CONTENTS

CHAPTER 1

Models of Change

> Order is Heav'n's first law.
>
> —*Alexander Pope*

> Quid sit prius actum respicere aetas
> nostra nequit nisi qua ratio vestigia monstrat.[1]
>
> —*Lucretius*

A point of departure

In this chapter, we provide the theoretical background for the chapters to follow. We begin with an overview of models of change—the same models that we apply in later chapters to specific cases. Here our goal is to equip the reader with a feel for the possibilities. Those possibilities look very different now than they did a generation ago. In the nineteenth century, change was the great topic of social theory, but by the mid-twentieth century, it had largely ceased to have analytical importance for the social sciences. Our point of departure is a brief exploration of the reasons why this occurred. Interestingly, those reasons vary from one field to the next. What role did change play in social and evolutionary theory circa 1965, before the discovery of deterministic chaos and the molecular revolution in genetics?

Anthropology and sociology

In 1962 Claude Lévi-Strauss published a profound challenge to the received wisdom of anthropology concerning the significance of cultural change. Nineteenth-century anthropology inherited a view of change based on stadial models, with roots that extend into classical antiquity. Between 700 and 300 BC, the ancient Greeks developed a theory of the evolution of human societies that persisted for more than two millennia. In these stadial models, societies are propelled from one stage to the next by innovations such as fire, cereal cultivation, language, metallurgy, and writing. Roman writers like Lucretius continued this speculative tradition, and in the seventeenth and eighteenth centuries, philosophers like

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[1] "What came before, our age cannot look back to, except insofar as reason shows the traces." Titus Lucretius Carus, *De Rerum Natura*, 5.1446–47.

Condorcet, Hegel, Comte, and others used stadial models to champion the progress of rational thought. Anthropologists such as Tylor, Morgan, and Spencer later sought to embed these models within an evolutionary framework. From this perspective, change is intrinsically purposeful; as Marx put it, “the five senses are the work of all previous history… history is the true natural history of mankind.”[2]

Lévi-Strauss’s challenge to this view was a logical extension of his structuralist program in language to encompass other cultural phenomena. In the influential structural theory of language developed by Ferdinand de Saussure, knowledge of the prior state of a language tells us nothing about its present workings. Lévi-Strauss adapted Saussure’s methods to create a powerful and predictive theory of how culture is organized by symbolic systems, affecting everything from cooking to cosmology. In culture as in language, argued Lévi-Strauss, knowledge of the antecedents of symbols is irrelevant to their current meaning. And more forcefully, the effect of change is to shatter the internal consistency of these systems of thought. Traditional societies seek “to make the states of their development which they consider ‘prior’ as permanent as possible. … There is indeed a before and an after, but their sole significance lies in reflecting each other.”[3]

Lévi-Strauss’s structuralist challenge subsequently loomed large in anthropology. As its influence grew, change came to be seen as little more than a source of disorder. Efforts to improve stadial models of culture and society were marginalized.

Economics

Economics took a similar path for different reasons. In the 1950s, economists proposed that the self-regulating capacity of market-based economies is founded on a state of general equilibrium. By the 1960s, the key theoretical questions in economics were the stability of equilibria to shocks and how the economy transitioned between equilibria. In considering both questions, economics takes the perspective that economies are either at equilibrium, returning to equilibrium following a perturbation, or heading toward a new equilibrium.

Genetics

As in economics, much early evolutionary theory also focused on the attainment of equilibrium. But the biologist’s concept of equilibrium was different from that of economists. In 1930, Ronald Fisher introduced

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[2] K. Marx. *Economic and Philosophic Manuscripts of 1844*. Penguin, 1974, p. 136.

[3] C. Lévi-Strauss. *The Savage Mind*. University of Chicago Press, 1966, p. 234.

Boltzmann's model of statistical equilibrium into genetics. According to Fisher's *Fundamental Theorem of Natural Selection*, "[t]he rate of increase in fitness of any organism at any time is equal to its genetic variance in fitness at that time."[4] In this view, natural selection operates on populations of organisms with varying fitness, propelling them toward fitness peaks that are statistical equilibria. These different definitions of "equilibrium" had analytical consequences: for general equilibrium in economics, any points lying away from equilibrium are merely transient states, and thus safely ignored, while in biology, Fisher's theorem proposes that variation provides the raw material for selection, determining the rate of change.[5]

Thus by the 1960s, the old stadial conception of change propelled by innovation was nearly forgotten across the social and evolutionary sciences, except by archaeologists and Marxist historians. For the equilibrium models that took its place, change was merely a transient state, and in some readings, a source of disorder. The new equilibrium models came in two forms. In economics, classical or Newtonian equilibrium meant the solution to a system of coupled differential equations.[6] In genetics, Boltzmannian statistical equilibrium described the average state of a collection of particles. Both concepts of equilibrium—classical and statistical—required external forces to shift from one equilibrium state to another.[7]

But this assumption only holds for linear systems. Nonlinear systems differ from Boltzmannian statistical ensembles in that initial differences may not average out. Instead, outliers can initiate large-scale spontaneous reorderings and movement to new attractors. As research on nonlinear dynamics continued, it became clear that spontaneous self-organization can achieve many of the outcomes traditionally assigned to impinging forces.[8] The mathematics showed, intriguingly, that self-organization can cause qualitative change in the behavior of dynamical systems, as Ilya

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[4] R. A. Fisher. *The Genetical Theory of Natural Selection*. Clarendon Press, 1930, p. 35.

[5] In this era, geneticists debated the significance of variation: is it a "genetic load"—that is, a burden imposed by misreadings in our genes—or is it instead the raw material from which we benefit evolutionarily as our environments change?

[6] Later, some economists began to reframe their models as statistical equilibrium, but "...the concept of statistical equilibrium remained unknown to most economists throughout all the XXth century and up to now." U. Garibaldi and E. Scalas, 2010 Tolstoy's dream and the question for statistical equilibrium in economics and the social sciences. In G. Naldi, L. Pareschi, and G. Toscani, eds. *Mathematical Modeling of Collective Behavior in Socio-Economic and Life Sciences*. Springer, p. 116.

[7] In genetics, these forces were caused by natural selection; in economics, by changes in the parameters affecting price.

[8] S. Kauffman. *The Origins of Order: Self-Organization and Selection in Evolution*. Oxford University Press, 1993.

Prigogine observed in his 1977 Nobel address. By the 1980s, the origins of order in nonlinear dynamical systems had moved to the forefront of research on complex systems. Biologist Robert May commented that "even in vastly complicated interactive networks, a few simple rules can easily—if amazingly—lead to order and self-organised patterns and processes. This represents a major advance in understanding how the living world works."[9]

The origins of order

May's reference to interactive networks reflects a shift in perspective on population structure. In economics, the concept of general equilibrium describes populations of economic actors engaged in buying and selling, whose actions depend on the state of the market. In genetics, following Fisher's model, chance mutations generate variation in populations of organisms, which in turn provides the raw material for natural selection. In both cases, a population is in effect a cloud of points. Clouds can drift, change shape, and become more or less dense, but they have no internal organization. In contrast, populations as networks have different properties than populations as clouds; points (or nodes) connected into networks can interact in vastly more complex ways. As another leading biologist, Richard Lewontin, commented, "[t]he facile claim that natural selection can accomplish every adaptive change fails to grapple with the problems posed by a highly structured system with its own laws of assembly and interaction."[10]

The image of populations as "vastly complicated interactive networks"[11] soon became an empirical reality for geneticists, as new technologies made it possible to decode genes and regulatory systems. In 1965 Jacques Monod received the Nobel Prize for describing the first example of a gene regulatory network. Five years later, in a book-length essay, *Chance and Necessity*, Monod argued that "chance alone is at the source of all novelty, all creation in the biosphere."[12] But progress in his own field soon contradicted this view. When it became possible to directly observe many gene regulatory systems, chance rapidly gave way to necessity. In time, the methods developed by geneticists to assess the role of chance began to be applied in other fields, from ecology to

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[9] Robert M. May, in a 1993 review of Kauffman's book published in *The Observer*.

[10] Richard C. Lewontin, in a back-cover endorsement of Kauffman's 1993 book.

[11] May, 1993 book review.

[12] J. Monod. *Chance and Necessity*. Vintage, 1972, p. 112 (first published in 1970 as *Le Hasard et la Nécessité*).

linguistics to archaeology. The combination of better empirical data and a greater theoretical understanding of nonlinear dynamics revived interest in change, and shifted the analytical focus from anonymous individuals to evolving networks, populations, and communities.

This intellectual pirouette merits careful attention. We will trace it by analyzing a series of key discoveries that brought unanticipated patterns of emergent behavior into focus. In the second part of this chapter, these threads are drawn together into a comprehensive framework that provides the starting point for the case studies. We begin with the discovery of molecular clocks, which made it possible to directly measure rates of change in evolving systems.

A clock that keeps good time

DNA is composed of strings of nucleotides—As, Cs, Ts, and Gs. Only part of this DNA represents genes and thus contains the blueprints for making proteins, but all nucleotides, even the ones that have no physical or behavioral effects, are subject to mutation. These mutations may change just one letter, or entire strings of letters. For many parts of our DNA, especially outside the genes, mutations accumulate at a steady rate, with that rate conceptually mimicking the ticking of a clock.

The possibility that such clocks might exist was anticipated before it became possible to observe them directly. In 1967, biologist Allan Wilson and his student Vincent Sarich published a paper in *Science*, in which they suggested that the origin of the human species could be dated by means of the genetic mutations that have accumulated since humans and chimpanzees last shared a common ancestor. At the time, it was not possible to actually count those mutations. Instead, Sarich and Wilson compared diversity in serum albumen (a blood protein) among a large number of primates, and found that "[l]ineages of equal time depth show very similar degrees of change in their albumins. The degrees of change shown would therefore seem to be a function of time." Using this "evolutionary clock or dating device," they estimated that humans and chimpanzees diverged around five million years ago.[13]

This proposal was met with profound skepticism by most anthropologists, who favored a date of about 25 million years based on the fossil record of the time. Donald Johanson's discovery of the fossil hominin Lucy in 1974 provided compelling support for this younger chronology, but arguments about the validity of the "molecular clock" concept

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[13] V. M. Sarich and A. C. Wilson. 1967. Immunological time scale for hominid evolution. *Science* 158:1200–3.

continued until the 1980s, when it became possible to sequence DNA and read off the mutations directly. That made it possible to find as many molecular clocks as one liked—from regions of the DNA that tick slowly to regions that tick fast. This discovery conclusively validated the method of molecular dating, and confirmed Sarich and Wilson's estimate of a five-million-year-old origin of our species. Today molecular clocks are no longer controversial (albeit more sophisticated); they are everyday tools in population genetics, and play a role in about half of the case studies in this book. But the very accuracy of molecular clocks triggered a new controversy: if mutations are regular, does this weaken the role of selection in the evolution of DNA?

Neutral drift

A year after the publication of Sarich and Wilson's paper on molecular clocks, geneticist Motoo Kimura predicted that the vast majority of evolutionary changes at the molecular level are caused not by selection, but by chance: the random drift of selectively neutral mutants. Even in the absence of selection, Kimura reasoned, evolutionary change will occur as a result of chance, and this could be analyzed with tools from probability theory. The idea that selection might have little or no role in shaping portions of the genome was not altogether new: in a famous disagreement with Ronald Fisher, Sewall Wright emphasized the importance of neutral processes such as drift as early as the 1930s. But Kimura took this idea further, offering a probabilistic method that can readily test for selective effects using data from the genome.

In genetics, the neutral theory was hotly debated for decades. As Kimura observed in his 1968 paper, the prevalent view in the 1960s held that almost all mutations are under selection, and this opinion was slow to change. But as Stephen J. Gould wrote in 1989, "[t]hese equations give us for the first time a baseline criterion for assessing any kind of genetic change. If neutralism holds, then actual outcomes will fit the equations. If selection predominates, then results will depart from [neutral] predictions."[14] This eventually led to a dramatic reversal in the way selection is viewed in molecular biology: geneticists now infer selection only when it can be shown that the assumption of neutrality has been violated. The success of the neutral theory triggered a shift in perspective, from the fitness of individual units of selection to the population-level consequences of both selection and drift.

[14] S. J. Gould. 1989. Through a lens, darkly: Do species change by random molecular shifts or natural selection? *Natural History* 98:16–24.

But is the neutral theory relevant above the molecular level? Theoretical ecologists began to consider this question in the 1990s. Previously, the prevalence of species in ecological communities was approached from a pan-selectionist perspective too: what are the special attributes of each species that explain its abundance in a given environment? Neutral theory offered an alternative hypothesis. If one assumes that species do not differ in their competitive abilities, what would the prevalence of species be if this depended only on the size of the total ecological community and the chance arrival of new species? In other words, do neutral processes of drift and replacement largely govern the formation and persistence of ecological communities? This question became one of the most hotly debated topics in theoretical ecology.[15] Mathematically, the neutral theory in ecology is faithful to its origins in genetics; both rely on the same underlying mathematical model.

Although the scope of the neutral theory in ecology is still being tested, a shift is underway from the assumption of pan-selectionism to the view that selection can only be inferred by showing departure from a null model of neutrality.[16] As in genetics, this represents a change in the level of analysis, from the fitness of individuals to the effects of selection at the community level. As Kimura wrote in 1983, "it is easy to invent a selectionist explanation for almost any specific observation; proving it is another story. Such facile explanatory excesses can be avoided by being more quantitative."[17]

Nonlinear systems

Kimura's linear equations for neutral drift have marvelous predictive power because there is only one neutral frequency distribution for any given population, depending solely on the mutation rate and the population size. (Thus, if we view genetic types or species of tree as a bag of marbles, the equilibrium distribution of colors reflects only the number of marbles in the bag and the rate at which new colors appear.) This is also true for the adaptations of Kimura's model in ecology and

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[15] J. Harte. 2003. Tail of death and resurrection. *Nature* 424:1006–7; D. Alonso, R. Etienne, and A. McKane. 2006. The merits of neutral theory. *Trends in Ecology and Evolution* 21:451–7.

[16] J. Hey. 1999. The neutralist, the fly and the selectionist. *Trends in Ecology and Evolution* 14:35–8; X. S. Hu, F. He, and S. P. Hubbell. 2006. Neutral theory in macroecology and population genetics. *Oikos* 113:548–56; E. J. Leigh. 2007. Neutral theory: A historical perspective. *Journal of Evolutionary Biology* 20:2075–91.

[17] M. Kimura. *The Neutral Theory of Molecular Evolution*. Cambridge University Press, 1983, p. xiv.

indeed for any related neutral processes occurring within populations. Neutral models provide a baseline from which to calculate the effects of selection: if certain colored marbles have a selective advantage, they will become more frequent and stand out in the overall distribution of colors.

But what about discontinuous, nonlinear change? Soon after Kimura published his neutral theory, biologist Robert May began to investigate the appearance of discontinuous change in ecological models. What causes a transition from linear growth to nonlinear fluctuations? As May discovered, such changes can occur with no external forcing. In an article that quickly became a seminal text in the emerging field of complexity science, May described the effects of varying the growth parameter in a simple linear model of population growth.[18] In this equation, P_t is the current population size, P_{t+1} is the population size in the next generation, and r the population's intrinsic rate of growth:

$$P_{t+1} = rP_t(1 - P_t) \tag{1.1}$$

For small values of r, the equation is linear: an increase in the population is proportional to an increase in the growth rates. But at $r = 3.44949$, the population begins to oscillate between two values (Figure 1.1). Between 3.44949 and 3.54409, it oscillates between four values, after which slight increases in the growth rate lead to oscillations between 8, 16, 32 values, etc. When r reaches 3.56995, regular oscillations begin to be replaced by chaotic fluctuations. At these higher growth rates, tiny differences in the initial population size yield all possible final population sizes within a given range. Even more surprisingly, between 3.56995 and 3.82843 several islands of stability appear (the white "stripes" in Figure 1.1).

Online Resource: The Logistic Map

The logistic map model is available in the online resources for *Islands of Order*:

https://www.islandsoforder.com/the-logistic-map.html

Thus, merely varying the growth rate triggers linear, oscillatory, and chaotic behavior. In the language of complexity, or more specifically of nonlinear dynamics, each of these features is called a *regime*, or *attractor*.

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[18] R. M. May. 1976. Simple mathematical models with very complicated dynamics. *Nature* 261:459–67.

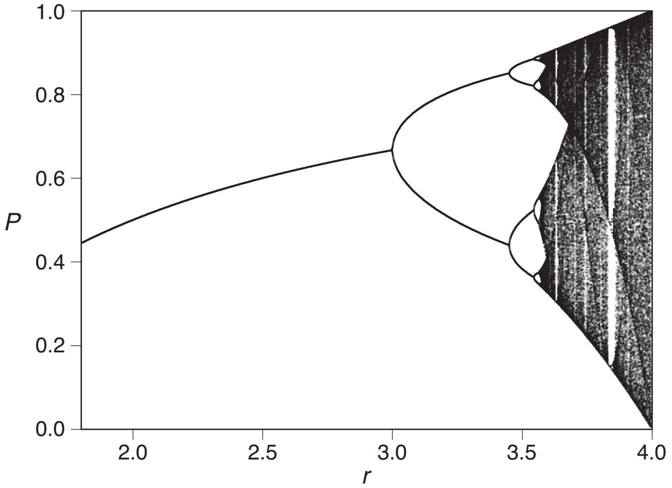

Figure 1.1. The logistic map. This phase portrait shows linear, cyclical, and chaotic behavior at different values of the intrinsic growth rate, *r*. Credit: Ning Ning Chung.

As long as the growth rate is less than 3.44949, the behavior is linear. But if the growth rate happens to fall in the chaotic regime, prediction is impossible, even if everything about the system is known exactly.[19]

This example allows us to make two observations. First, one need not seek very far to discover nonlinear processes. Indeed, as Stanisław Ulam famously quipped, “to speak of ‘nonlinear science’ is like calling zoology the study of ‘nonelephant animals.’ ”[20] Second, simple linear processes can trigger unexpected nonlinear effects, and if more than one attractor or regime exists—that is, if the system is not a simple equilibrium—the resulting variation in dynamical behavior can easily be mistaken for noise or error. As May observed, “the very simplest nonlinear difference equations can possess an extraordinarily rich spectrum of dynamical behavior, from stable points, through cascades of stable cycles, to a regime in which the behavior (although fully deterministic) is in many respects ‘chaotic,’ or indistinguishable from the sample function of a random process.”[21]

[19] Ibid.

[20] Quoted in D. Campbell, J. Crutchfield, J. Farmer, and E. Jen. 1985. Experimental mathematics: The role of computation in nonlinear science. *Communications of the Association for Computing Machinery* 28:374–84.

[21] May, Simple mathematical models.

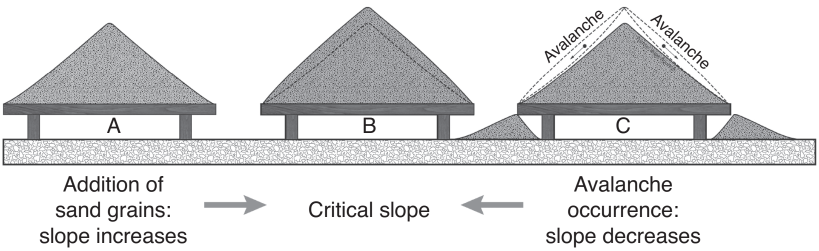

Figure 1.2. The sand pile experiment, showing critical transitions. Credit: Yves Descatoire.

Triggers for nonlinear transitions

Among the most interesting nonelephant animals are the ones that exhibit tendencies to self-organize. Stuart Kauffman, one of their discoverers, called this *order for free*. Even in the absence of selection, seemingly random local interactions can trigger the emergence of order at a higher scale.[22] An intriguing example is a behavior called *self-organized criticality* (SOC), for which the canonical example is not an equation, but an experiment often performed by toddlers at the beach.[23]

Take a flat surface, dribble grains of sand on it until it becomes a pile, and observe the occasional avalanches that occur as the sides grow steep (Figure 1.2). As the grains of sand fall, avalanches continue until the steepness of the sides remain constant. At this point, the sand pile has reached its attractor; the size of avalanches (the number of grains of sand that move) is inversely related to their frequency. That is, we see many small avalanches and few large ones. Having reached its attractor, the shape of the sandpile does not change, though it can grow larger, as long as sand flows onto it and there is enough room for the sand pile to spread.

This system has several interesting features, notably that it is self-organizing and generates a robust pattern of emergent, scale-invariant behavior (the relationship between the size and frequency of avalanches). This pattern is seen widely; for instance, the magnitude of earthquakes is inversely related to their frequency. Many social and cultural phenomena also exhibit this pattern. Self-organized criticality spontaneously generates scale-free networks, in which the degree distribution of nodes—how many connections they possess to other nodes—is inversely related

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[22] In some cases, order emerges from the collective behaviors of large ensembles of smaller-scale units; in other cases, the pattern is imposed by larger-scale restraints. S. A. Levin. 1992. The problem of pattern and scale in ecology. *Ecology* 73:1943–67.

[23] P. Bak, C. Tang, and K. Wiesenfeld. 1987. Self-organized criticality: An explanation of 1/*f* noise. *Physical Review Letters* 59:381–4.

to their frequency. Thus, self-organized criticality is governed by a single attractor that produces a characteristic signature.

Sand piles have a single attractor. The possibility that real-world complex systems might have more than one attractor was demonstrated by the discovery of alternate stable states in Dutch lakes. For decades after the Second World War, excess fertilizer flowed into lakes in the Netherlands, providing free nutrients and triggering algae blooms. Later, the amount of fertilizer entering the lakes was reduced, but intriguingly, the lakes did not return to their original clarity. It turned out that alternate stable states (or attractors) exist in these lakes: one turbid, the other clear. In ecology, these alternate stable states or attractors are called regimes. The effects of nutrient flows depended on which regime a given lake happened to be in, so earlier studies that generalized across all lakes obscured these differences. But once the existence of alternate regimes was recognized, a simple intervention was sufficient to restore the lakes to health. Temporarily removing the fish allowed sediment to settle and zooplankton populations to increase, whereupon water clarity could be improved by reducing the amount of fertilizer flowing into the lakes.[24] The fish were then re-introduced. A take-home message is that complex systems are not necessarily symmetrical: here, as is often the case, it was easier to get into a mess than get out of it.

The comparative study of processes like this produced new theoretical insights by ecologists into the transitions between attractors. As a dynamical system approaches the boundary between alternate attractors, it will exhibit certain generic properties. These telltale signs have now been observed in many natural systems.[25] This behavior has yet to be conclusively demonstrated for social phenomena, but has triggered substantial interest due to its potential relevance for understanding critical transitions in social systems.

Complex adaptive systems

As we have just seen, complex systems are simply aggregates of interacting elements. If the elements are adaptive agents (in other words, if they exhibit purposeful or goal-seeking behavior), then they form a complex adaptive system (CAS). Complex adaptive systems are ubiquitous in the life sciences, and we are just beginning to notice them in the social world.

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[24] J. L. Attayde, E. H. Van Nes, A. I. L. Araujo, et al. 2010. Omnivory by planktivores stabilizes plankton dynamics, but may either promote or reduce algal biomass. *Ecosystems* 13:410–20.

[25] M. Scheffer, J. Bascompte, W.A. Brock, et al. 2009. Early-warning signals for critical transitions. *Nature* 461:53–9.

Is a given system composed of adaptive agents, and does it exhibit emergent features that arise from their aggregate behavior? What might such emergent features look like? When do quantitative differences turn into qualitative transformations? Like the logistic equation for populations described above, even the simplest examples of complex adaptive systems can contain surprises.

To see this, we can turn the logistic equation from Figure 1.1 into an evolving complex adaptive system by adding a single environmental parameter—causing growth to be affected by some feature of the environment. The resulting model, created in 1992, helped trigger a revolution in the environmental sciences.

The model is called Daisyworld[26] and the environmental variable is temperature. Daisyworld is an imaginary planet orbiting a star like the sun and at the same orbital distance as the Earth. The surface of Daisyworld is fertile earth, sown uniformly with daisy seeds. As is true in our world, the daisies vary in color, and daisies of similar color grow together in patches. As sunshine falls on Daisyworld, the model tracks changes in the growth rate of each variety of daisy and changes in the amount of the planet's surface covered by different colored daisies.

The simplest version of this model contains only two varieties of daisies, white and black. Black daisies absorb more heat than bare earth, while white daisies reflect sunlight. Consequently, clumps of same-colored daisies create a local microclimate for themselves, slightly warmer (if they are black) and slightly cooler (if white) than the mean temperature of the planet. Both black and white daisies grow fastest, and at the same rate, when their local effective temperature (the temperature within their microclimate) is 22.5°C. They respond identically, with a decline in growth rate, as the temperature deviates from this ideal. As a result, at a given average planetary temperature, black and white daisies experience different microclimates and therefore have different growth rates.

If the daisies cover a sufficiently large area of the surface of Daisyworld, their color affects not only their own microclimate, but also the albedo or reflectance of the planet as a whole (Figure 1.3). Like our own sun, the luminosity of Daisyworld's star has gradually increased. A simulation of life on Daisyworld begins in the past with a cooler sun. This enables the black daisies to spread until they warm the planet. Later on, as the sun grows hotter, the white daisies grow faster than black ones, cooling the planet. So over the history of Daisyworld, the warming sun gradually changes the proportion of white and black daisies, creating the global phenomenon of temperature regulation: the planet's temperature is held near an optimum for—and by—the daisies.

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[26] J. E. Lovelock. 1992. A numerical model for biodiversity. *Philosophical Transactions of the Royal Society B* 338:383–91.

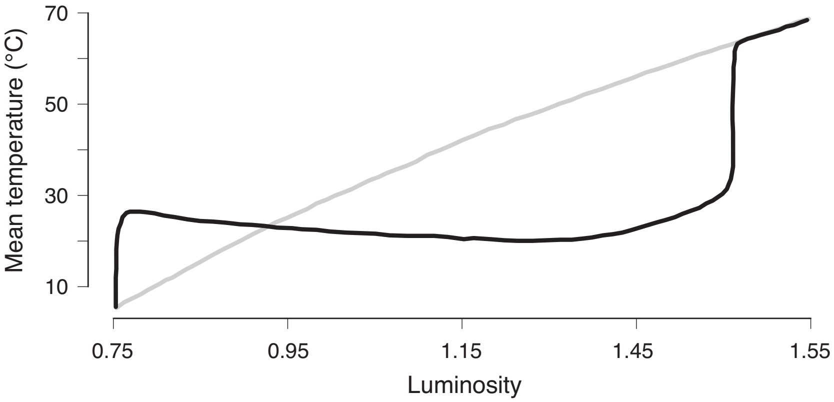

Figure 1.3. Simulated temperature regulation on Daisyworld. As the luminosity of its aging sun increases from 0.75 to 1.5 times the average value, the temperature of a bare planet would steadily rise (gray line). In contrast, the temperature of Daisyworld stabilizes close to 22.5°C when daisies are present (black line). Credit: Authors, adapted from James Lovelock's Daisyworld model.

Imagine that a team of astronauts and planners is sent to investigate Daisyworld. They would have plenty of time to study the only living things on the planet, and they would almost certainly conclude that the daisies had evolved to grow best at the normal temperature of the planet, 22.5°C. But this conclusion would invert the actual state of affairs. The daisies did not adapt to the temperature of the planet; instead they adapted the planet to suit themselves.[27] A Daisyworld without daisies would track the increase in the sun's luminance (gray line), rather than stabilizing near the ideal temperature for daisies (black line). But the role of the daisies in keeping the planet at a cozy temperature would not be obvious to the newcomers. Only when the sun's luminosity becomes too hot for the daisies to control—the abrupt transition in the black line on the right of the graph—would the daisy's former role in temperature stabilization become apparent.

Lacking this understanding, planners hoping to exploit Daisyworld's economic potential for the interstellar flower trade would fail to appreciate the possible consequences of different harvesting techniques. While selective flower harvests would cause small, probably unnoticeable tremors in planetary temperature, clear-cutting large contiguous patches of daisies would create momentary changes in the planet's albedo that

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[27] P. T. Saunders. 1994. Evolution without natural selection: Further implications of the Daisyworld parable. *Journal of Theoretical Biology* 166:365–73.

could quickly become permanent, causing temperature regulation to fail and daisy populations to crash. Something quite like this happened during the 1970s Green Revolution on the Indonesian island of Bali, as we will see in chapter 5.

The Daisyworld model soon became a canonical example of a self-organizing, self-regulating environmental system. As an example of a complex adaptive system, it has several interesting features. Unlike sand piles, this model is driven by a process of adaptation. And the biology of adaptation is as simple as its creator, James Lovelock, could possibly make it. The model shows how small-scale local adaptations can trigger an emergent global structure (temperature regulation at the planetary scale). And it also shows why such global structures can easily fade from view, becoming noticeable only when the system as a whole has been pushed past its limits.

Online Resource: Daisyworld

The Daisyworld model is available in the online resources for *Islands of Order*:

https://www.islandsoforder.com/daisyworld.html

Discovering islands of order

The doomed flower markets of Daisyworld conclude this overview of models of change, which we build upon in the case studies that follow. Older models of stadial change and stable equilibria remain of interest, but we suggest that they are best treated as special cases.

Where do we go from here? A broader conceptual framework is needed to detect complex emergent phenomena. Such a framework does not yet exist for the social sciences, but an obvious way forward is to take advantage of two existing frameworks that are commonly used in complexity research and offer complementary insights. The first is attractor basins from physics, the second adaptive landscapes from evolutionary biology. Because we will use both of these ideas in future chapters, we offer a brief introduction to them here.

Phase portraits and basins of attraction

Phase portraits offer a simple and intuitive snapshot of the behavior of dynamical, evolving systems. We have already encountered an example of a phase portrait in Figure 1.1, the logistic map. For convenience, this

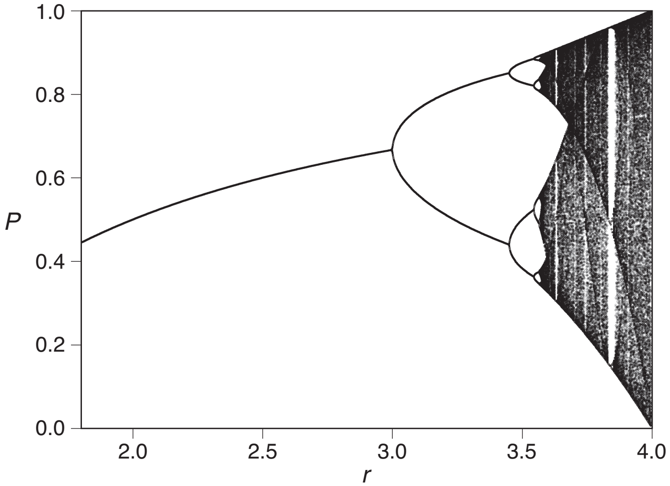

Figure 1.4. The logistic map, revisited. Credit: Ning Ning Chung.

figure is reprinted above (Figure 1.4). The way to read it as a phase portrait is to mentally slide along the horizontal axis, tracking increases in *r* (the growth rate) and glancing up to see how *P* (the population size) changes. At different values of *r*, the population undergoes stable, oscillatory, complex, and chaotic behavior. Each of these patterns is an attractor. The span of *r* values that trigger a particular pattern is the *basin of attraction* for that attractor. (The analogy being a geographical drainage basin, where rain falling on some area inexorably flows into the region's main river, here analogous to the attractor.) In Figure 1.4, the largest basin is for stable (linear) growth, which extends to $r = 3$. Above 3, there is a new basin of attraction for oscillatory dynamics, where the population oscillates between two values, which appear as "branches" on the figure. A third attractor appears around 3.4, where the population oscillates between four values (the "bubbles"). This basin is smaller, confined to the interval, $3.44949 < r < 3.54409$, after which another basin appears. Further increases in *r* explore many tiny basins, associated with oscillatory, complex, and chaotic attractors, and even a (brief) return to stable growth (the white "stripes"). Thus, in the region $r > 3.4$, this phase portrait is characterized by an abundance of many tiny attractors.

With this example, we draw your attention to the importance of basins of attraction. To create a phase portrait, the key question is not only the nature of the attractors, but the regions of the phase plane that drain into them: their basins of attraction. In general, it is rare to find systems that comprise a single basin draining to a point attractor (in other words, standard social science equilibrium models). But the simplicity of these models makes them ideal null or neutral baselines. An interesting example is Motoo Kimura's model of neutral equilibrium (described above), which describes patterns of change driven by chance alone. This system has a single attractor; the larger the population, the slower the approach to the attractor. Kimura's neutral model provides the theoretical framework for our analysis of male dominance in chapter 3.

Daisyworld is a slightly more complex model. It has three basins of attraction, which depend on the amount of sunlight reaching the planet.[28] This model is the starting point for our analysis of Balinese water temple networks in chapter 5. The Bali model is based on a simple dynamical relationship, much like Daisyworld. But what if the data are noisy and neither the attractors nor their basins are readily apparent? We will pick up that question in chapter 7, where we consider how to discover basins of attraction in noisy data from a social survey.

Definitions

Complex systems research uses a number of concepts and terms that you may not have seen before. Here are some basic explanations of key ideas we have encountered so far.

Emergent properties are a characteristic of systems in which you cannot predict outcomes by observing the actions of an individual, but only when you see many individuals interacting together. This is the opposite of reductionist science, which aims to reduce a system to its smallest parts. With an emergent property, seemingly random local interactions between individuals can often trigger the *emergence* of order at higher scales. We show some examples in later chapters.

A *phase space* is a mathematical construct that represents every possible state in a system, with each state having a unique point in the phase space. For a dynamical system with just two variables, like P and r in the logistic map, you can imagine the phase space as a two-dimensional plot with P and r on the axes. (Strictly, a phase space in two dimensions is usually called a *phase plane*.) If a system has three variables, the phase space is three-dimensional. If it has ten variables, the phase space is ten-dimensional. Mathematically, all of

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[28] Attractor basins can be calculated and plotted for discrete dynamical systems in 1, 2, or 3 dimensions using Discrete Dynamics Lab, http://www.ddlab.com.

these cases work exactly the same way. It is just harder to visualize examples with more than three dimensions.

A plot that shows the outcome of some set of initial conditions in a given phase space is called a *phase portrait*. For example, Figure 1.4 shows the phase portrait for the two-dimensional dynamical system of the logistic map.

In many dynamical systems, there is a part of the phase space where initial conditions inevitably evolve to a particular final state. That final point is called an *attractor* and the area around it is called a *basin of attraction*. An attractor is a set of states that neighboring states in a given basin of attraction asymptotically approach during the course of dynamic evolution. Think of a water analogy: rain falling within a watershed inevitably flows into the region's major river. The watershed is the basin of attraction and the river is the attractor.

You are already familiar with attractors, even if you do not know it. In many cases (but not always), data points that are normally distributed—like the lengths of leaves on a tree or the volume of a certain pot type in an archaeological assemblage—actually belong to a dynamical system with just one attractor. The peak of the bell curve is usually the attractor and the curve around it the basin of attraction. The dynamical systems in this book are novel in that they usually have multiple attractors, each with its own basin of attraction. The presence of—and interaction between—multiple attractors leads to more complex system dynamics. Describing those behaviors is a key purpose of this book.

Adaptive landscapes

The concept of adaptive landscapes[29] (also called *fitness landscapes*) was proposed by biologist Sewall Wright in 1932, and is now probably the most common metaphor used in evolutionary genetics.[30] Unlike

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[29] S. Wright. 1932. The roles of mutation, inbreeding, crossbreeding and selection in evolution. *Proceedings of the Sixth International Congress of Genetics* 1:356–66.

[30] "Adaptive landscape is probably the most common metaphor in evolutionary genetic[s]." D. J. Futuyma. *Evolutionary Biology*, Sinauer Associates, 1998, p. 403. For discussion of the limitations of the adaptive landscape concept in biology, see P.A.P. Moran. 1964. On the non-existence of adaptive topographies. *Annals of Human Genetics* 27:383–93; G. Gilchrist and J. Kingsolver. 2001. Is optimality over the hill?

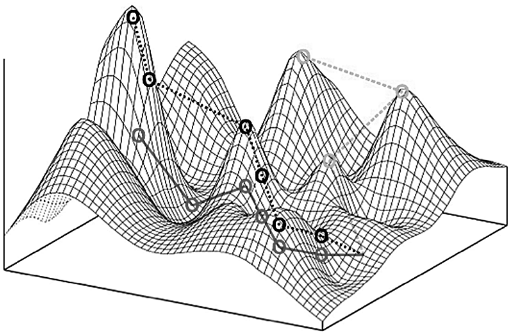

Figure 1.5. An example of a fitness landscape in two dimensions. The lines represent alternative mutational paths to reach different peaks in the landscape. Note that environmental and social change means that the landscape itself is not static, as might be the initial impression from this figure, but instead changes in dynamic ways over time. Credit: Randy Olson, Wikimedia Commons, CC BY-SA 3.0.

phase portraits, adaptive landscapes do not lend themselves to rigorous mathematical analysis. Instead they provide a way to visualize trajectories of change in evolving complex adaptive systems. We combine the concept of adaptive landscapes with phase portraits in chapter 7, where we investigate how social systems can move between basins of attraction.

The idea of an adaptive landscape is intuitively simple: imagine a collection of evolving agents—distinct entities such as organisms, people, or strategies—on a surface, where their height in this space reflects the relative fitness of each agent (Figure 1.5). An adaptive process, if one is present, will move the population from valleys to peaks. The fittest organisms cluster around the highest peaks, while the lowest fitness is represented by deep valleys.

These peaks can take different forms. The simplest is the “Mount Fuji” landscape with a single fitness peak (a Gaussian distribution of fitness). In contrast, if all the fitnesses are identical, the result is a flat fitness landscape. Here, there is no variation in fitness, so natural selection has nothing to work with. Between these extremes, more irregular distributions of fitness produce a rugged fitness landscape, with peaks of varying height. Because the rate of reproduction of an organism or agent is determined by its fitness, selection will cause an evolving population

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The fitness landscapes of idealized organisms. In S. Orzack and E. Sober, eds. *Adaptationism and Optimality*. Cambridge University Press, p. 219–41; M. Pigliucci and J. Kaplan. *Making Sense of Evolution: The Conceptual Foundations of Evolutionary Biology*. University of Chicago Press, 2006; B. Calcott. 2008. Assessing the fitness landscape revolution. *Biology and Philosophy* 23:639–57.

to climb uphill in the fitness landscape over time, until it reaches a local optimum. If more than one fitness peak exists, populations can get stuck on lower peaks, never reaching the higher ones.

Greater realism can be introduced into fitness landscapes in several ways. Instead of assigning a permanent fitness to each organism, fitnesses can be allowed to vary. For example, the fitness of organism (or strategy or agent) *A* may depend in part on organisms *B* and *C*. The landscape itself can also change shape as the populations explore it. This concept—dynamic adaptive landscapes—plays a prominent role in evolutionary game theory, in which the evolving entities are strategies and their payoffs (fitness) depend on their relative frequency.

In this book, we will follow the advice of a philosopher of science, Peter Godfrey-Smith, and use adaptive landscapes to help decide what kind of model is best suited to a given question. For Godfrey-Smith, the key question is scale. At very small scales of space and time, where all agents are visible as points on the landscape, movement on the landscape may be dominated by neutral drift rather than selection. After all, mutations are rare and most new mutations do not provide a fitness advantage. Instead, neutral mutations tend to accumulate. At this scale, natural selection is just one factor among many, and will rarely be dominant. So it makes sense to begin with a neutral model, and then look carefully for evidence of selection or other kinds of non-neutral change.

At longer time spans, evolutionary game theory starts to become relevant. Here, as Godfrey-Smith points out, "[t]he fine details of population movements on the landscape are washed out and replaced by idealized strategies, whose competition drives a selection process. Paleontologists often zoom out even further, considering observed forms in contrast to a broad range of hypothetical (unobserved) alternative types. At this coarsest grain of analysis, selection again recedes in perceived importance, as the large set of conceivable alternatives highlights the great importance of historical contingency in producing observed forms."[31]

Our most zoomed-out case study, the colonization of the Pacific, takes us back over 150 generations, just brushing the Pleistocene. And sure enough, at this scale there is unmistakable evidence of selection. At the other extreme, decisions about cooperation are nearly simultaneous and can appear to be nearly random. We agree with Godfrey-Smith that the question of scale is relevant to any theory of change in an evolving population, which makes adaptive landscapes a very useful metaphor. So we have taken his advice, and begin each of our case studies by posing a question or questions, and then zooming in to the relevant scale.

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[31] J. F. Wilkins and P. Godfrey-Smith. 2009. Adaptationism and the adaptive landscape. *Biology and Philosophy* 24:199–214.

Conclusion

In one of the foundational articles that launched complexity studies, physicist Philip Anderson rephrased Karl Marx's observation that quantitative differences become qualitative differences. "More is Different," Anderson observes, because at each new level of complexity entirely new properties appear.[32] The way to discover these emergent properties is by tracing patterns of interaction among the elements of a given system. The phenomenon of emergence is common to all of the examples we have considered in this chapter, and will continue to be relevant in each of the case studies in this book. But until recently the mathematical toolkit for analyzing adaptive change was not well suited to discovering emergence or other properties of out-of-equilibrium dynamical systems. As recently as 1990, philosopher of science Karl Popper argued that social scientists who wish to take advantage of mathematics have the choice of only two approaches.[33] The first is essentially Newtonian and is best represented by general equilibrium theories (for example, in economics). Such theories take the form of systems of differential equations describing the behavior of homogeneous social actors. Change occurs as a result of perturbations and leads from one equilibrium state to another. The second type of theory is statistical. If one cannot write the equations to define a dynamical system, it may yet be possible to observe statistical regularities in social phenomena. Both approaches have obvious weaknesses: the assumption of equilibrium is forced by the mathematics, not by observations of social behavior; and sifting for patterns with descriptive statistics is at best an indirect method for discovering causal or developmental relationships.

We are hardly the first to comment on these limitations. In fact, they were the central issue in what is generally reckoned to be the most influential debate about the methodological foundations of social science of the last century, the "Positivismusstreit" or "Positivist Dispute"[34] between Popper and the social theorists of the Frankfurt School from 1961 to 1963. Popper argued that progress in the social sciences was achievable only by the use of mathematics to falsify hypotheses. In response, Theodor Adorno observed that descriptive statistics provide no explanation for qualitative change, or what we would now call emergence: "only through what it is not will it disclose itself as it is."[35] This led

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[32] P. W. Anderson. 1972. More is different. *Science* 177:393–6.

[33] K. Popper. 1990. *A World of Propensities*. Thoemmes Press, 1990, pp. 18–19.

[34] T. W. Adorno, H. Albert, R. Dahrendorf, et al. *The Positivist Dispute in German Sociology*, transl. Glyn Adey and David Frisby, Heinemann, 1976.

[35] Ibid., 296.

Adorno to a critique of descriptive statistics as the primary tool for social inquiry. He observed that "a social science that is both atomistic, and ascends through classification from the atoms to generalities, is the Medusan mirror to a society which is both atomized and organized according to abstract classificatory principles. . . . " Adorno's point was that a purely descriptive, statistical analysis of society at a given historical moment is just "scientific mirroring" that "remains a mere duplication." To break the seal of reification on the existing social order, it would be necessary to go beyond descriptive statistics or equilibrium models to explore historical contingency. However, the mathematical tools that might enable this kind of investigation did not yet exist, and the Positivist Dispute ended in a stalemate.

Still, the question of historical contingency would not go away. In the 1980s, sociologist Anthony Giddens developed an influential theory of *structuration*, arguing that human social activities, like some self-reproducing items in nature, are recursive. That is to say, they are not brought into being by social actors, but continually recreated by them via the very means whereby they express themselves as actors. In and through their activities, agents reproduce the conditions that make these activities possible.[36] But Gidden's theory was pitched at a very general level, a description of the human condition rather than a methodology for investigating specific processes of change.

The theoretical landscape looks very different today. One important change since the 1980s has been the flourishing of computational modeling. But the availability of more powerful tools for statistical analysis is only part of the story. Our subject in this chapter has been the implications of the discovery of Ulam's nonelephant animals: attractors in nonlinear systems. As Robert May showed with his logistic map, they are not hard to find, once we learn to recognize them, and their discovery has opened up new vistas in physics and biology. As relative latecomers to this perspective, social scientists are in a position to benefit from several decades of theoretical work, including a substantial body of elegant mathematical tools.

But how to make use of these ideas? In the chapters that follow, we offer some suggestions.

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[36] A. Giddens. *The Constitution of Society: Outline of the Theory of Structuration.* University of California Press, 1984.

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