1   **Evolution and favored change: a principle of least selection**

2   Michael Yarus
3   Department of Molecular, Cellular and Developmental Biology
4   University of Colorado Boulder
5   Boulder, CO 80309-0347
6

7   Keywords: RNA world, replication, translation, genetic code, Normal distribution, truncation
8   selection, fitness

9   Mobile: (303) 618-8017
10   Email: yarus@colorado.edu
11   ORCID: 0000-0003-0295-9795

Abstract

Favored biological characteristics can evolve by a subtle path, but beneficial selection has
predictable qualities to guide thought. These favored pathways are paths of "least selection".
Faster evolution is least selection, more probable because earlier evolutionary success is simply,
"success". A more likely path also requires least selection in the form of least selected change.
Truncation selections, accepting only extreme values of a distributed quantity, produce greater
change in population means. Truncation selection therefore readily offers a least selection.
Assuming selection for a Normally-distributed quality, truncation is enhanced via simple
dependences on increased standard deviation and higher selection threshold (consistent with
some population survival). Least selection applies to both chemical and biological evolution,
and can be estimated in general form, without reference to its genetics, from an underlying
phenotypic distribution. Chemical truncation selection is free of the Haldane cost of natural
selection; potentially yielding very rapid early evolution. Notably, a principle of least selection
unifies prior examples of quick evolution. For example: the 'crescendo' of accurate codes
leading to the Standard Genetic Code facilitates a least selection. More generally, evolutionary
extinctions and radiations are events with multiple coercive thresholds; thus Earth's history
offers many wide-ranging truncation/least selection events.

Introduction

Evolution's path can meander. Evolution readily takes a devious route. A natural population
may include an opportune variant accidentally satisfying a proto-biological need. Those rare
structures, perhaps less related to previous materials, can still provide the most likely
evolutionary advance. Moreover, forms known from laboratory experiments are unlikely to
completely sample possible protobiological conformations or chemistry: we are unsure of initial
conditions. Finally, a conceptual barrier to study of evolution is that even the simplest
replication, metabolism or expression are complex molecular events – thus, there will be no

obvious primordial route to them. Research must therefore identify the *least improbable* routes
to biological complexity.

Given these conceptual and experimental barriers, there is an acute need for well-founded
predispositions about selected change. Is there a general way to anticipate favorable selection's
rate? Is there a coherent comparison that predicts probable evolutionary transitions? This text
concerns these problems, always with ancient conditions, and particularly election of the
Standard Genetic Code, in back-of-mind.

This text is meant to be semi-independently readable, starting with numerical examples (just
below), then previous studies of replication, translation and genetic coding as illustrations of
least selection (starting at **A principle of least selection**). Analytical background for all argument
is in **Methods**.

Results

The Normal distribution as an example. To quantitate the fate of exceptional qualities x, x
frequencies must be known. The Normal, or Gaussian, distribution (Methods) has a special
status documented by the Central Limit Theorem (1). The theorem shows that any property
which is the mean of random variables, which may individually be distributed in any way,
nevertheless approaches Normal distribution behavior as the number of variables increase.
Normal and near-Normal behavior is accordingly widespread, making it a cogent example.

Selection acting on an example Normal distribution. Explicit quantitation begins with selection
for x, denoted:

$$\varepsilon = a + bx \qquad\qquad\qquad (1)$$

where ε is the number of descendants of individuals possessing x; ε is usually termed fitness.
Within Eqn 1, a is increase independent of x quantity (for example, a concentration of x).
Increase dependent on the advantageous quality is bx, with fitness proportional to x.

Fig. 1 shows unselected and selected distributions for x, under selection for fitness. The
logarithmic vertical axis points up lesser change near the mean μ (including no change <u>at</u> μ),
and resolves the selected increase in upper tail x. An initial Normal population (blue) is
symmetrical around mean μ = 10. After selection for x, the selected, normalized population
(Fig. 1, red dotted) has depressed x frequencies on the left, and elevated x frequencies above
the mean on the right, required for selected frequencies to normalize to 1. $\Delta\mu_{fit}$ is the
fractional increase in mean x due to fitness, $\Delta\mu_{trunc}$ the fractional increase in mean x due to
truncation at x_t. In Fig. 1, fitness selection increases μ_{fit} by $\approx 4\%$ (Methods Eqn 7; $\Delta\mu_{fit} =$
$(\sigma/\mu)^2 \cong 0.04$; dashed red arrow, Fig. 1).

Truncation selection. Evolution may also truncate a distribution, propagating a favored greater
subset having more than some threshold x_t required to survive and reproduce (Fig. 1).

Z_t generalizes truncation discussion. Description of truncation is facilitated by Z co-ordinates.
Z values are distances from a mean in σ units:

$$x_t = \mu + Z_t\sigma \qquad\qquad\qquad (2)$$

Z and Z_t (the truncation threshold) can also be negative, measuring distance below the mean
(Fig. 1). Use of Z eases comparisons because standardized Normal distributions all have the
same probability at the same Z (Methods). $\Phi(x_t)$ and $\Phi(Z_t)$ reference the same x and are
unaltered by switching to Z (as are ϕ and ϕ/Φ), but x_t and Z_t are distinct (Eqn 2).

Truncation and fitness selection compared. Fig. 1 previews a general conclusion; truncation is
usually more effective; in fact, $\Delta\mu_{trunc}/\Delta\mu_{fit} > 12$ for this Fig. 1 example, comparing
downward red and blue dashed arrows for selected μ.

In greater detail: Fig. 2A shows that here, a small ε effect quickly reaches a maximum $\Delta\mu_{fit} =$
0.04 (blue data, $\sigma = 2$) as b (and the selective effect of x) increases. Non-linear improvement
of $\Delta\mu_{fit}$ with σ^2 is also shown by results for varied σ values (Methods Eqn 7; dotted and solid
lines are explained below).

In Fig. 2B, truncation behaves differently: as Z_t approaches the mean, $\Delta\mu_{trunc}$ becomes
increasingly significant, and ultimately increases steeply and linearly. Notably, with example
values, a threshold $Z_t \geq 4.8$ (Fig. 2B) more than doubles initial μ ($\Delta\mu_{trunc} \geq 1$). Substantial
evolutionary change occurs via one truncation, in contrast to fitness selection (Fig. 2A). The
superiority of truncation selection is retained even if x truncation is gradual rather than sharp
(2,3). Accordingly, threshold selection has a special role in biological change.

As the apposed straight (dotted, red) line in Fig. 2B indicates, truncation selections ($\Delta\mu_{trunc}$ and
$\Delta\mu_{fit,\ trunc}$ below) improve $\approx$linearly above $Z_t = 1$ (above $\approx$ 0.3-fold selected increase).

Effect of σ on evolutionary change. Fig. 3A shows how initial variability (as standard
deviation) σ alters selected improvement, $\Delta\mu$. Different selections exploit initial variation σ
with different efficiencies.

Selected $\Delta\mu_{trunc}$ increases precisely linearly with σ (at constant Z_t) with no selection possible
if there is no variability (Methods Eqn 11; Fig. 3A).

Calculation of $\Delta\mu_{fit,\ trunc}$ shows that combining fitness with truncation (Fig. 1) adds a few
percent to the superior effect of truncation on selection. $\Delta\mu_{fit}$ is generally less effective than
either truncation, even given its benefit from larger initial σ (Methods Eqn 6, Fig. 2A). Most
effective selection is via truncation or truncation+fitness, slightly better for both (Fig. 3B).

Fitness with increased σ creates truncations. $\Delta\mu_{fit}$ responds to σ^2 (Methods Eqn 7) and
$\Delta\mu_{trunc}$ to σ (Methods Eqn 11), thus decreasing the gap between fitness and truncation
selections as σ increases (Fig. 3A). However, increased variability σ does not yield indefinitely
effective fitness selection. Large σ broadens distributions, so that individuals with $x = 0$ will

exist. For usual qualities of evolutionary interest (concentration, height, weight, color...), $x < 0$
is often not meaningful. Thus, enhancing $\Delta\mu_{fit}$ by increasing σ creates truncations at $x = 0$
with better $\Delta\mu_{fit,\ trunc}$. This is shown in Fig. 2A, where dotted curves include the effect of
truncation at $x = 0$ due to broad distributions (Methods Eqn 14). For this reason, and given the
tendency to small fitness selection (Fig. 2A, 3A), over a large range of conditions, truncations
yield faster evolution.

Effect of threshold Z_t on evolutionary change. The above conclusion is reinforced by the effect
of varied thresholds (Fig. 3B). Here fractional selected mean increase, $\Delta\mu$, is presented versus
varied threshold Z_t (constant standard deviation, $\sigma = 2$). $\Delta\mu_{trunc}$ is small at $Z_t < -2$, but then
rapidly becomes significant, decisively increasing above the mean.

With simultaneous fitness and truncation, $\Delta\mu_{fit,\ trunc}$ is significantly increased even at $Z_t =$
-5 because it includes an intrinsic small but complete fitness selection (Methods Eqn 8).
However, such fitness is superior to truncation only far below μ; truncation becomes the major
effect at Z just below the mean (Fig. 3B).

Because of rapid decline in Normal *pdf(x)* at higher Z_t (Fig. 1), linear increase in $\Delta\mu_{trunc}$ and
$\Delta\mu_{fit,\ trunc}$ at high Z_t (Fig. 3B) are explicable. $\Delta\mu_{trunc}$ approaches Z_t as Z_t increases because
selected individuals above Z_t become increasingly close to Z_t, assuring similar behavior for Z_t
and $\Delta\mu$. Further, comparing the strict limit for $\Delta\mu_{fit}$ in Fig. 2B with this unlimited linear increase
in $\Delta\mu_{trunc}$ and $\Delta\mu_{fit,\ trunc}$ (Fig. 3B), truncation superiority is reinforced.

The cost of truncation. Truncation selection at greater Z_t is strongly constrained by the rarity of
exceptional x: population size required to expect one improved individual above Z_t is shown on
the righthand axis in Fig. 3B. Normal tails decline increasingly steeply with Z (Fig. 1), and the
population needed to recover one improved x individual increases steeply and non-linearly
with $\Delta\mu$. In Fig. 4, the population expected to contain one selected individual, $1/\Phi(Z_t)$, is
compared to selected improvement $\Delta\mu_{trunc}$ for different initial variabilities, σ.

Substantial improvements (e.g., 50% of μ, $\Delta\mu_{trunc} = 0.5$) can be selected in populations with
varied standard deviations. But such selection is critically dependent on initial variation -
decreasing initial σ 3-fold increases the population required more than 5 orders of magnitude
(Fig. 4). So, selection of an upper tail for moderate improvements is undemanding. But, if
exceptional increases are vital – much larger populations, low survivals, and/or elevated
variabilities (σ or σ/μ) are required. This constraint can be severe, with near-exponential
population increases required for small improvements. Accordingly, finely divided populations
with small individuals, unusually varied populations, or both were surely crucial to rapid
chemical evolution. Varied microbes probably executed Earth's emergent biology (Fig. 4).

Chemical selection is not slowed by the cost of natural selection. The cost discussion above
has a passing resemblance to the classical discussion of the cost of natural selection, due to JBS
Haldane (4). However, biological and chemical cases differ greatly. Haldane's cost was due to

replacement of genes in a modern, genetic population: possessors of an old gene configuration
must perish to be replaced by a new genetic constellation. Too much replacement yields
excessive perishing, and thus extinction. Haldane's cost may be mitigated by recombination (5),
so may help account for the prevalence of sexual reproduction. Still, the rate of <u>natural</u>
selection is cost-limited. However, in a non-genetic population, any fraction of a population
may be replaced in a short time if a small selected portion persists and reproduces. Thus,
chemical least selection may be sporadic, but much more rapid than natural selection. As
previously calculated, inheritance itself can emerge in a few days (6).

A principle of least selection. A particularly useful idea arises from minimizing time-to-select.
Maximal improvement $\Delta\mu$ minimizes selections and thus minimizes time-to-evolve a particular
x, thereby also indicating the most likely evolutionary route. Minimal time and least selected
change required can accommodate multiple evolutionary effects, incorporating both threshold
and truncation, evoking the faintly parallel physical principle of least action (7). Finding this
extremum identifies the most likely route to an improbable outcome. Call this joint
minimization of selections or time-to-select "least selection". Next, the explanatory value of a
principle of least selection is illustrated, using prior molecular biology examples.

Discussion

Outline. Fluctuation frequently is the crux of evolutionary progress (8). This makes some
evolutionary progress predictable (9). Here, this idea is quantified: functions of standard
deviation σ, coefficients of dispersion σ/μ, threshold Z_t , and/or selection parameters a and b,
numerically govern selection's Normal effectiveness. The results, viewed broadly, are simple.

For Normally-distributed x, truncating by requiring a threshold x_t yields maximal increase in a
favored quality. Truncation-selected change is usually greater than from selection of fitness,
and progress is proportional to standard deviation σ or dispersion σ/μ. Truncation's
Improvement in a favored property also is proportionate to an acceptable x threshold, Z_t, at
larger Z_t. However, threshold selection is effective even at $Z_t = 0$; such a threshold at the
mean sums a region of positive effects. Populations with highest σ and truncation threshold Z_t
require least selection, and evolve fastest. However, exploiting upper-tail x for large change
requires large populations (Fig. 2B, 4).

Here, selection applies only to phenotypes. Present calculations follow distribution properties,
thus conclusions do not reflect particular system features. Instead, only the initial and final
means of expressed qualities, on which selection acts, matter. An assumed genetic system is
required to deduce selection's genetic consequences. But ignoring genetics has a strategic
advantage: present selection quantitation applies to any genetic system whatever.

A phenotypic focus therefore cuts two ways; we cannot find out anything about genetic
systems, without further assumptions, and we assume that changes are substantially heritable.

However, results apply to any Normally-distributed property, seemingly particularly
appropriate to quickly varying primordial, pre-Darwinian systems.

Example: Starting bloc selection exploits an inevitable threshold. The starting bloc (10) was
encountered while calculating that known ribonucleotide reaction rates suffice for evolution of
encoded, and therefore heritable, chemical capacities (6).

Starting bloc heritability depended on two well-known RNA capabilities. The first is existence of
simple catalytic RNAs, homologues of the adenylate-dinucleotide-containing enzyme cofactors
(11,12). The second is observed templated synthesis of similar molecules via an ultimately
simple, geochemically plausible (13) RNA "gene", poly-U (14). Selection of such poly U-
templated cofactor congeners (in preference to untemplated chemical synthesis) is uniquely
effective early, when only some sites have begun synthesis – these early-acting individuals are
the "starting bloc" (10). Increases of templated synthesis selected in such a population are
nearly proportionate to dispersion (σ/μ) in the chemically active product over a large range of
product concentrations (10), just as calculated here for least selection (Fig. 3A).

Starting bloc selection employs distribution tails. The original starting bloc produced roughly
proportionately faster change when carried out with lower survival after selection, a condition
there called "stringency". This parallels present calculations: increased threshold Z_t and
decreased survival in Fig. 2B, 3B produce faster selection. Similarly, combining variability (as in
dispersion σ/μ or standard deviation σ) with survival in a single index best predicted starting
bloc success (10).

Starting bloc selection exploits an early threshold. The difference between starting bloc loci
that make an active molecule early and inactive ones with no product is particularly readily
selected. Starting bloc success via some, versus no, early activity exploits truncation, paralleling
least selection in Fig. 3B. Accordingly, selection of encoded chemical capacity in a starting bloc
(6,10) follows, with almost formulaic precision, the variability, survival and threshold
dependence for least selection (Fig. 3A, 3B, 4).

Starting blocs may be of fundamental evolutionary significance: nascent biological capabilities
are intrinsically selectable. In particular, encoded (genetic) expression is a crucial biotic
innovation. While replication is often cited as the foundational requirement for biology (15),
there seems small advantage in replicating unexpressed sequence information. Thus, effective
expression likely predates replication (12). Accordingly, a starting bloc's least selection
potentially speeds expression united by a genome, thereby initiating vertical inheritance and
Darwinian evolution.

Example: Chance utility captures favorable variation. Prebiotic systems must evolve toward
biological complexity before genomes, or genome-directed biology would be inaccessible.
Selected temporary, or especially, permanent change in chemical systems before the advent of
genetic inheritance has been called 'chance utility'. For example, variation in a 100-fold more

concentrated inhibitor frequently provides an opportunity to capture a useful, but apparently
overwhelmed minor reaction (16). This accidental contravariation of a substrate and its
competitor relies on favorable μ and σ for these reactants; that is, on chance resemblance to a
favorable result, an opportunity for least selection.

Example: Random reactant supplies necessarily support near-ideal reactions. Even given
random, uncontrolled nucleotide supplies, a hypothetical small RNA replication recurs (8).
Notably, most RNA replication in the randomly-fed reactor comes from a recurring subset of
near-ideal substrate arrivals. So, a randomly-fed pool produces recurrent specific results from
utterly unregulated inputs, an opportunity for least selection.

Least selection opportunities can flicker. The starting bloc, chance utility example, and
recurring near-ideal reactions illustrate a common theme: selection can exploit kinetics.
Opportunities for least selection can flicker: transiently appearing, though usually absent.
Truncation exploits favorable transients; thus relatively rapid selection in a world that varies
more slowly greatly enhances truncation and consequent least selection.

Example: Stable optima identify evolutionary paths. Just as flickering opportunities for
truncation predict evolutionary transitions, stable optima identify persistent probable paths. An
example is advent of initial, simplified wobble coding. In the forming genetic code, there
appears an optimal late time for wobble advent (17). A time of maximal SGC resemblance
offers a least selection, marking that era as plausible for wobble's rise.

Example: Bayesian convergence follows from least selection's extremum. Bayes' theorem says
that the best origin hypothesis explains all aspects of a phenomenon. However, an explanation
is uniquely effective if independent events are explained, and the hypothesis' probability is
elevated by the product of independent confirmations (18). For example, a fusion route to the
Standard Genetic Code (19) explains how metabolic, chemical and wobble order coexist
without mutual interference in a near-universal coding table. Bayesian convergence is robustly
supported by least selection, which maintains that the historical route to the genetic code was
distinct, perhaps unique, because it traverses a continuous extremum. This in turn overlaps
Orgel's dictum that evolution exhibits Continuity (20); that is, later evolutionary states are
necessarily linked to their precursors by continuous change.

Example: Distribution fitness is least selection, using different language. The fitness of a
superior group within a distribution is a key to apparently improbable outcomes. For example, a
small minority of nascent coding tables has unlikely coding properties (Table 2; Ref. 9). These
become ordered quickly, having made accurate Standard Genetic Code (SGC) assignments (9),
but leaving some unassigned triplets that will later be critical during final assembly of a
complete code (19). Optimal tables appear quickly by avoiding slow events, like assignment
decays (9). This useful minority of genetic codes short-circuits the outward problem of evolving
a complex pattern by accidently evolving it simply. Apparently implausible behavior; for
example, showing what seems to be foreknowledge of late coding early in code history, is

possible because they are a rare minority selected late. Their properties ultimately seem near-
ideal, but pre-exist without purpose. When selected as most functional among a population
(21), they immortalize their improbable histories, thus presenting a seeming paradox. This
peculiar quality is routine in truncation selections, which by definition capture improbable
states (Fig. 1, 4).

Thus, distribution fitness anticipates least selection - success from rare precursors with
unexpectedly close resemblance(s) to an upcoming biological achievement.

More recent work on coding (21) clarifies the search for excellent minorities. Fusion of early
partial codes strongly enforces code uniformity, because fused unlike codes assign ambiguous
codon meanings, and are less fit. Fusion therefore generates a long-lived series of codes that
increasingly resemble an underlying consensus, such as the Standard Genetic Code. Given a
progressive increase in code uniformity (called the 'crescendo') that presents a long series of
varied SGC-like encodings, code fusion proficiently implements least selection of the SGC (22).

Example: Least selection appears as similarity to archaic forms. Vast gaps in time can link
similar things, implementing the "least" in least selection. Ribosomal peptidyl transferase is an
example. CCdApPuro (23) is a rationally-designed oligonucleotide inhibitor that binds both
halves of the ribosomal active site, contacting A- and P-sites in a configuration that allows
peptide transfer between them. So, CCdApPuro emulates the transition state for peptide
synthesis (24). An RNA selected from randomized sequences to bind CCdApPuro with affinity
similar to ribosomes (25) exhibited two families of binding sites with 17 nucleotide matches to
the peptidyl transferase loop of rRNA. This homology included an exact 8-mer match with
among the most conserved of all RNA sequences, the ribosomal peptide transferase active site
AUAACAGG. CCdApPuro also bound this RNA octamer in the large ribosomal subunit (26), in an
orientation similar to selected RNA sequences (25,27). Selected sequences even included a
likely catalytic feature, an A with a shifted pKa, though catalysis was not selected (27). These
results support initial peptide synthesis in an RNA cradle, then least selection of a
ribonucleoprotein descendant, still resembling its RNA ancestor billions of years later.

Truncation is a major evolutionary event: extinctions. We know macroscopic evolution mostly
from durable fossils of relatively modern, multicellular creatures. Such evolution is sporadic,
with long periods of relatively slower change interrupted by shorter eras containing mass
extinctions (28,29). There have been $\geq$ 7 relatively recent, major extinctions. Hodgskiss et al
(30) present isotopic evidence for one such ending the Great Oxidation Event 2 gigayears ago.
For the last 540 million years, see Muscente et al (31) for such alternation of stability and
catastrophe in the "big five" extinctions (32). Ceballos (33) provide evidence of a current,
human-induced catastrophe. More evident quick species losses are followed by re-
diversification of surviving organisms (34). Thus major extinctions are also radical multiple
truncations, making least selection unmistakably relevant to life's history on Earth.

Truncation is a major evolutionary event: radiations. The mostly sessile oceanic life of the Edicaran era (588 - 539 Mya) had made major progress: it included metazoans who were bilateral, for example (35). However, these benthic creatures were almost completely replaced in a 'Cambrian explosion' (539 – 488 Mya) of novelty (36), in which most modern phyla were established (37,38). Exceptionally-preserved worldwide Cambrian fossils in Canadian Burgess shale (39) and at Qingjiang in Southern China (40) validate Cambrian radiation at the consensus origin of modern biota. Radiations, however radical, do not re-originate life. Thus major radiations are also radical multiple truncations, making least selection unmistakably significant to life's history on Earth.

Plausible biological change: least selections and biological intermediates. Seeking least selection will not suddenly manifest biotic history. For example, neutral and near-neutral change (41) have not been considered.

Even more significantly, plausible precursors may not yet be known, because our present molecular portfolio is deeply partial. For example, prebiotic nucleotide activation is an indispensable, but elusive missing link to both ancient translation and replication. Imidazole activates AMP for templated oligoRNA synthesis (42). Existence of a possible prebiotic, UV-activated imidazole activation of AMP (43) has guided related chemistry with 2-amino-imidazole and ensuing templated RNA synthesis from activated CMP and GMP (44). Thus, a vital activation gap may ultimately be filled - least selection will compare alternative solutions.

Least selection proposes a frequently-practical estimate of evolution's path. It overlaps the suggestion that the most plausible route yields a known intermediate with greatest probability (9). Assembling least selections to plausibly intersect a known biological result creates a credible evolutionary conduit. When that evolutionary change can be reduced to quantitative alterations in selected characters, one will likely see regions with slower change (fitness selections, Fig. 2A, 3A) interspersed with change an order-or-more steeper (truncations, Fig. 3A).

Acknowledgement. A preprint of this discussion is available (22).

Methods.

Selection from a varied population. The probability of x within its population is often
describable by a normalized **p**robability **d**istribution **f**unction, *pdf*:

$$\int_{-\infty}^{\infty} pdf(x)dx = 1 \qquad (3)$$

To follow a population's fate, average x, μ , is followed. If $pdf(x)$ is the probability of x:

$$\mu = \int_{-\infty}^{\infty} x\, pdf(x)dx \qquad (4)$$

Selection changes $pdf(x)$:

$$pdf(x) \rightarrow \varepsilon\, pdf(x) = (a + bx)\, pdf(x) \qquad (5)$$

Selection for fitness. Consider selected increase of a favored quality x; such selected increase
in mean x is described by the Price equation (45). The Price equation mathematically partitions
evolutionary change into that due to selection and that due to all other frequency changes for
qualities of interest (46). We are particularly interested in selection:

$$\mu_{fit} = \mu + cov(\varepsilon, x)/\bar{\varepsilon}$$

Where *cov* is covariance and $\bar{\varepsilon}$ is population mean fitness:

$$\bar{\varepsilon} = \int_{-\infty}^{\infty} \varepsilon\, pdf(x)\, dt = a \int_{-\infty}^{\infty} pdf(x)dx + b \int_{-\infty}^{\infty} x\, pdf(x)\, dt = a + b\mu$$

$$cov(\varepsilon, x) = \int_{-\infty}^{\infty}(\varepsilon - \bar{\varepsilon})(x - \mu)\, pdf(x)\, dx = b\sigma^2$$

Thus $$\mu_{fit} = \mu + \left(\frac{b}{a + b\mu}\right)\sigma^2 \qquad (6)$$

Fractional selected change in mean x is:

$$\Delta\mu_{fit} = (\mu_{fit} - \mu)/\mu = \left(\frac{b}{a + b\mu}\right)\sigma^2/\mu \qquad (7)$$

$\Delta\mu_{fit}$ defines selected improvement. $\Delta\mu$ is normalized to the initial mean, reducing
dependence on the choice of scale. $\Delta\mu = 0$ for no progress, and, scaled to μ, $\Delta\mu$ increases as
evolutionary change increases. For example, $\Delta\mu_{fit} = 1$ is selected mean doubling.

Fitness entirely dependent on x is particularly simple.

$$\Delta\mu_{fit} = \sigma^2/\mu^2 \qquad (8)$$

This plausible situation is emphasized in Fig. 2: selection requiring x and $\propto x$ $(a = 0)$ increases
average x precisely by coefficient of dispersion squared, $(\sigma/\mu)^2$, independent of b. $\Delta\mu_{fit}$ is
wholly defined by the initial distribution's shape. As intuition suggests, complete dependence
on x $(a = 0)$ yields maximal fitness selection; larger by the factor $(b\mu + a)/b\mu$, thus
necessarily the best selection. The Price equation is a mathematical identity (46) and so always

valid. Further, no specific system property is assumed in calculations. Thus Methods Eqn 6, 7

are true of any integrable $pdf(x)$, thus any well-behaved distribution. $\Delta\mu_{fit}$ consequently

describes genetic, non-genetic, prebiotic or solely chemical systems. Blue (before) and dotted

red lines (after selection) in Fig. 1 illustrate fitness selection, using a Normal distribution

example.

Calculating the fate of Normally-distributed qualities. Because of the broad application of the

Normal distribution, its integrals are evaluated in standard software. For example,

$$\int_{x_t}^{\infty} pdf(x)dx = \Phi(x_t) \tag{9}$$

where $\Phi(x_t)$ from spreadsheet or mathematical software is the population fraction exceeding a

threshold: e.g., for x between x_t and ∞ (Methods).

Mean x for selection above a threshold, μ_{trunc} , measures selection's success, and can be

evaluated by rearrangement:

$\mu_{trunc} = \int_{x_t}^{\infty} x\, pdf(x)dx = \Phi(x_t)\mu_{trunc} = \int_{x_t}^{\infty} \mu\, pdf(x)dx + \sigma^2 \int_{x_t}^{\infty} \frac{(x-\mu)}{\sigma^2}\, pdf(x)\, dx$

where $\Phi(x_t)$ is defined by Eqn 8, the integral-normalizing factor for μ_{trunc}. The rearrangement

on the right can be integrated, because the second rightward term integrates the negative

derivative of the Normal $pdf(x)$:

$$\Phi(x_t)\mu_{trunc} = \mu\, \Phi(x_t) - \sigma^2 \left[pdf(\infty) - pdf(x_t)\right]$$

$$\Phi(x_t)\mu_{trunc} = \Phi(x_t)\mu + \sigma^2\, pdf(x_t)$$

$$\mu_{trunc} = \mu + \sigma^2\, pdf(x_t)/\Phi(x_t) \tag{10}$$

Later we will use the fractional truncation-selected change in mean, in units of initial μ:

$$\Delta\mu_{trunc} = (\mu_{trunc} - \mu)/\mu = \left(\sigma^2/\mu\right)\mathrm{pdf}(x_t)/\Phi(x_t) = \left(\sigma/\mu\right)\phi(Z_t)/\Phi(Z_t) \tag{11}$$

where ϕ is a sometimes-convenient form related to pdf (Methods).

$\Delta\mu_{trunc}$ assumes a Normal distribution, but utilizes no underlying system properties. Thus,

Methods Eqn 11's truncation-selected change, as for Methods Eqn 7 above, is general. Methods

Eqn 11 is valid in any Normal system: genetic, pre-genetic, biological or chemical. Progress,

$\Delta\mu_{trunc}$, will be proportional to coefficient of dispersion (simplified to "dispersion" in the main

text), σ/μ, and to ϕ/Φ. The hatched blue region rightward in Fig. 1 illustrates a truncation

selection.

Truncation is somewhat enhanced by concurrent fitness. Threshold selection can also be

somewhat more effective. Suppose that a characteristic being selected undergoes a truncation.

For example, toleration of elevated temperature can aid survival, but a sudden temperature

spike still truncates those beneath a new maximum. In Fig. 1, this selects the rightward blue

hatched area, but now including individuals below the red dotted line. Below, such truncation
on a selected background is quantitated.

We have already written the pdf for a fitness selection in Methods Eqn 4, and normalized it so
that its range includes all valid x (Methods Eqn 6).

$$pdf_{fit}(x) = (a + bx/a + b\mu)\ pdf(x) \tag{12}$$

387 If we instead truncate the fitness distribution:

$$\mu_{fit,\ trunc} = \left(\frac{1}{a\Phi(x_t)+b\mu_{trunc}}\right) \int_{x_t}^{\infty} x\ (a + bx)\ pdf(x)dx = \left(\frac{1}{a\Phi(x_t)+b\mu_{trunc}}\right)(a\mu_{trunc} + b\overline{x^2_{trunc}}) \tag{13}$$

389 where $\overline{x^2_{trunc}}$ is the mean square x above the truncation. And $\overline{x^2_{trunc}} = \mu^2_{trunc} + \sigma^2_{trunc}$ where,
390 importantly, all quantities are for the initial Normal, and all are known. μ_{trunc} is Methods Eqn 10, and

$$\sigma^2_{trunc} = \sigma^2[1 + Z_t\frac{\phi(Z_t)}{\Phi(Z_t)} - \left(\frac{\phi(Z_t)}{\Phi(Z_t)}\right)^2]$$

392 comes from standard sources (47). Combining all above as in Methods Eqn 13:

$$\mu_{fit,\ trunc} = \frac{1}{a\Phi(Z_t)+b\mu_{trunc}}\left(a\left[\mu + \sigma^2\frac{\phi(Z_t)}{\Phi(Z_t)}\right] + b\left[\sigma^2 + \mu^2 + (Z_t\sigma + 2\mu)\frac{\sigma\phi(Z_t)}{\Phi(Z_t)}\right]\right) \tag{14}$$

All quantities refer to the initial Normal, so are available via standard software. Moreover,
combined selection and truncation in Methods Eqn 14, like separated fitness (Methods Eqn 6)
and truncation (Methods Eqn 10) above, assume only properties of the distribution itself. The
result is therefore again valid for any initially Normal system: protobiological, chemical or
biological, independent of genetic or chemical detail.

Numerical illustrations. Calculations were executed on a Dell XPS computer with an Intel Core
i9-8950HK CPU @ 2.90GHz and 32 GB of RAM, running 64-bit Windows 10 Enterprise v. 20H2.
Figures were prepared with Microsoft Excel 2016 16.0.5161.1002, making particular use of the
Excel norm.dist function for Normal pdf, ϕ, and cumulative distributions, Φ.

As an example, in Methods Eqn 9, $\Phi(x_t)$ is an integral not expressible in closed form using
simple functions. But $\Phi(x_t)$ is readily accessible via the widely-available cumulative Normal
distribution function $C(\mu, \sigma, x_t)$ (which yields the fraction of the distribution between $-\infty$ and
x_t): $\Phi(x_t) = 1 - C(\mu, \sigma, x_t)$.

The Normal probability distribution function. The Normal probability distribution function
used here appears in multiple forms:

$$pdf(x) = e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2}\Big/\sqrt{2\pi}\sigma = e^{-\frac{Z^2}{2}}\Big/\sqrt{2\pi}\sigma = \phi(Z)\Big/\sigma$$

using text notation. The denominator's standard deviation σ at right is significant because it
differs from what is sometimes called the Standard Normal distribution ϕ, often seen in
mathematical references (47). The Standard Normal has $\mu = 0$, $\sigma = 1$, thus is not suited to

investigation of variations. For example, the above denominator σ cancels an external factor of
σ, clarifying $\Delta\mu_{trunc}$ dependence as $\propto \sigma$, not σ^2 (Methods Eqn 10, Fig. 3A). In the text, pdf and
ϕ are interspersed where each was thought clearest.

Competing interests. The author is aware of no competing interests.

Figure legends

Figure 1. **Fitness and threshold selection on a Normal distribution**. The Normal probability of x, $pdf(x)$, is plotted as a solid blue line against a logarithmic ordinate: in this example, mean $\mu = 10$, standard deviation $\sigma = 2$. This distribution is selected, multiplying by $\varepsilon = a + bx$ (dotted red line); $a = 0.1, b = 0.5$. A labeled red dashed arrow marks the resulting selected mean, $\mu_{fit} = 10.39$, and black arrows illustrate the relation between the distributed quantity x and the generalized Z co-ordinate for the initial Normal. The dashed blue vertical line marks a selection threshold at $x_t = 14, Z_t = 2$, and its selected mean ($\mu_{trunc} = 14.746$) is right-adjacent, and dashed blue. Visible threshold-selected area is hatched with light blue diagonal dash-and-dotted lines.

Figure 2A. Selected fitness increase in mean x, $\Delta\mu_{fit}$, with varied dependence on x. $\varepsilon = a + bx$, with a = 0.1 and b varying. Normal distribution parameters are those in Fig. 1. Solid lines are calculated for full distributions (Methods Eqn 8), dotted lines for truncation of broad fitness distributions at $x = 0$ (Methods Eqn 14). The lines for $\sigma = 2$ are too similar to be resolved.

Figure 2B. Selected truncation increase, $\Delta\mu_{trunc}$, across a Normal distribution as the acceptable threshold Z_t varies. Z_t ranges from below the mean ($Z_t = -3$) to far above ($Z_t = 5$). An arbitrary linear red dotted line has been superposed on data to emphasize linearity at $Z_t \geq 1$. Normal parameters are those in Fig. 1.

Figure 3A. Selected increase in mean x, , $\Delta\mu_{fit}$, $\Delta\mu_{trunc}$, $\Delta\mu_{fit, trunc}$ as a function of increasing initial standard deviation σ. This example assumes $Z_t = 1$ throughout. Other Normal parameters are those in Fig. 1.

Figure 3B. Selected increase in threshold-selected means, $\Delta\mu_{trunc}$ and $\Delta\mu_{fit, trunc}$ as a function of threshold Z_t. Standard deviation is $\sigma = 2$. The righthand ordinate is the population size required to find one improved individual above threshold Z_t, using truncation alone. Other Normal parameters are those in Fig. 1.

Figure 4. Population sizes to recover one superior individual as a function of selected improvement, $\Delta\mu_{trunc}$. Population sizes , $1/\Phi(Z_t)$, are plotted on a logarithmic ordinate, assuming different starting variabilities, σ (Methods Eqn 11). Normal parameters are those in Fig. 1.

Data availability.

All data analyzed during this study or required for its understanding are included in the manuscript.

References.

1. Feller, William. An introduction to probability theory and its applications, v II, 2nd edition, p. 258–
274. John WIley and Sons, Inc.; 1970.

2. Kimura M, Crow JF. Effect of overall phenotypic selection on genetic change at individual loci. Proc
Natl Acad Sci U S A. 1978 Dec;75(12):6168–71.

3. Crow JF, Kimura M. Efficiency of truncation selection. Proc Natl Acad Sci U S A. 1979 Jan;76(1):396–
9.

4. Haldane JBS. The cost of natural selection. J Genet. 1957 Dec 1;55(3):511.

5. Hickey DA, Golding GB. Sex solves Haldane's dilemma. Genome [Internet]. 2019 Sep 3 [cited 2021
Jun 16]; Available from: https://cdnsciencepub.com/doi/abs/10.1139/gen-2019-0051

6. Yarus M. Efficient Heritable Gene Expression Readily Evolves in RNA Pools. J Mol Evol. 2017
Jun;84(5–6):236–52.

7. Feynman, RP, Leighton, RB, Sands, M. The Feynman Lectures on Physics. Millenium Edition. Vols. 2,
Ch. 19. California Institute of Technology; 2010.

8. Yarus M. A ribonucleotide origin for life - fluctuation and near-ideal reactions. Orig Life Evol Biosph.
2013 Feb;43(1):19–30.

9. Yarus M. Evolution of the Standard Genetic Code. J Mol Evol. 2021 Jan 24;89(1–2):19–44.

10. Yarus M. Eighty routes to a ribonucleotide world; dispersion and stringency in the decisive selection.
RNA N Y N. 2018 Aug;24(8):1041–55.

11. White HB. Coenzymes as Fossils of an Earlier Metabolic State. J Mol Evol. 1976;7:101–4.

12. Yarus M. Getting past the RNA world: the initial Darwinian ancestor. Cold Spring Harb Perspect Biol.
2011 Apr 1;3(4):doi: 10.1101/cshperspect.a003590. PMID: 20719875; PMCID: PMC3062219.

13. Ferris JP, Hill AR, Liu R, Orgel LE. Synthesis of long prebiotic oligomers on mineral surfaces. Nature.
1996 May 2;381(6577):59–61.

14. Puthenvedu D, Janas T, Majerfeld I, Illangasekare M, Yarus M. Poly(U) RNA-templated synthesis of
AppA. RNA. 2015;21(10):1818–25.

15. Joyce GF. The antiquity of RNA-based evolution. Nature. 2002 Jul 11;418(6894):214–21.

16. Yarus M. Biochemical Refinement Before Genetics: Chance Utility. J Mol Evol. 2016 Sep 1;83(3):89–
92.

17. Yarus M. Optimal Evolution of the Standard Genetic Code. J Mol Evol. 2021 Feb;89(1–2):45–9.

18. Yarus M, Caporaso JG, Knight R. Origins of the genetic code: the escaped triplet theory. Annu Rev
Biochem. 2005;74:179–98.

19. Yarus M. Fitting the standard genetic code into its triplet table. Proc Natl Acad Sci U S A. 2021 Sep
7;118(36):e2021103118.

20. Orgel LE. Evolution of the Genetic Apparatus. J Mol Biol. 1968;38:381–93.

21. Yarus M. A crescendo of competent coding (c3) contains the Standard Genetic Code. RNA N Y N.
2022 Jul 22;rna.079275.122.

22. Yarus M. Evolution and change: a principle of least selection [Internet]. bioRxiv; 2022 [cited 2022
Dec 23]. p. 2021.06.27.450095. Available from:
https://www.biorxiv.org/content/10.1101/2021.06.27.450095v3

23. Welch M, Chastang J, Yarus M. An inhibitor of ribosomal peptidyl transferase using transition-state
analogy. Biochemistry. 1995;34(2):385–90.

24. Pauling L. Nature of Forces between Large Molecules of Biological Interest. Nature. 1948 May
1;161(4097):707–9.

25. Welch M, Majerfeld I, Yarus M. 23S rRNA Similarity from Selection for Peptidyl Transferase Mimicry.
Biochemistry. 1997;36:6614–23.

26. Ban N, Nissen P, Hansen J, Moore PB, Steitz TA. The complete atomic structure of the large
ribosomal subunit at 2.4 A resolution. Science. 2000 Aug 11;289(5481):905–20.

27. Yarus M, Welch M. Peptidyl transferase: ancient and exiguous. Chem Biol. 2000 Oct;7(10):R187-190.

28. Jablonski D. Background and mass extinctions: the alternation of macroevolutionary regimes.
Science. 1986 Jan 10;231(4734):129–33.

29. Jablonski D. Survival without recovery after mass extinctions. Proc Natl Acad Sci U S A. 2002 Jun
11;99(12):8139–44.

30. Hodgskiss MSW, Crockford PW, Peng Y, Wing BA, Horner TJ. A productivity collapse to end Earth's
Great Oxidation. Proc Natl Acad Sci U S A. 2019 Aug 27;116(35):17207–12.

31. Muscente AD, Prabhu A, Zhong H, Eleish A, Meyer MB, Fox P, et al. Quantifying ecological impacts of
mass extinctions with network analysis of fossil communities. Proc Natl Acad Sci. 2018 May
15;115(20):5217–22.

32. Benton MJ. Diversification and extinction in the history of life. Science. 1995 Apr 7;268(5207):52–8.

33. Ceballos G, Ehrlich PR, Raven PH. Vertebrates on the brink as indicators of biological annihilation
and the sixth mass extinction. Proc Natl Acad Sci U S A. 2020 Jun 16;117(24):13596–602.

34. Hull P. Life in the Aftermath of Mass Extinctions. Curr Biol CB. 2015 Oct 5;25(19):R941-952.

35. Droser ML, Gehling JG. The advent of animals: The view from the Ediacaran. Proc Natl Acad Sci.
2015 Apr 21;112(16):4865–70.

36. Conway-Morris S. The Cambrian "explosion" of metazoans and molecular biology: would Darwin be
satisfied? Int J Dev Biol. 2003;47(7–8):505–15.

37. Briggs DEG. Extraordinary fossils reveal the nature of Cambrian life: a commentary on Whittington
(1975) 'The enigmatic animal Opabinia regalis, Middle Cambrian, Burgess Shale, British Columbia.'
Philos Trans R Soc B Biol Sci. 2015 Apr 19;370(1666):20140313.

38. Budd GE, Jensen S. The origin of the animals and a "Savannah" hypothesis for early bilaterian
evolution. Biol Rev Camb Philos Soc. 2017 Feb;92(1):446–73.

39. S. Conway Morris. The crucible of creation [Internet]. Oxford University Press; 1999 [cited 2022 Jul
26]. 282 p. Available from: http://archive.org/details/crucibleofcreati00conw

40. Fu D, Tong G, Dai T, Liu W, Yang Y, Zhang Y, et al. The Qingjiang biota-A Burgess Shale-type fossil
Lagerstätte from the early Cambrian of South China. Science. 2019 Mar 22;363(6433):1338–42.

41. Kimura M, Ohta T. On the rate of molecular evolution. J Mol Evol. 1971 Mar 1;1(1):1–17.

42. Weimann BJ, Lohrmann R, Orgel LE, Schneider-Bernloehr H, Sulston JE. Template-directed synthesis
with adenosine-5'-phosphorimidazolide. Science. 1968 Jul 26;161(3839):387.

43. Mariani A, Russell DA, Javelle T, Sutherland JD. A Light-Releasable Potentially Prebiotic Nucleotide
Activating Agent. J Am Chem Soc. 2018 Jul 18;140(28):8657–61.

44. Zhang SJ, Duzdevich D, Szostak JW. Potentially Prebiotic Activation Chemistry Compatible with
Nonenzymatic RNA Copying. J Am Chem Soc. 2020 Sep 2;142(35):14810–3.

45. Price GR. Selection and covariance. Nature. 1970 Aug 1;227(5257):520–1.

46. Frank SA. Natural selection. IV. The Price equation. J Evol Biol. 2012 Jun;25(6):1002–19.

47. Greene, William H. Econometric Analysis; Section 22.2, Truncated DIstributions. 5th ed. Prentice
Hall; 2003.

Fig. 1

Fig. 2A

Fig. 2B

Fig. 3A

Fig. 3B

Fig. 4