Tit Temperament, or all-or-nothing locus in the Chakrabarti (2014) paper.

Cases 3, 4. Do these two have specific names in biology? Partha was talking about some papers when they corresponded. Case 3 looks like the stiff / flexible locus in the carpet fish Graham (2013) paper.

Supplementary Note H.3 gives a progress report on the categorization of fitness landscapes in fitness space. The above review may be of help.

A:

The answer may be seen by reflecting on how biological fitness is measured. The other answer is that fitness for TIT-FOR-TAT games is simply 1 minus the benefit of mutual defection. Which isn't to say that replicator dynamics I don't think can be instructive. These answers really are similar in a way you see when you think about time in population dynamics. The only real question is what properties of the fitness landscape one varies over.

Fitness Landscapes are functions $f: D^k \rightarrow \mathbb{R}$. Where the domain is a k -dimensional projected view of sequence space. In other words the domain of f is all possible k letter amino acid sequences.

A point $(f_1, \dots, f_k) \in D^k$ is called a local optimum if there exists a half line, dense in the domain that does not approach (f_1, \dots, f_k) , along which the function increases (either in the forward or the reverse direction).

The landscape value of a sequence is uniquely defined as the first term of any half line not ending at (f_1, \dots, f_k) .

From this definition the claim that a fitness landscape is characterized by deep narrow valleys does not seem to hold. The key concept upon which the fitness landscape analysis rests is that the majority of variants between a pair of points on the landscape have higher fitness, and any given sequence can be improved on in many directions.

A fitness landscape is essentially a quantum graph; many models of spatial structure have appeared recently in connection with the study of spatial searches and other search processes (where by “many”, I mean more than a single paper; you may have seen, for instance, Section 8.8 of Boettcher and Percus’s “Statistical Physics and the Geometry of Fitness Landscapes”, Phys. Rev. Lett. 96, 034302 (2006)).

In particular, my paper with Eric Smith identified a way of making complicated 2, 3, and 4-dimensional fitness landscapes out of 1-dimensional graphs, by considering the problem of moving from one vertex to another in a particular geometry. Here’s how it happens:

Large-scale separation of timescales. In contrast to the use of spatial structure to encode the notion of separation in the above figure, we consider a different problem that can be encoded as a graph. In this problem, there is a single scale of time and space, but there are many possible ways to move from one vertex in the graph to another. These movements are ‘slow’ relative to some other motion that we can define, for instance, the speed of an understanding or the phylogenetic length of a move in a phylogenetic tree. We take advantage of the large-scale separation of timescales in this problem to uncover an equivalent structure described by a 1-dimensional row-finite graph. As a consequence of preserving slow relative to fast, extensive properties (such as the value of a ‘fitness’) are conserved at vertices and changes are not. In other words, there is no Darwin’s law of diminishing returns. Instead, fitness is large for the largest spaces of velocity within which some property remains fixed at its high value.

The geometry is exactly that of a single line in 3-space (+ 1 space of velocity and +1 time). Each vertex could be a class of genomes $\in G$ in the case of a phylogenetic tree. We can think of moves as repeat sequences of 1 mutation or move (terms which I have omitted to emphasize that a move unfolds on its own very fast timescale).

So what is spatial structure, in the sense used in this paper? Why did you not ask your question in Mailing list DPD?

In an introductory sense, I would say that spatial structure is a way to describe a loss of generality due to a particular coordinate system.

Example: Consider an atomic system with a configuration $\vec{R} = (x, y, z)$ and Hamiltonian (energy eigenvalue) of the form $H = \frac{1}{2} J \vec{R}^2 - \mu \vec{R} \cdot \vec{R}$. Here $\vec{R} \cdot \vec{R}$ is a special case of the more general dot product in 1,2,3 (or, more generally, k) dimensional space, and where this spatial structure gives rise to several possible mechanical interpretations of H .

But we also observe the fact that when it is plotted, and we examine the geometry of trajectories, that it has the shape of a one-dimensional mountain range or a valley.

A:

Consider a network of chemical (H, O, C, etc) and biosignal related (ECG, EEG, MEG, etc) data, where each data-point consists of multiple topological transformations (node), e.g. an ECG "sample" should ideally be representative of a specific instant, and of pathlength, i.e. distance or time spent in between them. For particles in a fluid ($3N$ space) this is a tedious task at best and prohibitive at worst. For such a "high dimensional" network of point-data, I think that a computational geometry perspective could make sense:

Linear, or first-order, models would minimize the sum-distance between the data-points;
 Quadratic models, or second-order, would minimize the sum of squared distances;
 Higher order models or even "non-linear" could be considered, e.g. $O(n^3)$ or higher.
 "Free" models ($\omega(0)$ weighing) could be considered as well, assuming each growing factor would approximately double the model's complexity

The "intuition" behind this is that the measures $\|\vec{P} - \vec{p}\|$ were "integral" of the exponential map.

Motion in a high-dimensional space (understand as "continuous trajectory" with regard to a given basis) could perhaps not be described with too much rigor, if not defined properly.

If we define our space as \mathbb{R}^{3N} , then moving in any of its coordinates will effectively amount to moving in the other $3N-1$, since these are linear transformations.

Let us assume the usual $3N$ -dimensional cube \mathcal{B} and unit cube on the subspace \mathcal{U} of center $p \in \mathcal{B}$, of dimension $3N-1$, where p will serve as reference position, i.e. $p_i=1$ for all $p_i=1$.

We could then think of any path drawn by a particle in the cube \mathcal{B} as a family of 2D line segments \mathcal{L} connecting its end points $\vec{p}(l(t))$ with $l(t) \in \mathbb{Z} \times \{1, \dots, 3N-1\}$, that is, projecting on the subspace $\mathcal{U} \subset \mathcal{B}$:

$$\vec{p}(t) = \vec{p}(l(t)).$$

All that is required is to consider for each particle $p(i) \neq 1$ at time $t \in \mathbb{R}$ a new position

$$p(i;t) = l(t) + p(i) - 1 \rightarrow \vec{p}(t) = \vec{p}(l(t)) + \vec{p}(i) - \vec{p}(1) = \vec{p}(i;t).$$

Summing up the coordinates along the direction \vec{e}_k or the given basis $\mathcal{B}_{m:n}$ now would correspond to summing the coordinates of the k -th particle $\vec{p}(m)$ or in the composite case of all the $3N-1$ particles but the k -th

$\vec{p}(m;l)$ or in the compound case of all \mathcal{B} 's sides orthogonal to $\vec{e}_k: L_k=1$.

If we want to weight these trajectories differently, then we would add to each projected position an additional $\omega(0)$.

This additional weighting can be seen as an amount that the potential energy rises as one position is 'moved along a path'.

More abstractly, under a free particle assumption (homogeneous mass, no friction, surface interaction) the conservative motion of the system is described by potential energy $U(p)=U(p_1,\dots,p_{3N-1})$ and the kinetic energy

$$T(t)=\frac{1}{2}\|\dot{p}\|^2$$

where $\|\vec{v}\|=(\sum_{i=1}^M v_i^2)^{1/2}$, v_i being the velocity in the i th coordinate direction \vec{c}_i of \mathcal{L} or $\mathcal{B}_{m:n}$, can be seen as the action of a 'particle mass' of potential $U'(q)=-U''(q)$ which we can accept to be the proper kinetic energy of a free particle if we accept other other standard definitions.

I must nevertheless stress that all this sound like classical mechanics and I don't quite see the way in which there could be something that generalizes 'space' and 'time' into Hilbert space: it's only a probabilistic representation of the problem.

I think then that for two simple and common statistical applications, namely clustering and vector quantization, these ideas could apply meaningfully:

We could say that clustering m vectors $\vec{p}_1,\dots,\vec{p}_m$ into n

Fitness is a measure of the "goodness" of a genetic coding system as implemented by a computer:

given a set of possibilities for a set of variants, fitness measures the suitability of the configuration as an overall architecture for some task (performing a certain computation, achieving a desired ancestor-building-pattern etc).

it is possible to place the solution in a 2-d visualization of solutions (using tools like computer vision). The complexity of the landscape increases with number of variants, but it's not computationally intractable to evaluate fitness functions on small examples.

this functions "descends": starting from the fitness objectives, you could take genetic algorithms to find the best configuration; but GA is slow at iterating on a large solution space; thus ideally, it's better to start at a random partially filled solution, and try to "mutate" and add additional aspects to the system.

Fitness is usually associated with survival / reproduction. Sample: a easy means of assessment would be "number of offspring" verses distance covered, naturally insects will just want to go as far as possible, not see how long they can do it.

<http://biovel.com/biology/index.php?section=cpan1>More offtopic

Rather than any exact definition, the general framework for language learning would suggest that fitness in evolution would be assessed not by just learning. The selector measures something other than a percept in order to decide who makes the next generation. IMHO that's closer to the truth. There are many methods generally simulated e.g. self-organised criticality etc., but you need only consider how quickly you can make a mental model of the functions of objects, and whether a (reasonably detailed) internal representation of said object allows you to predict future behaviour.

Fitness landscape is a graph that takes "gene strings" as input and returns an evaluation (it is, in that sense, a function).

Then the question asks for "prefer" when this graph goes from 0 to 1.

So let's visualize a "gene string" as follows:

[0][1][2][0]

So, then, let's say that 0 means a brach is impossible, 1 means as difficult as possible and 2 means as easy as possible.

So then when we do the evaluation for 1, the fitness landscape will have an entry:

[X][1][0][Y]

with X and Y being the result.

So in this case any possible value gets a 1.

When going to 2, the fitness landscape will have an entry:

[X][1][2][Y]

with X and Y being the result.

So any possible 2 will have a 2 and 2 will also get an 1 and an 0 and an X, Y and Z value will be 0 - so if there was a gene string with as, bs and cs present, that gene string will be at the end of the fitness landscape.

You can see the paper: <http://gordon-closson.net/fitnessland/> for more information.

Fitness is a mathematical property of an algorithm which determines the extent to which the mutations you apply are actually contributing to a solution to the problem you're solving.

A fitness landscape is a method of visualising the suitability of those mutations you choose to instantiate within your evolving algorithmic structure. A perfectly smooth white noise

weather map isn't going to be terribly conducive to rapid adaptation, but a hellscape packed with incredibly hazardous cliffs and spikes will.

The idea is to find a way to visualise the relative suitability of all the places your mutated algorithm happens to be in. In the case of the weather map, green areas are the nicest you'll find - perhaps rain or a bit of lightning, snow or the odd tornado. The most desirable climates are particularly pleasing, and relatively safe - you'll find them in temperate, northwestern Europe and parts of East Asia.

Harsh climates are less appealing, and seem to perpetuate further round your landscape. Larger basins will act as more stable equilibria than constricted valleys, and rarely (if ever) taste of sweet respite.

In general, a solution in a more preferable area - one which often results in positive feedback and rapid progression - will find itself spatially separated from less fruitful areas. A local improvement in one area by a tiny, random mutation will often result in poor shrinkage, and in fact a slightly less favourable environment in another part of the landscape. This phenomenon is termed as Constraint of Adaptivity in Evolutionary Computation jargon [1].

So, that was nice and all, but what's the point? You can do more than look at it aesthetically. You may, in fact, optimise your solution to seek out and inhabit environments of peak fitness, in a way.

Terms such as Genetic Algorithm Optimization and the Simplex Crossover on Random Networks method change your evolving population's algorithmic structure to better suit the problems you're solving. But, because we don't quite know what the best "fit" algorithm looks like, nor do we really know how to describe what is good or bad about the fitness of an algorithmic structure, we don't in general know how to optimise for fitness without specialised training in that discipline.

As such, the algorithm will be trying to find the solution, and any observable pattern in its population will be trying to find the best (especially in comparison to other or just superstitious or silly) "solutions" it can find.

We might call a Specialist to come and sniff your results out for you, observe their fitness, and recommend a course of action.

Where the algorithmic structure is hardwired to a number of positionable sensors (real ones will obviously have far better positioning skills), a builtin advisor can simply select the most likely outcome for you. If the advisor feels your run's about to fail and you need to start avoiding the hostile areas, it upgrades all the sensors in these areas.

Note that you are not limited to Evolutionary Algorithms. Any sufficiently complex system, and most especially any system of emergent engineered individuals, has the ability to operate using some variant of this "Fitness Landscaping" method. Perhaps you evolve your invader's behaviour by considering its effect on the populace it has already conquered, not just the behaviour it is likely to attempt with.

This is a genuine question Greg Egan, by the way.

[1][http://www.research.ibm.com/people/lesp/noahs_grad.pdf][attachment #7]
] noahs-grad.pdf

A:

In the particular example calculus professor is referenced, I suspect the authors had some other bit of mathematical maturity in mind when they referenced Fitness Landscapes. I thought I should share this.

A fitness landscape is a very simple, two-dimensional mathematical model of natural evolution. The value at each step in the fashoined world, plus one, gives us an estimation (read 'assumption') of the fitness. Fitness is notoriously difficult to precisely measure, although it is fairly quick to get an idea of fitness qualitatively.

Image Source: Conifer Pines Film Creation

The example from the textbook is not a particularly good illustration of how calculus is used in real life. We have a bifurcation. Calculus does not mean a wild Heisenberg uncertainty principle, either.

That said, convection and fragmentation does play a significant role in both heating and then cooling of a lava chamber. At any given time the Earth is a roughly 80°C furnace in Space. Part of that heat output must disappear before the second part, "reach the lower troposphere." That process is broken up in the first few thousand kilometers due to wind shear and the buoyancy of the troposphere. Although the tropopshere never reaches liquid perfection, the heating and the cold of night are substantial.

The high concentrations of CO₂ and H₂O continue to lower the absolute value of the boiling point as you move towards the center of the Earth. Particularly as CO₂ actually increases the boiling point of some compounds, in theory, by 33 kelvin.

The energy remaining, that is not used to liquefy water to make steam, interacts with the already-existing atmospheric water.

I admit I haven't slept in two days.

Image Source: Conqois.net

I'm terribly sorry for the atrocious writing. This is because you lied to me, and all writing instantly translated to gibberish! You can find reasons, mostly bad textbooks, for assuming that "fitness landscape" even means anything. With that in mind let's move on to the continuation of this discussion.

The authors do include the Maxwell relationship of $F = Q \wedge \alpha C \wedge \gamma$. In this equation, α is a near-one for simplicity. That means the more powerful the system's energy source, the more power is applied to a process, is the measure of its effect on a system. Professor may

be missing the point, because very few systems care how much power is supplied to them directly.

Assuming a mostly unpolarized light source I suspect the relationship of force to temperature is a function of how much energy it actually has. We can say that increasing either the light penetration of a crystal or the post-crater temperature of a medium creates a gradient. Thereby allowing for "real-time" convection of atoms and focus in a useable particle for heat absorption.

The Boltzmann Constant and Eddy Diffusion

Calculus brings us to the apparent conflict of conclusions. We observe the motion of fluids, clouds, and weather, and often recover insight into systems that are terribly underrepresented with a scientific reality.

The assumption of $F\text{-}\alpha\text{-}\gamma$ must include two factors: the convection point source and the diffusion of clouds and water. One everything involved in velocity must come into play. The Clouds are influenced by the heat in the soil, and a corresponding wind.

@Robert Cieri brings up a very valid point with his induced velocity. The convection induced by heat and pressure changes needs to be understood. The F too places a limit on the usable energy through the system. However, if cloud formation, over a wide area, allows for more rain in all areas of the Earth, the resulting energy over a given area is far stronger.

With sufficient energy application, and a system with a strength limit (the F within $1.0001 = F\text{-}\alpha\text{-}\gamma$), what effect might we see?