What Makes the Behavior of a System Predictable?

Can the complex system approach be useful to you?

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Linear models

- AR, MA, ARMA, ARIMA,…

\[
\left(1 - \sum_{i=1}^{p} \phi_i L^i \right) (1 - L)^d X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i \right) \varepsilon_t
\]

- linear trends

- linear correlation

- extrapolations work as long as there is not a change of trend, of regime

\[
m_t \equiv \frac{1}{B(t, t)} \sum_{i<t} B(i, t) r_i
\]
Low dimensional chaos

• Local vs global prediction methods
• Parameter estimations in the presence of noise
  – leads to inconsistent MLE
  – confluence analysis
• Local vs global prediction

\[ S_i = x_i + \eta_i, \]
\[ x_{i+1} = F(x_i, a) \equiv 1 - ax_i^2 \]


• Most systems are NOT low dimensional!
• Large scale “coherent structures”
Bilinear stochastic models

\[ r(t) = e(t) + be(t - 1)e(t - 2) \]

\[ e(t) \text{ is i.i.d. with std } = s \]

The simplest case of the class of “Volterra discrete series”

\[ x(t) = H_1[e(t)] + H_2[e(t)] + H_3[e(t)] + \cdots + H_n[e(t)] \]

\[ H_n[e_{t,\Sigma}] = \sum_{j_1=0}^{+\infty} \cdots \sum_{j_n=0}^{+\infty} h_n(j_1, \ldots, j_n)e_{t-j_1} \cdots e_{t-j_n} \]

- Zero linear correlation at all lags
- Non-zero three-point correlation function

\[ E[r(t - 2) r(t - 1) r(t)] = bs^3 \]

(some) **NONLINEAR** predictability!

**Bilinear stochastic models**

\[ r(t) = e(t) + be(t - 1)e(t - 2) \]

\( e(t) \) is i.i.d. with std = s

Problems: (i) estimation of b and s; (ii) derive e(t), e(t-1),..., from r(t), r(t-1)...

\[ e(u) = r(u) + b'e(u - 1)e(u - 2); \quad u = 1, 2, \ldots, \]

where \( b' = -b \).

Impulse response to:

\[ r(u) = \begin{cases} a; & a > 0; u = 1, 2; \\ 0; & u \neq 1, 2, \end{cases} \]

\[ |e(u)| = |b|^\Gamma(u) a^{\Gamma(u)+1} = a(|b|a)^\Gamma(u) \]

\[ \Gamma(k) = (1/\sqrt{5})[(1 + \sqrt{5})/2]^k - (1/\sqrt{5})[(1 - \sqrt{5})/2]^k \]

Conclusions: (i) explosive exp(exp) sensitivity on initial conditions for \( a|b|>1 \) (ii) the probability for a stable inversion depends on the length of the realization (not warranted with certainty: strong sample to sample fluctuations)
Hierarchical complexity

- (low-dimensional) chaos
- Spatio-temporal chaos
- Turbulence
- Complex systems
Algorithmic complexity theory: most complex systems have been proved to be computationally irreducible, i.e. the only way to decide about their evolution is to actually let them evolve in time.

The future time evolution of most complex systems appears inherently unpredictable.
A new kind of Science?

Stephen Wolfram (Mathematica)

All in one: the simple 'rule 110' can perform the same range of calculations as any physical computer.
Lesson from bottom-up hierarchical grouping

Computational Irreducibility and the Predictability of Complex Physical Systems

256 nearest neighbor 1D cellular automata (Wolfram)

Class 3  
Class 1

N-block approach with N=2, 3 or 4

240 coarse-grainable

Coarse-graining rule 110: CIR => C1

Lesson from bottom-up hierarchical grouping

FIG. 1. Examples of coarse-graining transitions. (a) and (b) show coarse-graining rule 146 by rule 128. (a) shows results of running rule 146. The top line is the initial condition and time progress from top to bottom. (b) shows the results of running rule 128 with the coarse-grained initial condition from (a). (c) and (d) show coarse-graining rule 105 by rule 150. (c) shows rule 105 and (d) shows rule 150.

\[ C(f^T_A a(0)) = f^t_B C(a(0)). \]

Namely, running the original CA for \( T t \) time steps and then coarse-graining is equivalent to coarse-graining the initial condition and then running the modified CA \( t \) time steps. The constant \( T \) is a time scale associated with the coarse graining.

FIG. 2. Coarse-graining transitions within the family of 256 elementary CA. Only transitions with a cell block size \( N = 2, 3, \) and \( 4 \) are shown. An arrow indicates that the origin rules can be coarse grained by the target rules and may correspond to several choices of \( N \) and \( P \).

N-block approach with N=2, 3 or 4

Coarse-graining rule 110: CIR => C1

Navot Israeli and Nigel Goldenfeld PhysRevLett.92.074105
Complexity vs simplicity of gas law

• Extraordinary complexity of the $10^{25}$ trajectories of molecules in this room (maximum complexity and unpredictability)

• Contrast with “ideal gas law” \[ pV = nRT \]

or even Van der Waals equation

**Physics works** and is not hampered by computational irreducibility because we only ask for answers at some coarse-grained level.  \(^{10}\)
Black Swan Uncertainty

1. 95 Red, 5 White

3. Taleb’s demon

5. 

2. White 5% Red 95%

4. Odds of a white?

6. Odds of a black?

The Black Swan: The Impact of the Highly Improbable, by Nassim Nicholas Taleb

courtesy P. Taylor
Self-organized criticality

Earthquakes Cannot Be Predicted
Robert J. Geller, David D. Jackson, Yan Y. Kagan, Francesco Mulargia
Science 275, 1616-1617 (1997)

Turcotte (1999) Grid = 50 x 50

Best fit line
slope = -1.03
log10(N) = -1.03*log10(A) + 2.99

Cumulative number of earthquakes
Magnitude (M)

Intermediate
Shallow
Deep
Heavy tails in pdf of earthquakes

Heavy tails in pdf of seismic rates

Heavy tails in pdf of rock falls, Landslides, mountain collapses

Turcotte (1999)
Heavy tails in pdf of forest fires


Heavy tails in pdf of Solar flares

(Newman, 2005)

Heavy tails in pdf of Hurricane losses

Damage values for top 30 damaging hurricanes normalized to 1995 dollars by inflation, personal property increases and coastal county population change

\[ Y = M_0 X^{M_1} \]

- \( M_0 = 57911 \)
- \( M_1 = -0.80871 \)
- \( R = 0.97899 \)

Heavy tails in pdf of rain events

Peters et al. (2002)
Fig. 2. Tail cumulative distribution function of U.S. firm sizes, by receipts in dollars. Data are for 1997 from the U.S. Census Bureau, tabulated in bins whose width increases in powers of 10. The solid line is the OLS regression line through the data and has slope of 0.994 (SE = 0.064; adjusted $R^2 = 0.976$).
Heavy-tail of pdf of book sales

Heavy-tail of pdf of health care costs

Heavy-tail of pdf of terrorist intensity

Heavy-tail of pdf of war sizes
Heavy-tail of cdf of cyber risks

ID Thefts

Heavy-tail of YouTube view counts

Software vulnerabilities

Number

After-tax present value in millions of 1990 dollars

Heavy-tail of Pharmaceutical sales

Exponential model 1
data

Exponential model 2
Dragons and PREDICTION
Beyond power laws: six examples of “Dragons”


Population geography: Paris as the dragon-king in the Zipf distribution of French city sizes.

Material science: failure and rupture processes.

Hydrodynamics: Extreme dragon events in the pdf of turbulent velocity fluctuations.

Brain medicine: Epileptic seizures

Geophysics: Gutenberg-Richter law and characteristic earthquakes.
Crashes as “Black swans”?

Traditional emphasis on Daily returns do not reveal any anomalous events


“Black swans”
Better risk measure: drawdowns
A. Johansen and D. Sornette, Stock market crashes are outliers, European Physical Journal B 1, 141-143 (1998)


\[ N (DD) = A \exp \left( -\left( |DD|/\chi \right)^\zeta \right). \]
“Dragons” of financial risks
(require special mechanism and may be more predictable)
The market is never following the average growth; it is either super-exponentially accelerating or crashing.

Patterns of price trajectory during 0.5-1 year before each peak: Log-periodic power law.
Beyond power laws: six examples of “Dragons”


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Brain medicine: Epileptic seizures

Geophysics: Gutenberg-Richter law and characteristic earthquakes.
Paris as a king-dragon

Fig. 7. French agglomerations: stretched exponential and “King effect”.

Beyond power laws: six examples of “Dragons”


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Material science: failure and rupture processes.

Hydrodynamics: Extreme dragon events in the pdf of turbulent velocity fluctuations.

Brain medicine: Epileptic seizures

Geophysics: Gutenberg-Richter law and characteristic earthquakes.
Fig. 4. Frequency of elastic shocks under increasing stresses in materials with different heterogeneity. From Mogi [1962]
Energy distribution for the [±62] specimen #4 at different times, for 5 time windows with 3400 events each. The average time (in seconds) of events in each window is given in the caption.

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Hydrodynamics: Extreme dragon events in the pdf of turbulent velocity fluctuations.

Brain medicine: Epileptic seizures

Geophysics: Gutenberg-Richter law and characteristic earthquakes.
Mathematical Geophysics Conference   Extreme Earth Events
Villefranche-sur-Mer, 18-23 June 2000
Fig. 3.2. Apparent probability distribution function of the square of the fluid velocity, normalized to its time average, in the eleventh shell of the toy model of hydrodynamic turbulence discussed in the text. The vertical axis is in logarithmic scale such that the straight line, which helps the eye, qualifies as an apparent exponential distribution. Note the appearance of extremely sparse and large bursts of velocities at the extreme right above the extrapolation of the straight line. Reproduced from [252].
Pdf of the square of the Velocity as in the previous figure but for a much longer time series, so that the tail of the distributions for large fluctuations is much better constrained. The hypothesis that there are no outliers is tested here by collapsing the distributions for the three shown layers. While this is a success for small fluctuations, the tails of the distributions for large events are very different, indicating that extreme fluctuations belong to a different class of their own and hence are outliers.

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Geophysics: Gutenberg-Richter law and characteristic earthquakes.
Epileptic Seizures – Quakes of the Brain?

with Ivan Osorio
KUMC & FHS
Mark G. Frei - FHS
John Milton - The Claremont Colleges

(arxiv.org/abs/0712.3929)

Focus

Key: L=Left
R=Right
A=Anterior
M=Mesial
P=Posterior
D=Depth
T=Temporal
F=Frontal
Bursts and Seizures
Gutenberg-Richter distribution of sizes

- PDF estimates
- Event Size: $S/S_0$ (N-m), $E$ (s)
- SCSN '84–'00: Seismic Moment PDF
- Human Seizures: Total Energy PDF
- Slope: $\beta + 1 = 1.67$

Omori law: Direct and Inverse

- The longer it has been since the last event, the longer it will be since the next one!

pdf of inter-event waiting times

- Inter-Seizure Cdf
- Inter-Castie-Interval(s)
- Expected Time (s) to next EQ w/ M ≥ 2

Unconditional Expected Waiting Time

- Time (s) since last EQ
- Expected Time (s) to next EQ
19 rats treated intravenously (2) with the convulsant 3-mercapto-propionic acid (3-MPA)
Distribution of inter-seizure time intervals for rat 5, demonstrating a pure power law, which is characteristic of the SOC state. This scale-free distribution should be contrasted with the pdf’s obtained for the other rats, which are marked by a strong shoulder associated with a characteristic time scale, which reveals the periodic regime.
The pdf’s of the seizure energies and of the inter-seizure waiting times for subject 21.

Note the shoulder in each distribution, demonstrating the presence of a characteristic size and time scale, qualifying the periodic regime.

Some humans are like rats with large doses of convulsant.
Beyond power laws: six examples of “Dragons”


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Geophysics: Gutenberg-Richter law and characteristic earthquakes.
Complex magnitude distributions

Characteristic earthquakes?

Singh, et. al., 1983, BSSA 73, 1779-1796

Knopoff, 2000, PNAS 97, 11880-11884

Main, 1995, BSSA 85, 1299-1308

Wesnousky, 1996, BSSA 86, 286-291
Complex Systems approach to Prediction

- positive feedbacks
- non sustainable regimes
- rupture
For humans data at the time could not discriminate between:
1. exponential growth of Malthus
2. logistic growth of Verhulst

But data fit on animal population: sheep in Tasmania

- exponential in the first 20 years after their introduction and completely saturated after about half a century. => Verhulst
Symbiosis between human population growth and artifacts

- **Human propagation follows**
  
  rate of change of population = \( R(t) \times \text{population} \)

- **Assume increase in technology follows**
  
  rate of change of technology = \( C \times \text{population} \)

- **Assume also**
  
  \( R(t) = K \times \text{technology} \)

- **Implies double geometric growth**

  \[ \text{population} = \frac{A}{(t_c - t)} \]

  \( A = \text{const.} \)

  \( t = \text{time} \)

  \( t_c = \text{critical time} \)
Positive feedbacks

\[ \frac{dp}{dt} = cp^d \]

\[ p(t) = \left( \frac{c}{m} \right)^{-m} (t_c - t)^{-m} \]

\[ m = 1/(d - 1) > 0 \text{ and } t_c = t_0 + mp_0^{1-d}/c. \]

Faster than exponential transient unsustainable growth
Finite-time Singularity

- Planet formation in solar system by run-away accretion of planetesimals
- PDE’s: Euler equations of inviscid fluids and relationship with turbulence
- PDE’s of General Relativity coupled to a mass field leading to the formation of black holes
- Zakharov-equation of beam-driven Langmuir turbulence in plasma
- rupture and material failure
- Earthquakes (ex: slip-velocity Ruina-Dieterich friction law and accelerating creep)
- Models of micro-organisms chemotaxis, aggregating to form fruiting bodies
- Surface instability spikes (Mullins-Sekerka), jets from a singular surface, fluid drop snap-off
- Euler’s disk (rotating coin)
- Stock market crashes...
Simplest Example of a “More is Different” Transition

Water level vs. temperature

Extrapolation?
The breaking of macroscopic linear extrapolation

$95^\circ C$  $97$  $99$  $101$

BOILING PHASE TRANSITION

More is different: a single molecule does not boil at $100^\circ C^0$
Generically, close to a regime transition, a system bifurcates through the variation of a SINGLE effective “control” parameter

**Bifurcation:** Qualitative change in behavior as parameter is (slowly) varied  
**Bifurcation surface:** $B$

**Strategy 1:** understand from proximity to a reference point as a function of a small parameter

**Strategy 2:** a few universal “normal forms”

Space of all dynamical systems: $\mathcal{M}$  
a particular dynamical system: $M \in \mathcal{M}$

(after J. Crutchfield)
BIFURCATIONS, PHASE TRANSITIONS, CATASTROPHES, TIPPING POINTS...

Phase Transitions
Haken 1983 Synergetics: An Introduction Springer-Verlag
Kelso 1995 Dynamic Patterns MIT Press

Tap the left index finger in-phase with the tick of the metronome.

Try to tap the right index finger out-of-phase with the tick of the metronome.

(after Liebovitch)
As the frequency of the metronome increases, the right finger shifts from out-of-phase to in-phase motion.

(after Liebovitch)
This bifurcation can be explained as a change in a potential energy function similar to the change which occurs in a physical phase transition.

Order parameter: difference in phase between right and left fingers

(control parameter)

Frequency of metronome

Phase Transition
Haken 1983 Synergetics: An Introduction
Springer-Verlag
Kelso 1995 Dynamic Patterns MIT Press

(after Liebovitch)
Disorder: $K$ small

Renormalization group:
Organization of the description scale by scale

Critical:
$K =$ critical value

Order $K$ large

$s_i(t - 1) = \text{sign} \left( K \sum_{j \in N_i} s_j + \varepsilon_i \right)$
For much of Earth history, the climate has been considerably warmer than it is today. But 33.7 million years ago, at the Eocene-Oligocene boundary, the world became trapped in the glacial state that continues to this day.

Data from multiple ocean basins elucidate an ancient climate transition from greenhouse to icehouse.
SYNCHRONISATION AND COLLECTIVE EFFECTS IN EXTENDED STOCHASTIC SYSTEMS

Fireflies

Earthquake-fault model

FIG. 1. Evolution of the cumulative earthquake slip, represented along the vertical axis in the white to black color code shown above the picture, at two different times: (a) early time and (b) long time, in a system of size $L=90$ by $L=90$, where $\Delta t=1.9$ and $\beta=0.1$.

Miltenberger et al. (1993)
Dynamics of an order parameter (OP) and of the corresponding control parameter (CP): within the sandpile picture, $\frac{\partial h}{\partial x}$ is the slope of the sandpile, $h$ being the local height, and $S$ is the state variable distinguishing between static grains ($S = 0$) and rolling grains ($S \neq 0$).

Normal form of sub-critical bifurcation

$$\frac{\partial S}{\partial t} = \chi \{ \mu S + 2\beta S^3 - S^5 \} \tag{1}$$

where

$$\mu = \left[ \left( \frac{\partial h}{\partial x} \right)^2 - \left( \frac{\partial h}{\partial x} |_c \right)^2 \right] \tag{2}$$

and $\beta > 0$ (subcritical condition).

Diffusion equation

$$\frac{\partial h}{\partial t} = -\frac{\partial F(S, \frac{\partial h}{\partial x})}{\partial x} + \Phi \tag{3}$$

L. Gil and D. Sornette
Mechanism:
Negative effective Diffusion coefficient

System sizes range from $L/a = 64$ to 2048.

$$P(M) dM \approx M^{-(1+\mu)} dM.$$
FIG. 3. Distribution $P(J)$ of flux amplitudes at the right border, in the same conditions as for Fig. 1.
Generic phase diagram $\Rightarrow$ pdf (I)

Coupling strength increases
Generic phase diagram => pdf (II)

Coupling strength increases
Illustration: THE GREAT MODERATION

Source: SIR JOHN GIEVE, Deputy Governor, Bank of England, Feb 2009

Notes: Shaded bars indicate recessions. The dashed red line indicates the onset of the current recession. Volatility is computed using deviations of the GDP growth rate from a constant mean and a GARCH (1,1) with a 0.729 first-order serial correlation. Sources: Bureau of Economic Analysis; authors' calculations.

Illustration: The 2007-???? crisis

Non-Borrowed Reserves of Depository Institutions (BOGNONBR) continue to plummet. This makes sense as under capitalized banks continue to hemorrhage money via outright losses and write downs of over valued assets. The result is that these banks now have to borrow money from the Fed to maintain their reserves so that when you go to the ATM money actually comes out...

This also explains why all interbank lending rates from LIBOR and EURIBOR to HIBOR all did moonshots. You see, there were few banks capable of lending in any size, and even fewer willing.
The Disappearing Money Multiplier

Econ prof Bill Seyfried of Rollins College:
The M1 money multiplier just slipped below 1. So each $1 increase in reserves (monetary base) results in the money supply increasing by $0.95 (OK, so banks have substantially increased their holding of excess reserves while the M1 money supply hasn't changed by much).
Who initiates parturition?

You said how many weeks?

It’s about time

Figure 47-6. Changes in plasma levels of pregnancy hormones.
Generic Critical Precursors to a Bifurcation

Braxton hicks contractions

(Simple example of Catastrophe theory)

-Amplitude of fluctuations
-Response to external forcing


D. Sornette, F. Ferre and E.Papiernik
Mathematical model of human gestation and parturition: implications for early diagnostic of prematurity and post-maturity
Critical Precursory Fluctuations

\[
\frac{dA}{dt} = (\mu - \mu_c)A - \frac{A^3}{A_s^2} + f(t)
\]

Without NL term:

\[
A(t) = \int_0^t e^{-\delta(t-\tau)} f(\tau) \, d\tau
\]

\[
\delta = \mu_c - \mu
\]

\[
\langle [A(t)]^2 \rangle = \int_0^t d\tau \int_0^t d\tau' e^{-\delta(t-\tau)} e^{-\delta(t-\tau')} \langle f(\tau)f(\tau') \rangle
\]

\[
= D \int_0^t e^{-2\delta(t-\tau)} \, d\tau
\]

\[
\rightarrow \frac{D}{2(\mu_c - \mu)}
\]
Our prediction system is now used in the industrial phase as the standard testing procedure.

J.-C. Anifrani, C. Le Floc'h, D. Sornette and B. Souillard
Various Bubbles and Crashes

Each bubble has been rescaled vertically and translated to end at the time of the crash.
Fig. 1. (Color online) Plot of the UK Halifax house price indices from 1993 to April 2005 (the latest available quote at the time of writing). The two groups of vertical lines correspond to the two predicted turning points reported in Tables 2 and 3 of [1]: end of 2003 and mid-2004. The former (resp. later) was based on the use of formula (2) (resp. (3)). These predictions were performed in February 2003.

Fig. 5. (Color online) Quarterly average HPI in the 21 states and in the District of Columbia (DC) exhibiting a clear upward faster-than-exponential growth. For better representation, we have normalized the house price indices for the second quarter of 1992 to 100 in all 22 cases. The corresponding states are given in the legend.
Index price vs. time, Hang Seng

PDF of crash dates, Hang Seng

- 28 intervals such that:
  - t1 >= 2003-05-20 and
  - t2 >= 2007-07-08 and
  - t2 <= 2007-07-15
- 12 intervals have modeled crash dates <= 2008-01-15 (solid line at right)
- Analysis date (solid line at left): 2007.07.15
- Actual peak date (dash-dot line): 2007.10.30
- tc at max pdf (dashed line): 2007-10-04
- Median tc (dotted line): 2007-10-01
- 80-20 quantile range: 2007-08-31 - 2007-11-23

Source: R. Woodard (FCO, ETH Zurich)
Typical result of the calibration of the simple LPPL model to the oil price in US$ in shrinking windows with starting dates \( t_{\text{start}} \) moving up towards the common last date \( t_{\text{last}} = \text{May 27, 2008} \).

Eight reconstructed time series of abrupt climate shifts in the past. (A) The end of the greenhouse Earth, (M) the end of the Younger Dryas, (K) the Bolling-Allerød transition, (O) the desertification of North Africa, (I) the end of the last glaciation, and (G, E, and F) the ends of earlier glaciations. In all cases the dynamics of the system slow down before the transition, as revealed by an increasing trend in autocorrelation (B, D, F, H, J, L, N, and P). The gray bands identify transition phases. The arrows mark the width of the moving window used to compute slowness. The smooth gray line through the time series is the Gaussian kernel function used to filter out slow trends. Data in A come from tropical Pacific sediment core records, data in M are from the Cariaco basin sediment, data in K come from the Greenland GISP2 ice core, data in O from the sediment core ODP Hole 658C off the west coast of Africa, and data presented in C, E, G, and I are from the Antarctica Vostok ice core.
Eight reconstructed time series of abrupt climate shifts in the past. (A) The end of the greenhouse Earth, (M) the end of the Younger Dryas, (K) the Bølling-Allerød transition, (O) the desertification of North Africa, (I) the end of the last glaciation, and (G, E, and F) the ends of earlier glaciations. In all cases the dynamics of the system slow down before the transition, as revealed by an increasing trend in autocorrelation (B, D, F, H, J, L, N, and P). The gray bands identify transition phases. The arrows mark the width of the moving window used to compute slowness. The smooth gray line through the time series is the Gaussian kernel function used to filter out slow trends. Data in A come from tropical Pacific sediment core records, data in M are from the Cariaco basin sediment, data in K come from the Greenland GISP2 ice core, data in O from the sediment core ODP Hole 658C off the west coast of Africa, and data presented in C, E, G, and I are from the Antarctica Vostok ice core.
Third-party game calibration on a black-box game

**FIG. 1.** Estimation of the parameter set for the black-box game. The correlation between $N_{0-1}$ and $S_{0-1}$ is calculated over 200 time steps for an ensemble of candidate third-party games. The third-party game that achieves the highest correlation is the one with the same parameters as the black-box game.

Crash prediction

**FIG. 3.** Comparison between the forecast density function and the realized time series $H(t)$ for a typical large movement. The large, well-defined movement is correctly predicted. An AR(8)-based prediction has been included for comparison.
Decomposition of total action:

\[ A^{\mu_m}(t) \equiv A_{\text{coupled}}^{\mu_m}(t) + A_{\text{decoupled}}^{\mu_m}(t) \]  \hspace{1cm} (3)

Condition of certain predictability

\[ |A_{\text{decoupled}}^{\mu_m}(t+n+1)| > \frac{N}{2} \]

For \(N=25\) and \(N=102\), very small probability for these pockets of predictability to occur by chance (assuming decoupling between agents)

\[ Pr_{\text{pred}} < 7 \cdot 10^{-4} \text{ and } Pr_{\text{pred}} < 2.5 \cdot 10^{-15} \]
Mechanism for and Detection of Pockets of Predictability in Complex Adaptive Systems

FIG. 1: $A_{\text{decoupled}}$ defined in (3) as a function of time for the MG with $N = 101$, $s = 12$, $m = 3$. Circles indicate one-step prediction days, crosses are the subset of days starting a run of two or more consecutive one-step prediction days.

| $|A|$ | 0  | 0.5 | 1  | 1.5 | 2  | 2.5 | 3   | 3.5 | 4   | 4.5 |
|-----|----|-----|----|-----|----|-----|-----|-----|-----|-----|
| %   | 53 | 61  | 67 | 65  | 82 | 70  | 67  | 67  | 100 | 100 |
| Nb  | 62 | 49  | 39 | 23  | 17 | 10  | 6   | 3   | 2   | 1   |

TABLE I: Out-of-sample success rate % (second row) using different thresholds for the predicted global decoupled action (first row) of the third-party $S$-games calibrated to the Nasdaq Composite index. Nb (third row) is the number of days from $t = 62$ to 123 which have their predicted global decoupled action $|A_{\text{decoupled}}|$ larger than the value indicated in the first row.


A Mechanism for Pockets of Predictability in Complex Adaptive Systems
Predictability of large future changes in major financial indices

D. Sornette and W.-X. Zhou


Sparse-data pattern recognition method


PATTERN RECOGNITION APPLIED TO EARTHQUAKE EPICENTERS IN CALIFORNIA

I.M. GELFAND 1, Sh.A. GUBERMAN 1, V.I. KEILIS-BOROK 2, L. KNOPOFF 3, F. PRESS 4, E.Ya. RANZMAN 5, I.M. ROTWAIN 6 and A.M. SADOVSKY 2

1 Institute of Applied Mathematics, Academy of Sciences, Moscow (U.S.S.R.)
2 Institute of Physics of the Earth, Academy of Sciences, Moscow (U.S.S.R.)
3 Institute of Geophysics, University of California, Los Angeles, Calif. (U.S.A.)
4 Department of Earth and Planetary Sciences, Massachusetts Institute of Technology, Cambridge, Mass. (U.S.A.)
5 Institute of Geography, Academy of Sciences, Moscow (U.S.S.R.)
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Trait: array of answers to set of questions

Feature: a treat which is frequent in class I and unfrequent in class II

Alarm index(t): moving average of number of features at time t
A novel methodology: Reverse Tracing of Precursors (RTP), is developed for short-term (months in advance) earthquake prediction.

The RTP methodology uses increase of earthquake correlation range as a short-term premonitory signal.

An experiment in advance prediction has been launched in four seismically active regions around the World; first results are encouraging.

A case history:

Advance prediction of San Simeon (M6.5, Dec. 22, 2003)

- Precursor detected May, 2003
- Precursor reported to the group of experts in June, 2003
- San Simeon earthquake, M6.5 occurred on Dec. 22, 2003 within the alarm.

Potential applications to other geological, geotechnical disasters. Collaboration with experts in geodynamics, complex systems, pattern recognition, and disaster management from US, Russia, Japan, France, Italy and UN.
Parameter for positivity of crash hazard rate

\[ h(t) \geq 0. \]
\[ b = Bm - |C| \sqrt{m^2 + \omega^2} \geq 0 \]

Figure 1: Density distribution \( p(\omega|I \text{ or } II) \) of the DSI parameter \( \omega \) obtained from (1) and complementary cumulative distribution \( P(b|I \text{ or } II) \) of the constraint parameter \( b \) obtained from (2) for the objects in classes I (dotted, dashed, and dotted-dashed) and II (continuous) for three different values of \( t_i \).
Figure 2: Alarm times $t$ (or dangerous objects) obtained by the multiscale analysis. The alarms satisfy $b \geq 0$, $6 \leq \omega \leq 13$ and $0.1 \leq m \leq 0.9$ simultaneously. The ordinate is the investigation “scale” in trading day unit. The results are robust with reasonable changes of these bounds.
Extension to a multi-scale LPPL analysis with Gelfand’s method of pattern recognition to predict

Figure 3: (Color online) Alarm index $A(t)$ (upper panel) and the DJIA index from 1900 to 2003 (lower panel). The peaks of the alarm index occur at times indicated by arrows in the bottom panel.
We obtain very significant prediction gains.

Figure 5: Error diagram for our predictions for two definitions of targets to be predicted $r_0 = 0.1$ and $r_0 = 0.15$ obtained for the DJIA. The anti-diagonal line corresponds to the random prediction result. The inset shows the prediction gain.
Feynman's Appendix to the Rogers Commission Report on the Space Shuttle Challenger Accident

It appears that there are enormous differences of opinion as to the probability of a failure with loss of vehicle and of human life. The estimates range from roughly 1 in 100 to 1 in 100,000. The higher figures come from the working engineers, and the very low figures from management. What are the causes and consequences of this lack of agreement? Since 1 part in 100,000 would imply that one could put a Shuttle up each day for 300 years expecting to lose only one, we could properly ask "What is the cause of management's fantastic faith in the machinery?"

On January 28, 1986 seven crew members died when the space shuttle Challenger exploded just over a minute after take-off. The Report of the Presidential Commission on the Space Shuttle Challenger Incident (1986) concluded that neither NASA nor Thiokol, the seal designer, “responded adequately to internal warnings about the faulty seal design. . . . A well structured and managed system emphasizing safety would have flagged the rising doubts about the Solid Rocket Booster joint seal.”
Challenger disaster

Technical cause:
- failure of a pressure seal ("O-ring") in the aft field joint of the right solid rocket motor
- Solid rocket motor assembled from four cylindrical sections, 25 feet long, 12 feet diameter, containing 100 tons of fuel
- 2 O-rings seal gaps in the joints caused by pressure at ignition

Factors:
- temperature: cold reduces resiliency of the O-ring
- chance of O-ring failure increased by test procedures causing blow holes in the putty used to pack the joint

But this was just the point failure…
Finding patterns to predict RISKS

O-ring damage index, each launch

Temperature (°F) of field joints at time of launch

26°–29° range of forecasted temperatures (as of January 27, 1986) for the launch of space shuttle Challenger on January 28

EDWARD R. TUFTET

VISUAL AND STATISTICAL THINKING:
DISPLAYS OF EVIDENCE FOR MAKING DECISIONS
Finding patterns to predict RISKS

“The dog that did not bark” (Sherlock Holmes)

Edward R. Tufte

Visual and Statistical Thinking: Displays of Evidence for Making Decisions
A Formalized Iterative Approach to Verification and Validation (V&V), with Examples

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Summary

• A four-step approach for a quantitative validation step:
  1. Start with a prior “potential trust” of a model’s value: $V_{prior}$.
  2. Conduct an experiment, use the model, compare results.
  3. Grade the comparison between data $y_{obs}$ and model $M$.
  4. Update posterior “trust”: $V_{posterior}/V_{prior} = F[p(M|y_{obs}), q; c_{novel}]$
     – The multiplier $F$ must satisfy certain (plausible) constraints.

• Iterate the validation process:
  
  $V^{(1)}_{prior} \rightarrow V^{(1)}_{posterior} = V^{(2)}_{prior} \rightarrow V^{(2)}_{posterior} = V^{(3)}_{prior} \rightarrow ... \rightarrow V^{(n)}_{posterior}$

• 4 simplified examples—using discrete values of $p/q$ and $c_{novel}$—illustrated the nature of this process.
  
  ➢ Olami-Feder-Christensen model of seismicity
  ➢ Compressible CFD code for Richtmyer-Meshkov instability (induced mixing and shock tests)
  ➢ Multifractal random walk as a model of financial returns
  ➢ Anomalous diffusion as a model for solar reflectivity in cloudy atmosphere

A Formalized Iterative Approach to Verification and Validation (V&V), with Examples

### Validation as a Constructive Iterative Process

<table>
<thead>
<tr>
<th>n</th>
<th>Test Description</th>
<th>(c_{\text{novel}})</th>
<th>(p/q)</th>
<th>(V_{\text{before}}^{(n)} = V_{\text{after}}^{(n-1)})</th>
<th>(F(...))</th>
<th>(V_{\text{after}}^{(n)})</th>
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