# The Observer Effect in a Planetary Ecosystem

Moby-Dick

October 30, 2024

*In memory of Alexandre Grothendieck, a mathematician committed to ecology and world peace.*

We will approach the ecological problem from the angle of the mathematical structure of thermodynamics [Jør2004, Mich2005, Niel2020, Svir2000], which is essentially information theory [Heg2011, Ulan2001]. In this essay, we hypothesize that the planetary ecosystem functions as a closed system in the thermodynamic sense, where life is possible. A closed system is a system without an exchange of matter with the outside, but where energy exchanges are allowed. For Earth, these energy exchanges primarily come from received solar energy and energy radiated back into space. Although our planet interacts materially with its environment, for example by receiving cosmic dust, we will neglect this input in our modeling to simplify the analysis.

By life, following the definition proposed by Erwin Schrödinger [Sch2012], we mean a system capable of reducing its internal entropy. In a planetary ecosystem, a *sapiens* is defined as a living being capable of knowing its planetary ecosystem, that is to say, of estimating the parameters of the probability distributions linked to a model of the planetary ecosystem. A sapiens is not necessarily unique: for example, there was a time in prehistory when *Homo sapiens* shared its existence with other intelligent species, such as *Homo neanderthalensis* and Denisovans.

A perfect sustainable development project is the solution to an optimization problem in which the objective function to be maximized is the probability of long-term survival of a given sapiens in a planetary ecosystem. A sustainable development project is simply an approximation of the perfect sustainable development project. A naive sapiens might think that scientific research will always improve the planning of a sustainable development project. However, since the sapiens belongs to the system it studies, one must consider the observer effect [Den2005], that is, the perturbation of an observed system by the act of observation. Indeed, Professor Hugo Chapdelaine [Chap2024] noted that when considering the environmental cost of certain scientific projects intended to protect the environment, it could exceed the benefits.

To study the observer effect in a planetary ecosystem, we will start with very specific examples of systems in which there is a notion of knowledge and a notion of return. Then, we will consider more general systems. Note that in our methodology, we do not move from simple models to complex models, as is done in statistics, but rather from specific models to general models, following the process of mathematical abstraction.

Our first toy model of a planetary ecosystem, called the Kelly model, is the game of coin toss, in which "nature" (player 1) tosses a coin and the sapiens (player 2) bets on the side that lands. As a sustainable development project, we will use the Kelly criterion [Kel1956], a betting strategy that consists of maximizing the expectation of the logarithm of the gain. The return is simply the natural logarithm of the ratio of the money at the end of the game divided by the money at the beginning of the game. Knowledge is the binary logarithm of the inverse of the absolute value of the difference between the true probability that determines the Bernoulli process of the game and its estimation by the sapiens. The observer effect is modeled as a constant cost for the sapiens to obtain elements of knowledge.

The Kelly criterion is a strategy used to determine the optimal fraction of capital to risk in a bet in order to maximize the expected logarithmic growth of wealth over the long term. Mathematically, the optimal fraction $f^*$ of the capital to bet is given by:

$$f^* = \frac{p(1+b)-1}{b} \tag{1}$$

where $p$ is the probability of winning the bet, and $b$ is the ratio of the net gain to the wagered amount (for example, if you bet 1 unit and win 1 additional unit, then $b = 1$). This formula maximizes the expected logarithm of future wealth, that is:

$$\max \mathbb{E}[\ln(W_{\text{final}})] \tag{2}$$

where $W_{\text{final}}$ is the wealth after the bet.

The sapiens seeks to estimate the true probability $p$ of the game, but obtaining a precise estimate $q$ has a cost, which must be paid to nature. The Kelly fraction estimated with an erroneous probability is:

$$f^*_{\text{estimated}} = \frac{q(1+b)-1}{b} \tag{3}$$

where $q$ is an estimate of $p$.

In our model, the cost of information is proportional to the number of bits of information needed to reduce the uncertainty about $p$. The number of required bits is given by:

$$\text{Information} = -\log_2 |p - q| \tag{4}$$

Generally, this number is not an integer, but it is sufficient to approximate it by the smallest integer that is not less than this value (the ceiling function) to obtain the number of bits in the manner used in computer science. The total cost of information is then:

$$\text{Information Cost} = c \times \text{Information} \tag{5}$$

where $c > 0$ is the cost per bit of information. In a more realistic model, the formula for the cost of information would be provided by a domain expert. It could be nonlinear. The net logarithmic return is given by:

$$\text{Net Logarithmic Return} = \ln\left(\frac{W_{\text{final}}}{W_{\text{initial}}}\right) - c \times \text{Information} \tag{6}$$

Figure 1 illustrates how wealth $W_n$ evolves over $n = 1, 2, 3, \ldots, 50$ iterations using the Kelly criterion with a probability of winning $p = 0.7$ and a payoff per successful bet $b = 1$. At each iteration, the individual wagers a fraction $f^*$ of their current wealth.

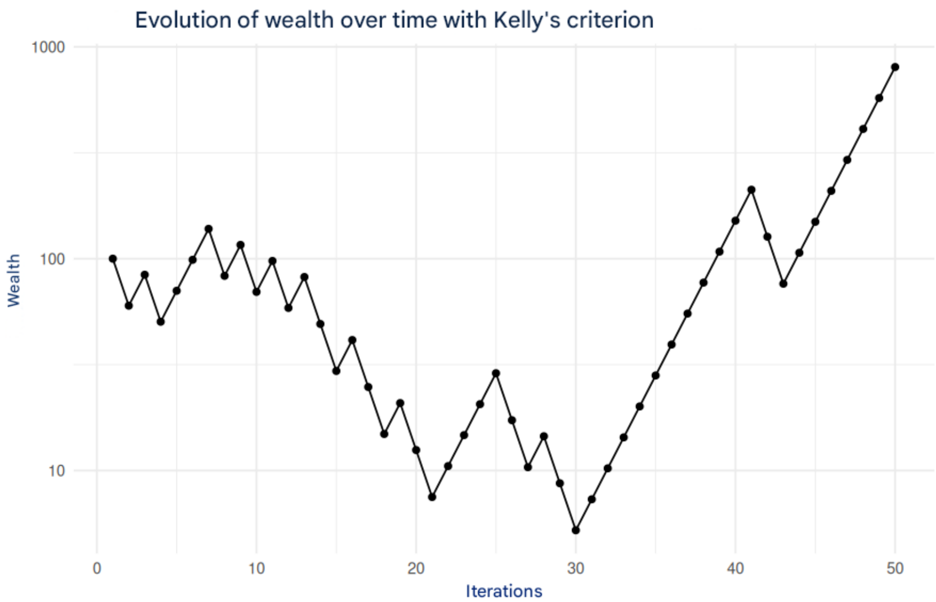


Figure 1: Evolution of Wealth over time with Kelly's criterion.

Figure 2 compares the distribution of final wealth after 50 iterations in two scenarios:

1. Perfect information: the individual knows the exact probability $p = 0.7$ and calculates the optimal fraction $f^*$ accordingly.

2. Partial information: the individual thinks that the probability is $q = 0.9$ (overestimation), and uses this value to calculate $f^*$.

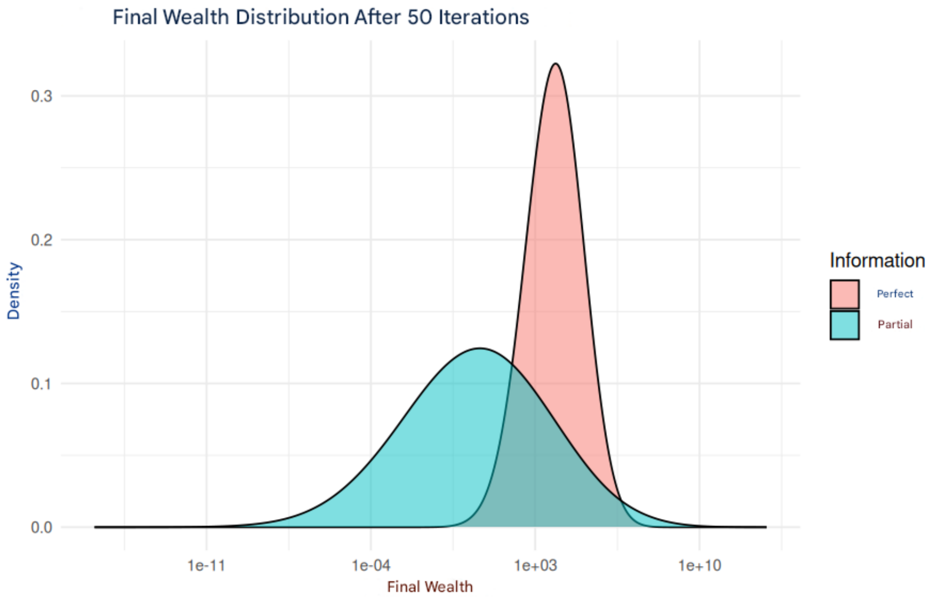


Figure 2: Final Wealth Distribution After 50 Iterations.

Figure 3 explores how the median logarithmic return, after deducting the cost of information, varies according to the number of bits of information acquired. The ordinate corresponding to an abscissa value $s$ is the median of the values of the net logarithmic return conditional on information of at least $s$ bits:

$$\text{Median Log Return}(s) = \text{median}(\text{Net Log Return} \mid \text{sapiens info} \geq s \text{ bits}) \tag{7}$$

Initial wealth is fixed at $W_{\text{initial}} = 100$ units, and the simulation extends over a maximum number of 50 iterations per bet. The parameter $b = 1$ represents a net gain of 1 for each successful bet. The true probability of winning, $p$, varies randomly in the interval $[0.5, 1.0]$, simulating an uncertain environment, while the estimated probability $q$ also follows a random distribution in the same interval to reflect the variability of the individual's estimation. The unit cost per bit of information is fixed at $c = 0.5$, which means that acquiring more precision in the estimation entails a linearly increasing cost, proportional to the number of bits of information obtained to refine the value of $p$.

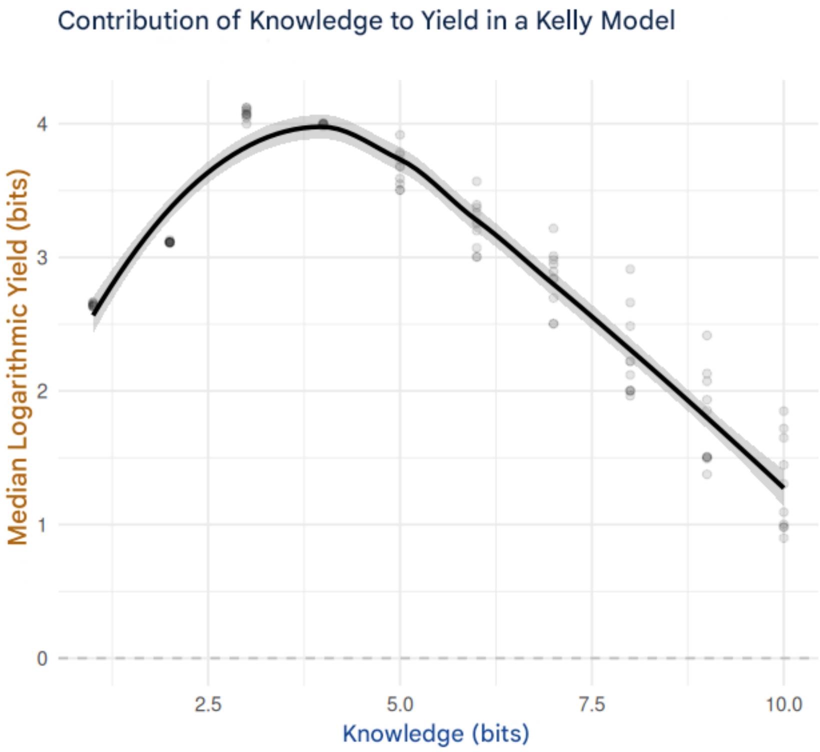


Figure 3: Contribution of Knowledge to Yield in a Kelly Model

The fact that the variance of the estimation increases with knowledge is merely a property of the estimation method used, and not a property of the studied phenomenon. In Figure 3, we observe the phenomenon anticipated by Professor Hugo Chapdelaine [Chap2024]: the return of the system increases with the accumulation of knowledge, but only up to an optimal saturation point. Beyond this maximum value, the return begins to decrease and crosses a threshold from which the acquisition of knowledge becomes counterproductive. This reversal illustrates how, past a certain level of information, the cost of observation exceeds the benefits, making additional knowledge harmful to the net return of the system.

The next steps of the project would consist of extending the Kelly model to more general cases, by integrating ecological models commonly studied in the literature, while taking into account the pollution cost associated with the acquisition of scientific knowledge about the environment.

## References


- [Chap2024] Chapdelaine, Hugo, Personal communication. October 2024.
- [Den2005] Dent, Eric B. "The observation, inquiry, and measurement challenges surfaced by complexity theory." Managing the Complex: Philosophy, Theory and Practice. Greenwich: IAP (2005): 253-268 .
- [Heg2011] Hegyi, Gergely, and László Zsolt Garamszegi. "Using information theory as a substitute for stepwise regression in ecology and behavior." Behavioral Ecology and Sociobiology 65 (2011): 69-76.
- [Jør2004] Jørgensen, Sven E., and Brian D. Fath. "Application of thermodynamic principles in ecology." Ecological complexity 1, no. 4 (2004): 267-280.
- [Kel1956] Kelly, John L. "A new interpretation of information rate." The Bell System Technical Journal 35, no. 4 (1956): 917-926.
- [Mich2005] Michaelian, Karo. "Thermodynamic stability of ecosystems." Journal of Theoretical Biology 237, no. 3 (2005): 323-335.
- [Niel2020] Nielsen, Søren Nors, Felix Müller, Joao Carlos Marques, Simone Bastianoni, and Sven Erik Jørgensen. "Thermodynamics in ecology—An introductory review." Entropy 22, no. 8 (2020): 820.
- [Sch2012] Schrödinger, Erwin. What is life?: With mind and matter and autobiographical sketches. Cambridge University Press, 2012.
- [Svir2000] Svirezhev, Yuri M. "Thermodynamics and ecology." Ecological Modelling 132, no. 1-2 (2000): 11-22.
- [Ulan2001] Ulanowicz, Robert E. "Information theory in ecology." Computers & chemistry 25, no. 4 (2001): 393-399.