Two Modes of Evolution: Optimization and Expansion

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Introduction

From data we qualitatively document and discuss two different modes of evolutionary processes across multiple systems. Evolutionary *optimization* is associated with conserved fundamental interaction types, where fitness improvements are distributed homogeneously on a *logarithmic* time axis and fitness consequently increases at a *decelerating* rate. Evolutionary *expansion* is associated with a growing number of fundamental elements and interaction types, and the resulting fitness improves at an *accelerating* rate. The same system may operate in both evolutionary modes at different times and/or in different regions of its configuration space.

Evolutionary optimization

Spin glass and E. coli monoculture evolution: Physical glassy systems have clearly fixed constituents and interactions. After a sudden change of external parameter, e.g. a temperature decrease in spin-glasses or a density increase in hard-sphere colloid, they visit a series of increasingly long-lived metastable states in a process called 'aging'. The salient non-equilibrium events marking the transitions from one metastable state to the next may be called 'quakes' and are distributed homogeneously on a *logarithmic* time axis [7]. The quake dynamics $F(t)$ can be expressed in dimensionless units as

$$
\begin{aligned}
F(t) &= A - t^{-\alpha} = A - e^{\ln(t^{-\alpha})} \simeq A' + \alpha\ln(t) \\
&= \alpha\ln(Kt) = \ln(I(t)^{\alpha})
\end{aligned} \quad (1)
$$

where A is the asymptotic equilibrium state, α defines the decelerating dynamics (we have expanded the logarithm), and where $A' = \ln(K^{\alpha})$, see Fig. 1. In this formalism we may interpret $I(t)$ as related to the number of components and interactions in the system, which is constant $dI(t)/dt = K$ as they are in a spin glass. It should be noted that the value of α is neither universal across systems nor within the same system of different size or with different environmental conditions (e.g. temperature).

Lenski and Travisano [2] measured cell size and Malthusian fitness of cultures of E. coli grown in a constant envi-
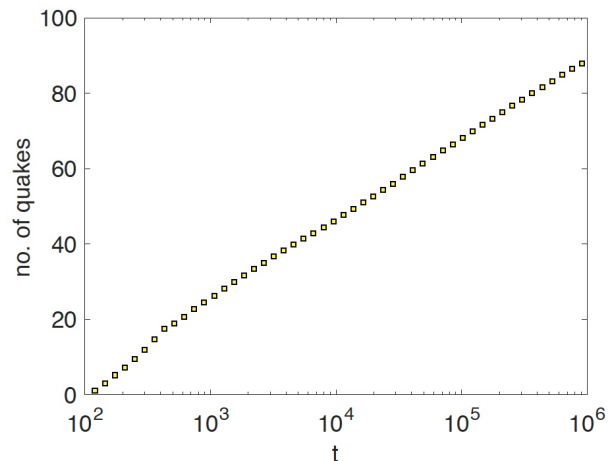

Figure 1: Optimization dynamics in a spin glass shown by the number of quakes as a function of time. Note how the quakes are distributed homogeneously on a *logarithmic* time axis.

ronment. Our analysis of their data shows that the evolutionary dynamics of a bacterial monoculture also seems to be distributed homogeneously on a logarithmic time axis. If we identify quakes as the mutations with a fitness impact, the dynamics seem to belong to the same universality class as ageing physical systems and we may interpret the fundamental interaction types within the bacterial monoculture as being constant over time. This means that both the internal cellular biochemical ecology of interactions and the cell-cell interactions should be of qualitatively similar types over time. This seems to be a reasonable assumption although we have not provided any detailed specification of the involved interaction types. In this context, however, it is still an open question how to interpret A and α as expressed in equation (1), so that these parameters could be compared across and within systems. How would α e.g. vary across different biological organisms?

Biological macro-evolution after the Cambrian explosion is also characterized by a logarithmic time growth of the cu-

mulated number of extinctions [3], a feature mirrored by an agent based model of ecological evolution [1]. Evolutionary optimization processes are frequently reported in both the Artificial Life and the Machine Learning litterature.
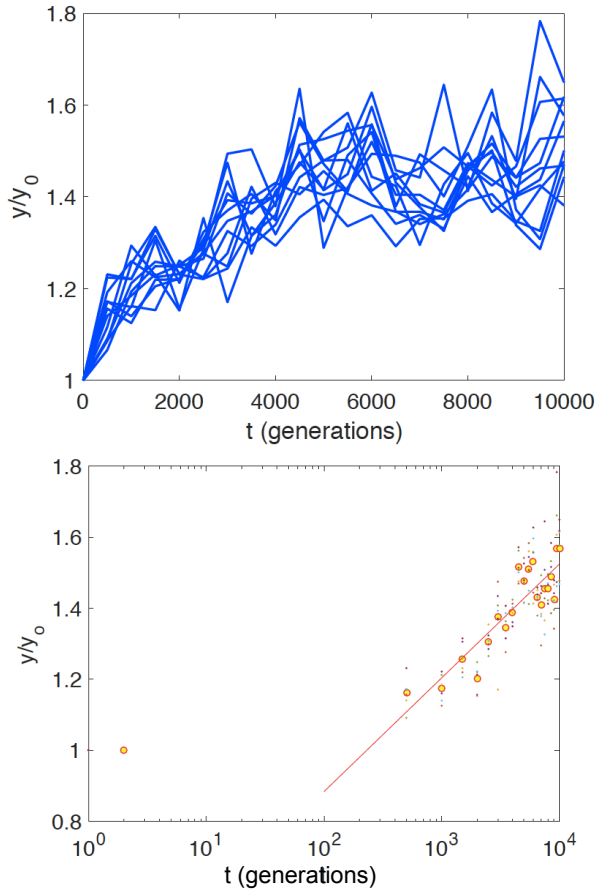

Figure 2: *Upper panel*: Evolutionary fitness optimization (normalized) of an E. coli monoculture after an initial change of food substrate depicted as a function of time. All 12 experiments are included where change in average cell size is measured. *Lower panel*: Same dynamics depicted as a function of logaritmic time where the average over the 12 fitness experiments is used. The dynamics is depicting the number of quakes as a function of time. Note how the quakes are distributed homogeneously on a *logarithmic* time axis for the processes both in Figs 1 and 2 while α differs.

Evolutionary expansion

Human cultural and technological evolution: The evolution of human technology is different from the above examples, because qualitative changes and expansions of human-human and human-technology interaction patterns are commonplace. This means an expansion of new components and interactions as expressed by $I(t)$ although we shall not specify the details of these growing interactions. We assume we

can use the accumulated wealth production, the gross domestic product per capita per year $GDP(t)$, as a proxy measure for human fitness over time. The growth of the $GDP(t)$ is mainly the result of technological evolution of both the physical technologies (e.g. hammer and nail, steam engine, computers, internet) and the social technologies (e.g. governance, institutions, laws, education, religion, myths, social norms). Examples of areas within which qualitatively different and increasing interaction components and types have emerged include communication, transportation, production, energy, education, governance and religion, thus both physical and social technologies. Over the last two centuries new interaction types e.g. within communication include introduction of the telegraph, the telephone, the TV, and the Internet, transportation includes introduction of the rail road, the automobile and the airplane, while governance includes democracy and women's rights to vote. All of these and many more new technologies have generated radical societal changes and increased the overall fitness/capita.

We further assume human fitness evolution to have both an optimization and an expansion component.

To quantify the *difference* between a baseline evolutionary optimization and the evolutionary expansion for $GDP(t)$, we may find an expression for $I(t)$ by using the same ansatz as in equation (1) and detrending the time series for $GDP(t)$. In previous section we learned to express the fitness evolution as a function of $\log(I(t))$, because $\log(I(t))$, and not t, is expected to be the natural variable for the ongoing optimization process for any given set of interaction, while a change of $I(t)$ over time t should express the ongoing expansion process. In the following we use data form England form 1270 till today 2017 [4].

Detrending the English $GDP(t)$ timeseries we get

$$GDP(t) \sim e^{P(t)}, \qquad (2)$$

and using the ansatz from equation (1) we get

$$
\begin{aligned}
GDP(t) &\sim & \ln(I(t)^{\alpha}) \sim e^{P(t)} \Leftrightarrow \\
I(t) &\sim & e^{(1/\alpha)e^{P(t)}}, \qquad (3)
\end{aligned}
$$

where $P(t)$ is estimated to be a best fit 3rd order polynomial, where the goodness of the fit does not change significantly using higher order polynomials. At present we do not have an independent (microscopic) theory to estimate the evolutionary expansion expressed through $I(t)$, and in the previous section we learned that α is expected to vary across and within systems. This means that α cannot be uniquely derived from data. We imagine the double exponential expansion of $I(t)$ expresses a combinatorial explosion among the human-human, human-technology and the technology-technology interactions, where the details still have to be worked out. For the quantitative estimates shown in Fig 3 (lower panel), we have used $\alpha = 1.0$.
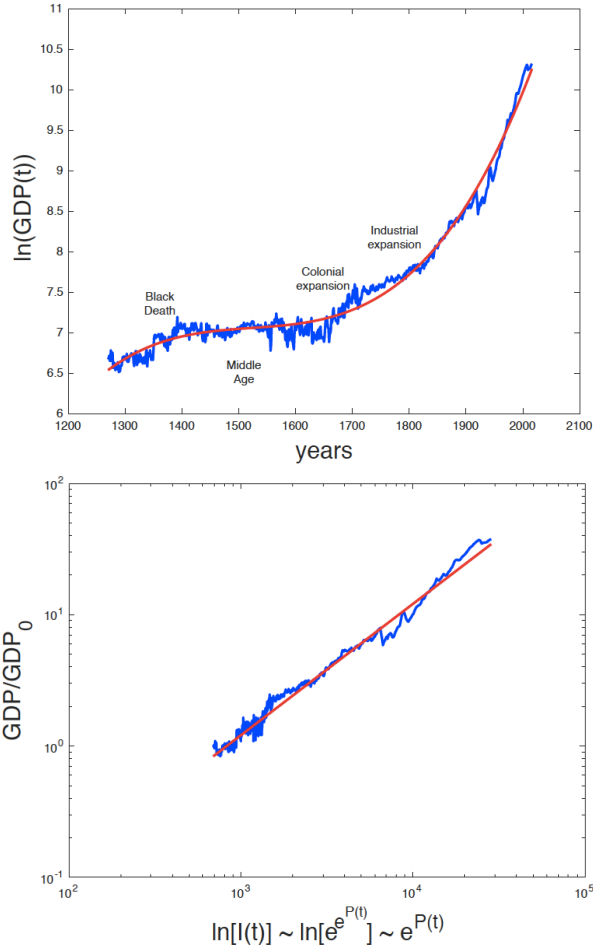
Figure 3: *Upper panel*: $\ln(\text{GDP}(t))$ and $P(t)$ (trend) as a function of time. Evolution of human wealth per year per capita $\text{GDP}(t)$ for England years 1270-2017 is used as a proxy for human fitness. In these data the Black Death is notable due to a significantly decimated population, which is reflected in a wealth growth of the survivors. Wealth expansions are seen at the onset of the Colonial Period and even more dramatically as the Industrial Revolution takes off. Also note the long period of relative wealth stasis during the Middle Ages. $P(t)$ is estimated as a best 3rd order polynomium trend fit for the $\ln(\text{GDP}(t))$ data. *Lower panel*: Log-Log plot of the evolutionary expansion expressed through (normalized) GDP as a function of $\ln(I(t))$, where $I(t) \sim e^{(1/\alpha)e^{P(t)}}$ and α is a constant, see text for details. The line corresponding to $\alpha = 1.0$ is also shown. Note that by applying the ansatz from equation (1) on our data we can obtain a quantitative estimate for the evolutionary expansion through $I(t)$.

An expansion of $I(t)$ over time is of course not limited to complex ecosystems and sociotechnical systems. Even in a simple protocellular system, events that increase the physic-ochemical complexity could increase the number and quality of interactions and thus $I(t)$. We have previously demonstrated this in self-assembly of dynamical hierarchies [5] and we have proposed how to expand $I(t)$ for a protocellular system that has already obtained the ability for evolutionary optimization [6].

Discussion

Strikingly, systems of very different nature feature similar evolutionary traits: the cumulated number of salient evolutionary events, or quakes, grows logarithmically in time for complex physical and simple biological systems. The process itself can be understood as an optimization process in the complex configuration space of systems with given components and interactions. This optimization mode of evolution is complemented by an expansion mode, where new agents and interactions are introduced. The evolutionary expansion can be quantified as the difference away from a baseline optimization process with one free scaling parameter. To eliminate this parameter we need an independent microscopic theory for either the evolutionary optimization or expansion processes. Open-ended evolution is in a fundamental way associated with processes that at least sporadically have evolutionary expansion epochs.

References

[1] N. Becker and P. Sibani. Evolution and non-equilibrium physics: A study of the Tangled Nature Model. *EPL*, 105: 18005, 2014.

[2] R. Lenski and M. Travisano. Dynamics of adaptation and diversification: A 10,000-generation experiment with bacterial populations. *Proc. Natl. Acad. Sci.*: 91: 6808, 1994.

[3] M. E. J. Newman and Gunther J. Eble. Decline in extinction rates and scale invariance in the fossil record. *Paleobiology*, 25: 434, 1999.

[4] Our World in Data, https://ourworldindata.org/grapher/GDP-per-capita-in-the-uk-since-1270?overlay=sources

[5] S. Rasmussen, N.A. Bass, B. Mayer, M. Nilsson, MW Olesen. Ansatz for dynamical hierarchies. *Artificial Life* 7(4): 329-53, 2001.

[6] S. Rasmussen, A. Constantinescu and C. Svaneborg. Generating minimal living systems from nonliving materials and increasing their evolutionary abilities. *Phil. Trans. R. Soc. B* 20150440 (2015)

[7] D. M. Robe, S. Boettcher, P. Sibani, and P. Yunker. Record dynamics: Direct experimental evidence from jammed colloids. *EPL (Europhysics Letters)*, 116(3): 38003, 2016.

[8] M. Rosenlyst, H. Siboni and S. Rasmussen (2018), *Artificial Life 2018 Proceedings*.