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THE PREDICTION OF CRITICAL TRANSITIONS IN COMPLEX SYSTEMS: COLLIDING CASCADES MODEL AND REAL DISASTERS

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'The reactions and the attitudes with respect to such complexity are linked between two extremes: on the one hand there is the person who identifies as the sole possible solution to the problem a meticulous treatment of every process operating on the...system; on the other hand there is the person who sees the only hope as lying in "guessing" the right equations.'
(G. Puppi and A. Speranza)

1. Introduction

One of the most important and least understood features of complex systems is *the persistent re-occurrence of abrupt overall changes*, called 'critical transitions' or 'critical phenomena'. At the applied level they are referred to as crises, catastrophes, and disasters. In this paper I will consider hierarchical dissipative complex systems, which play an important role in the global village. Among such systems are the *Earth's crust*, prone to geological disasters, which in turn trigger ecological and socio-economic catastrophes; the *economy*, prone to depressions; *society*, prone to bursts of large-scale violence; the *mega-city*, on its way to self-inflicted collapse; etc.

As in the case of the study of gravity at the time of T. Brahe and J. Kepler, the study of such systems is at the 'pre-equation stage': the heuristic search for major regularities necessary for the development of a fundamental theory. At this stage, prediction is necessary to achieve a fundamental understanding of the system, as well as to reach the practical goal of being prepared for disasters.

The problem. Complex systems are not predictable with absolute precision in the Laplacean sense. However, after a coarse-graining (averaging), the regular behaviour patterns emerge; among them are scenarios of the development of critical transitions. The problem of prediction – the focus of this paper – is then posed as a consecutive, step-by-step reduction of the time-space domain, where a critical transition has to be expected (Keilis-Borok, 1996, 1990, 1999). At each step we consider the system at different levels of averaging, in a 'holistic' approach – from the whole to details. Coarse-graining limits the accuracy of prediction, but it remains important at a practical level (Molchan, 1990, 1991, 1997).

The division into consecutive approximations is dictated by the stage-by-stage development of critical transitions (Kossobokov *et al.*, 1999). At the same time this division corresponds to the needs of disaster preparedness (Kantorovich and Keilis-Borok, 1991).

A more specific version of this problem is reviewed here. Consider the dynamics of a system. Let t be the current moment in time, m – the scale ('magnitude') of a critical transition. Given the behaviour of the system prior to t, our problem is *to decide whether a critical transition with magnitude* $m>m_0$ *will occur or not during the subsequent time interval* $(t, t+\Delta)$. In other words, we have to localise in time-space a specific singular trait of the process. This formulation is considerably different from a more traditional one – the extrapolation of a process in time. The decision rule is called *the prediction algorithm* (an example is described in 2.3.2).

The dual nature of critical transition. The phenomena precursory to critical transitions were first encountered in seismicity, where the critical transitions are strong earthquakes (Keilis-Borok ed., 1990). Mathematical modelling and the analysis of real data show that these phenomena are partly 'universal', common to complex systems with different origins. Against this background the system-specific precursors emerge.

Relevance to statistical physics. The premonitory seismicity patterns discussed below are qualitatively reminiscent of the asymptotic behaviour of a system near the point of phase transition of the second kind. However, our problem is unusual for statistical physics: we do not consider the equilibrium state but the growing *disequilibrium*, which culminates in a critical transition.

Raw data include the observable background ('static') activity of the system and the external factors affecting it. Examples of the static are small earthquakes; variations in macroeconomic indicators; flow of misdemeanors; etc. The static in hierarchical systems may include critical transitions of a smaller magnitude, which form their own hierarchy (Holland, 1995); the same phenomenon may be regarded as a part of the static for the whole system and as a critical transition for some part of the system.

Pattern recognition. Having to be heuristic, the data analysis is based on the 'pattern recognition of infrequent events' – the methodology developed by the school of I. Gelfand (Gelfand *et al.*, 1976). It allows us to overcome the complexity and imprecision of the data in situations where the data are insufficient for more traditional statistical analysis.

The performance of a prediction algorithm is quantitatively characterised by the rate of false alarms, the rate of failures to predict, and the total volume of alarms (see 2.3.2). The trade-off between these characteristics is summed up by *error diagrams*. They also provide an interface between prediction and preparedness (Molchan, 1997, Kantorovich and Keilis-Borok, 1991).

Validation: ('with four exponents I can fit the elephant', E. Fermi). Inevitably, in the absence of adequate fundamental equations there is some freedom in the design of a prediction algorithm. The validation of the algorithms, taking a lion share of the efforts, involves the following three stages:[1]

(*i*) '*Sensitivity analysis*': Retrospective check as to whether the performance is insensitive to variations in the raw data and in adjustable numerical parameters.

(*ii*) '*Out of sample*' retrospective evaluation of performance through independent data not used in the design of the algorithm.

(*iii*) *Advance prediction* – the only decisive test of a prediction algorithm.

Content. *Section 2* describes the recently developed *model of colliding cascades* propagating in hierarchical chaotic systems (Gabrielov *et al.*, 2000a, 2000b, 2001, Zaliapin *et al.*, 2001a, 2001b). This is one of the lattice models of a statistical physics type intensely used in the study of critical transitions. We here consider that specific model because it exhibits a wide set of known precursors to a critical transition (Keilis-Borok, ed., 1990, 1999) and some unknown precursors to be tested by observation. The next two sections demonstrate prediction of the real (observed) critical transitions. *Section 3* discusses earthquakes. *Section 4* deals with economic recessions and unemployment.

[1] *Each* algorithm described below was validated at the first two stages and tested by advance prediction. Hereafter this point will not be repeated, so as to avoid monotonous repetitions.

2. Colliding cascades

The model of colliding cascades (Gabrielov *et al.*, 2000a, 2000b, 2001, Zaliapin *et al.*, 2001a, 2001b) summarises the three major factors responsible for the generation of critical transitions in complex systems.

(*i*) *The hierarchical structure*. Specifically we consider the ternary tree shown in Fig. 1a.

(*ii*) '*Loading*' by external sources. The load is applied to the largest element and transferred downwards, thus forming direct cascades.

(*iii*) *The 'Failures'* of the elements under the load. The failures start from the smallest elements and gradually expand upwards the hierarchy, thus forming inverse cascades. A broken element eventually 'heals", which ensures the continuous operation of the system.

Cascades are realised through the interaction of adjacent elements, as shown in Fig. 1b. Direct and inverse cascades collide and interact: loading triggers the failures, while failures release and redistribute the load. The dynamics of the model are described in Gabrielov *et al.*, 2000a.

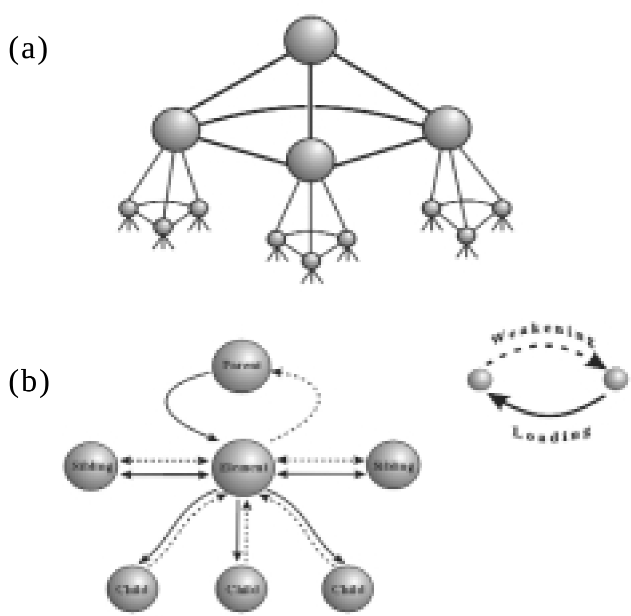

Figure 1. Structure of the colliding cascades model. a) Three highest levels of the hierarchy. b) Interaction with the nearest neighbors. [After Gabrielov *et al.* 2000b].

Fig. 2 shows an example of the sequence of failures. What is the relevance of this sequence (and of the whole model) to reality? The answer is that it fits the major heuristic constraints, derived from earthquake studies, and exhibits still unknown regularities, which can be tested through observation [acc, roc].

Separately, the cascades of each type have been intensely studied in many fields. Among classical examples are the direct cascades of eddies in the three-dimensional turbulent flow (Kolmogoroff, 1941a, 1941b, Frish, 1995), and inverse cascades in percolation (Stauffer and Aharony, 1992). Pioneering lattice models of seismicity (Burridge and Knopoff, 1967, Bak *et al.*, 1988, Allégre *et al.*, 1982) have been focused on the inverse cascades. This paper concerns a much less explored phenomenon – the *interaction* of direct and inverse cascades. It has also been considered in a model of magnetic field reversals (Blanter *et al.*, 1999).

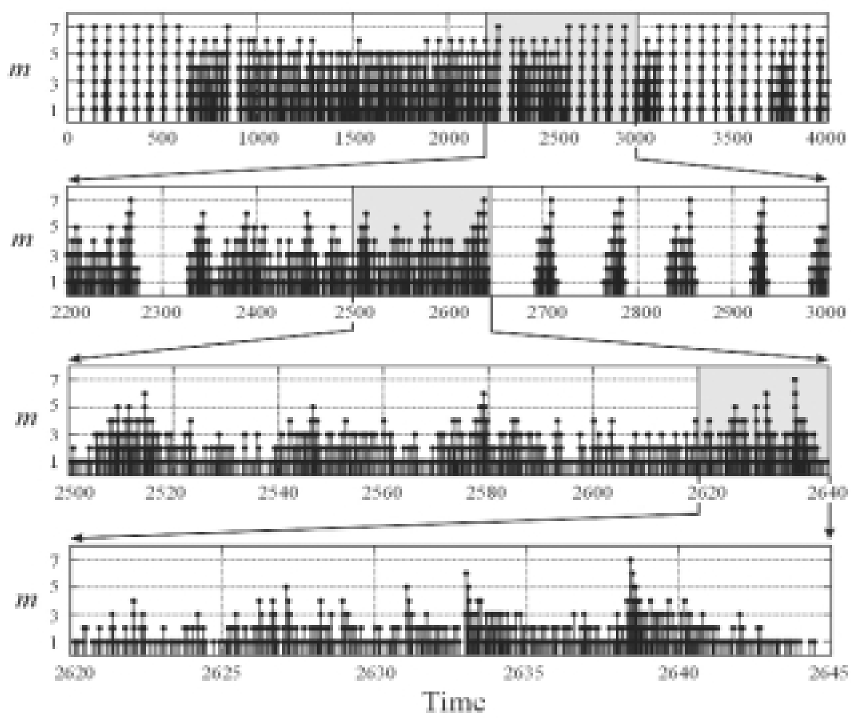

Figure 2. Synthetic earthquake sequence generated by the colliding cascades model. The complete sequence is shown in the top panel; exploded views - in the following three panels. [After Gabrielov *et al.* 2000b].

3. Earthquakes

2.1. *Definitions*

To interpret colliding cascades in terms of seismicity, we associate the loading with the impact of tectonic forces, and the failures with earthquakes. The simplest standard representation of an observed earthquake sequence is

$$\{t_k,\ m_k,\ g_k\},\ k = 1, 2,... \quad (1).$$

Here, t_k is the occurrence time of an earthquake; m_k is its magnitude, i.e. logarithmic measure of energy released by the earthquake; g_k indicates coordinates of the hypocenter; and k is the sequence number of an earthquake, $t_k \leq t_{k+1}$.

Identifying the failures in the model with the real (observed) earthquakes, we regard m as the magnitude; this is a natural analogy since the size of the rupture that originates a real earthquake is strongly correlated with magnitude. The position of an element in the tree is regarded as a hypocenter; this is an admittedly coarse analogy, since, strictly speaking, the model has no Euclidean hypocenter space.

2.2. *Heuristic constrains*

Synthetic sequence of failures, shown in Fig. 2, exhibits, upon averaging, the major regular features of observed seismicity: *seismic cycles, intermittency, scale invariance, and a specific kind of clustering* (Gabrielov *et al.*, 2000a, 2000b, 2001). (The reader will recognize also a qualitative similarity with many other processes, e.g. the dynamics of an economy). In the next section we describe one more constraint, central for the problem of prediction: the set of the spatio-temporal patterns of seismicity preceding a strong earthquake.

(*i*) *Seismic cycles*. Our synthetic sequence is dominated by easily identifiable cycles, each culminating in a major earthquake. A single cycle is shown in the bottom panel of Fig. 2. It comprises three consecutive phases (Scholz, 1990): an increasing level of seismic activity culminating in one or several major earthquakes; gradual decline of activity; and period of low activity, eventually followed by the next cycle.

(*ii*) *Intermittency of seismic regime.* From time to time the sequence of cycles abruptly changes its basic features: maximal magnitude, degree of periodicity, and duration of separate cycles (compare for example three intervals: 100-500, 1000-1200 and 1500-1700 in the top panel of Fig. 2).

(*iii*) *Scale invariance*. Typically for complex systems with persistent critical transitions, the distribution of the magnitude of earthquakes follows the power law, known in seismology as the Gutenberg-Richter relation:

$$dN(m) \sim 10^{-bm}\,\mathrm{d}m \qquad (2),$$

with the value of b being constant in considerable magnitude ranges (Gutenberg and Richter, 1954, Molchan and Dmitrieva, 1990, Turcotte, 1997, Kagan, 1999). This relation emerges after a sufficient averaging over territory and time. Fig. 3 shows that synthetic seismicity does follow this law (perhaps too perfectly); this is partly predetermined by the design of the model.

(*iv*) *Clustering*. Real earthquakes are clustered in time and space. The clustering is hierarchical, taking place in different scales. A most prominent type of clusters consists of a *main shock*, closely followed by a decaying sequence of weaker *aftershocks*. Also, about 30% of main shocks are close-

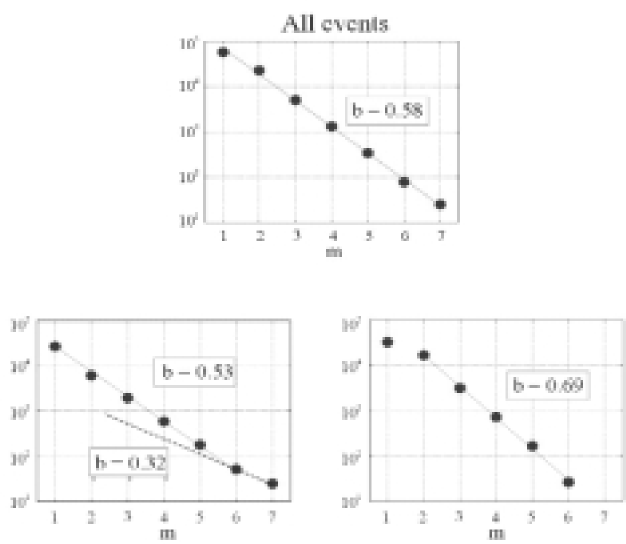

Figure 3. Magnitude distribution, log $N(m)$ = a - bm, $N(m)$ is the number of events with magnitude m. Note that the magnitude has discrete integer values from 1 to 7. a) All events. b) Main shocks. c) Aftershocks. [After Gabrielov *et al.* 2000b].

ly preceded by few weaker *foreshocks* (Molchan and Dmitrieva, 1990). The modeled sequence does exhibit the aftershocks as well as some other forms of clusters (Gabrielov *et al.*, 2000a). As in reality, the slope b in the distribution (2) is steeper for the aftershocks than for the main shocks (Fig. 3).

2.3. *Premonitory seismicity patterns*

2.3.1. Three types of premonitory phenomena. Studies of observed and modeled seismicity show that an earthquake of magnitude m_0 is preceded by certain patterns of seismicity in an area and magnitude range normalized by m_0. Specifically, these patterns reflect the following changes in seismicity (Keilis-Borok, 1994, 1996, Turcotte, 1997, Sornette and Sammis, 1995):

(*i*) Rise in the earthquakes' clustering in space and time.
(*ii*) Rise in the intensity of the earthquakes' flow.
(iii) Rise in the range of correlations between the earthquakes.

Premonitory patterns of the first two types belong to heuristic constrains for the model. They have been found mainly by the analysis of observations and are used in the intermediate-term earthquake prediction algorithms, with characteristic duration of alarms years (Keilis-Borok, ed., 1990, 1999). The third type of patterns has been found very recently in the CC model (Gabrielov *et al.*, 2000a, 2000b, 2001), although it was previously hypothesized in (Keilis-Borok 1994, 1996).

2.3.2. General scheme of prediction (Gabrielov *et al.*, 1986, Keilis-Borok, ed., 1990, Keilis-Borok and Shebalin, eds., 1999).

(*i*) *Areas.* The territory considered is scanned by overlapping areas; their size is normalised by the magnitude m_0 of the earthquakes targeted by prediction.

(*ii*) *Functionals.* An earthquake sequence in each area is described by a time function $F(t)$, depicting the premonitory changes of seismicity (see 2.3.1). Each type of change can be depicted by different functionals (for example; the clustering of the earthquakes may be measured by the generation of aftershocks and by the swarms of main shocks).

The functionals are also normalised by m_0.

(*iii*) *Premonitory patterns.* The emergence of a premonitory pattern in the area considered is recognised by the condition

$$F(t) \geq C_F \qquad (3).$$

The threshold C_F is an adjustable parameter. It is usually defined as a certain percentile of the functional *F*.

(*iv*) *Prediction algorithms*. An algorithm based on a single pattern is formulated as follows. Whenever $F(t) > C_F$, an alarm is declared for a time period Δ_F in the area considered. The prediction is *correct* if an earthquake with a magnitude belonging to the range (m_0, $m_0 + c$) occurs in that area and time interval; the opposite case is a *false alarm*. A *failure to predict* is the case where a major earthquake occurs outside of an alarm area and period.

Performance of an algorithm is quantitatively defined by three parameters: the rate of false alarms, the rate of failures to predict, and the total space-time, occupied by the alarms.

Most of the algorithms of that kind are based not on one but on several premonitory patterns. An alarm is declared when certain combinations of the patterns emerge (Gabrielov *et al.* 1986; Keilis-Borok, ed., 1996; Keilis-Borok & Shebalin 1999).

(*v*) *Robustness*. A highly complex process (an earthquake sequence) is described in this analysis by the few averaged functionals, which in turn are defined at the lowest (binary) level of resolution – above or below certain threshold. Predictions themselves are also binary, of a 'yes or no' kind, with unambiguous definition of the area and duration of alarm. The probabilistic aspect of prediction is reflected in the errors diagram, showing the tradeoff between the parameters characterising the performance of a prediction method (see item (*iv*) above).

Such robustness, usual in the exploratory data analysis (Gelfand *et al.*, 1976; Tukey, 1977), allows us to overcome the high complexity of the process considered and the chronic incompleteness of the data. This is achieved at a price, however: the limited accuracy of prediction.

2.3.3. *Application to synthetic seismicity*

The colliding cascades model reproduces the whole set of premonitory patterns described above. Prediction algorithms, based on each pattern, have been applied to synthetic earthquake sequence, as shown in Fig. 2 (Gabrielov *et al.*, 2000b). Prediction was targeted at the 25 'major earthquakes', with $m = 7$. For the patterns of the first two types, depicting clustering and level of seismic activity, we used the *a priori* definitions, developed in the analysis of observations (Keilis-Borok ed., 1990). For the patterns of the new type, depicting correlation range, we used definitions developed in (Gabrielov *et al.*, 2000a).

Fig. 4 summarises the performance of these patterns. The top panel shows, in separate boxes, the emergence of the patterns before each major earthquake. The bottom panel shows the false alarms. Evidently, most of them are close to the earthquakes with a magnitude of $m = 6$.

2.3.4. *Applications to real seismicity*

Premonitory patterns of the first two kinds have been subjected to tests by advance prediction worldwide by scientists from Russia, the USA,

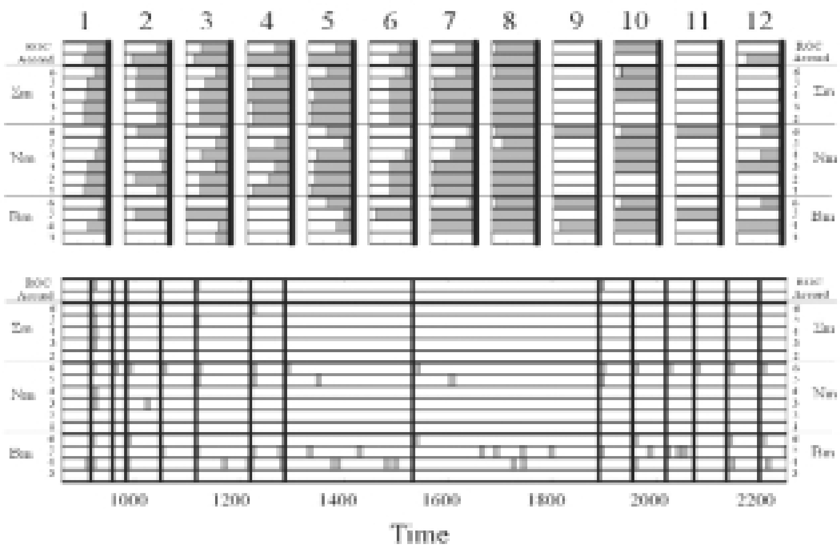

Figure 4. Collective performance of premonitory patterns. Prediction is targeted at the first 12 major events ($m = 7$) from synthetic sequence shown in Fig. 2. Figure juxtaposes alarms generated by all 17 precursors considered in Gabrielov *et al.* 2000b. The patterns *ROC* and *Accord* reflect correlation range, the patterns Σ and N – seismic activity, the pattern B – clustering (Gabrielov *et al.* 2000a, 2000b). The top panel shows, in separate boxes, emergence of precursors before each of major earthquakes in the synthetic sequence. The right edge of each box is the moment of a major earthquake. The time interval of three units is considered before each one. The bottom panel shows the alarms determined during the time periods when strong earthquakes did not occur; those are the false alarms. Vertical lines show the moments of events with magnitude $m = 6$. Evidently, $m = 6$ events are associated with most of the false alarms. Each row shows the track record of a single precursor. Shaded areas show the alarms determined by the precursor. Values of m indicate the magnitude range in which a precursor is determined. [After Gabrielov *et al.* 2000b].

France, Italy, and New Zealand; the tests, unprecedented in rigor and volume, established the high statistical significance of predictions (Molchan 1990; Kossobokov *et al.*, 1999; Vorobieva 1999; Harte *et al.* 2000 and references therein), though the probability gain is low so far, between 3 and 10. Among those predicted were 7 out of the last 8 strongest earthquakes, of magnitude 8 or more.[2]

Patterns of the third type have yet to be validated by observations. The first applications to observed seismicity, in S. California (Zaliapin *et al.* 2000) and Lesser Antilles (Shebalin *et al.* 2000), are encouraging.

Figs. 5-7 illustrate the predictions described above. Figure 5 shows successful prediction of the Sumatera earthquake $M = 8$ (Fig. 5, see p. XI). Figure 6 shows prediction of the second strong earthquake – Northridge – which followed the Landers earthquake within two years. Figure 7 depicts similarity of premonitory seismicity patterns preceding the Aquaba earthquake and a major starquake – the flash of energy radiated by a neutron star in the form of soft γ-rays repeaters (Kossobokov *et al.* 2000) (Fig. 7, see p. XI).

3. Recessions and unemployment

The lattice models used in the studies of seismicity (Burridge and Knopoff, 1967; Turcotte, 1997; Rundle *et al.*, 2000; Gabrielov and Newman, 1994; Shnirman and Blanter, 1999; Huang *et al.*, 1998), the colliding cascade model included, are not necessarily specific to seismicity only. The notions central in such models – *hierarchy, loading, failures, and healing* – might be interpreted in terms of different complex processes.[3] Here, we describe the application of similar approach to socio-economic predictions (Keilis-Borok *et al.*, 2000a, 2000b; Lichtman and Keilis-Borok, 1999; Lichtman, 1996).

3.1. *American economic recessions*

Each of the five recessions which have occurred in the USA since 1962 was preceded by a specific pattern of 6 macroeconomic indicators determined in Keilis-Borok *et al.*, 2000a. This pattern emerged within 5 to 13

[2] Results of that test are routinely available on the website: http://www.mitp.ru

[3] Hypothetically, we encounter in the studies reviewed here an ‘arithmetic’ of critical transitions – the basic precursory phenomena, common for a wide class of complex systems. However, if that is true, the universality is not unlimited: in the background of ‘universal’ precursors the system-specific ones do emerge (Keilis-Borok, ed., 1990, 1999).

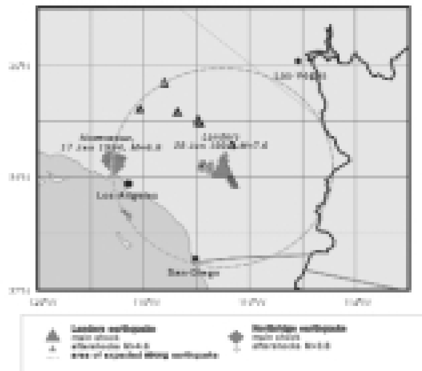

Figure 6. Prediction of the second strong earthquake. The Landers earthquake (28 June, 1992 M 7.6) was followed by the Northridge earthquake (17 January, 1994, M 6.8). The circle in the figure shows the territory, pointed by the algorithm, where occurrence of the second strong earthquake should be expected. [After Vorobieva, 1999].

months before each recession and at no other time, suggesting a hypothetical prediction algorithm. It has been put to the test by advance prediction beginning in 1996. Since then no more recessions have occurred, up to April 2001, when this is paper is being written, the algorithm has generated no alarms.

3.1.1. *Raw data.* The following routinely available monthly macroeconomic indicators have been analysed:

1. The difference between the interest rate on ten-year U.S. Treasury bonds, and the interest on federal funds on an annual basis.

2. The 'Stock-Watson index' of overall monthly economic activity. This is a weighted average of four measures, depicting employment, manufacturing output, and retail sales, which emphasise services.

3. The index of 'help wanted' advertising. This is put together by a private publishing company which measures the amount of job advertising (column-inches) in a number of major newspapers.

4. The average weekly number of people claiming unemployment insurance.

5. Total inventories in manufacturing and trade, in real dollars. This includes intermediate inventories (for example held by manufacturers, ready

to be sent to retailers) and final goods inventories (goods on shelves in stores).

6. The interest rate on ninety-day U.S. Treasury bills at an annual rate.

These indicators happen to be sufficient for prediction; other potentially relevant indicators have not yet been considered in this approach.

3.1.2. Hypothetical premonitory patterns. The premonitory behaviour of each indicator was defined (see 2.3.2) by a robust binary condition (3). An example is shown in Fig. 8a (see p. XII). It was found that the following patterns of the above indicators are premonitory, emerging more frequently as a recession approaches: a low value of indicator *1*; a strong downward trend of indicators *2* and *5*; and a strong upward trend of the three other indicators. Qualitatively, this would be expected from the nature of each indicator.

A hypothetical prediction algorithm based on these patterns generated retrospective alarms, juxtaposed with recessions in Fig. 8b (see p. XII). In the advance prediction such performance would be quite satisfactory.

Comparison with the more traditional multiregression analysis is summarised in Sect. 4 below.

3.2. *Unemployment*

Here, we summarise the study (Keilis-Borok *et al.*, 2000b) of the prediction of unemployment in Western Europe and USA. The targets of prediction are the formally defined episodes of a sharp increase in the rate of unemployment, named 'FAUs', 'Fast Acceleration of Unemployment'. The FAUs in France, Germany, Italy, and USA since the early sixties have been considered. Most of them are preceded by a uniform pattern of three macroeconomic indicators. A hypothetical prediction algorithm based on these patterns is put to the test by advance prediction.

3.2.1. Raw data. The algorithm is based on the following three indicators, selected to start with from many relevant ones:

1. The industrial production index, composed of weighted production levels in numerous sectors of the economy, in % relative to the index for 1990.
2. The long-term interest rate on ten-year government bonds.
3. The short-term interest rate on three-month bills.

3.2.2. The hypothetical premonitory pattern. Most of the FAUs considered are preceded by a steep increase of all three indicators. The corresponding (hypothetical) prediction algorithm has been developed for France and then applied to Germany, Italy and USA. The alarms determined by that algorithm are juxtaposed with FAUs in Fig. 9 (see p. XII). Such results would be quite satisfactory in real time prediction, and encourage the further tests of an algorithm. So far, only one prediction, for the USA, was made in advance (Fig. 10). An alarm was determined for the period from February to November 2000 (a shaded area in Fig. 10) and unemployment did start to rise in July 2000.

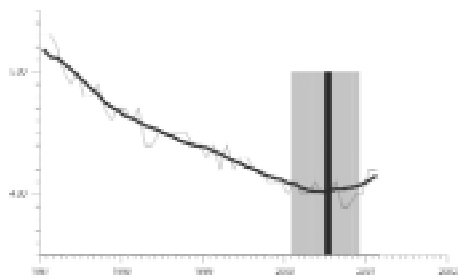

Figure 10. Unemployment rate in the U.S., July 2000: thin curve shows original data; thick curve show the rates with seasonal variations smoothed out. The gray bar shows the alarm period, defined by analysis of microeconomic indicators. The black bar – actual start of the unemployment rise, defined by analysis of monthly unemployment rates for the U.S. civilian labor force.

4. Summary

1. The following findings seem promising:

– In each case the prediction rule was uniform, transcending the immense complexity of the process considered, the diversity of the prediction targets, and the change of circumstances in time. For the earthquakes, premonitory seismicity patterns happen to be similar for microcracks in laboratory samples, the largest earthquakes of the world, in the energy range from 10^{-1} erg to 10^{26} erg; possibly, also, for ruptures in a neutron star, 10^{41}erg. For recessions and unemployment, similarity overcomes the changes in the economy since 1962; in the case of FAUs, the differences between countries as well.

– Prediction was based on the routinely available data - global catalogues of earthquakes, major macroeconomic indicators, etc.

– In each case, predictability was achieved by extremely robust analysis. It is interesting to quote how an economist with an excellent track record in the prediction of recessions describes his impressions of such a robustness: 'Prediction of recessions...requires fitting non-linear, high-dimensional models to a handful of observations generated by a possibly non-stationary economic environment...The evidence presented here suggests that these simple binary transformations of economic indicators have significant predictive content comparable to or, in many cases, better than that of more conventional models.' J.Stock, from Keilis-Borok *et al.*, 2000a.

The accuracy of prediction is limited. However, only a small part of relevant models and available data was used, so that a wealth of possibilities for better prediction remains unexplored.

2. A similar approach was successfully applied to the prediction of president and mid-term senatorial elections in the USA (Lichtman and Keilis-Borok, 1989; Lichtman, 1996).

3. Although, obviously, neither a panacea, nor an easy ride are implied, the approaches, discussed here, open up reasonable hope that we can break the current stalemate in disaster prediction.

4. The studies summarised here involve the cooperation of about twenty institutions in twelve countries and several international projects. Still, this review is not intended to be encyclopedic and covers a specific part of the much broader effort.

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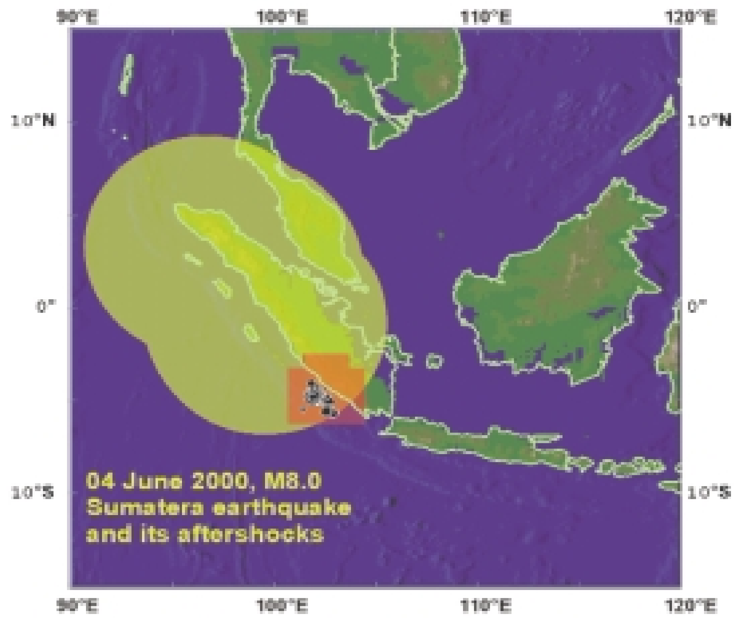

Figure 5. Successful advance prediction of the Southern Sumatera earthquake (4 June 2000, magnitude Ms = 8.0). The alarm areas in the first (M8 algorithm) and the second (MSc algorithm) approximations are highlighted by yellow and red respectively. [From the web site: http://www.mitp.ru].

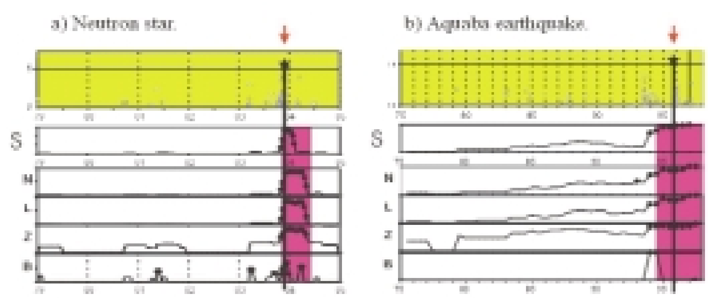

Figure 7. Similarity of premonitory seismicity patterns in Aquaba gulf (panel b) and on neutron star (panel a). Top - sequence of events. Major ones are shown by a star: Aquaba earthquake, 1995, energy ~ 10^{23} erg and the starquake recorded in 1983, energy ~ 10^{41} erg. Other boxes show premonitory patterns used in earthquake prediction. *S* depicts the change in energy distribution, *N* – the rate of earthquake occurrence, *L* – its deviation from long term trend, *Z* – concentration of events in space, *B* – clustering in space and time. Dots show the values, exceeding a standard threshold. [After Kossobokov *et al.* 2000].

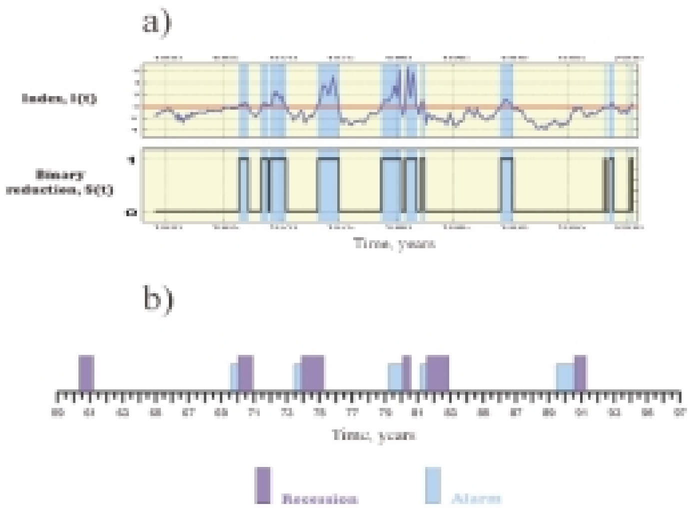

Figure 8. Prediction of US recession by premonitory patterns of 6 macroeconomic indicators. a) Each index *I(t)* is replaced by its binary representation *S(t)*. Here *I(t)* is the difference between the interest rate on short-term and long-term bonds. When $I(t)>0$ $S(t)=1$ (typical before recessions). When $I(t)<0$, $S(t)=0$. b) Performance of hypothetical prediction algorithm: an alarm is declared for 9 months when 4 or more indicators signal approach of a recession.

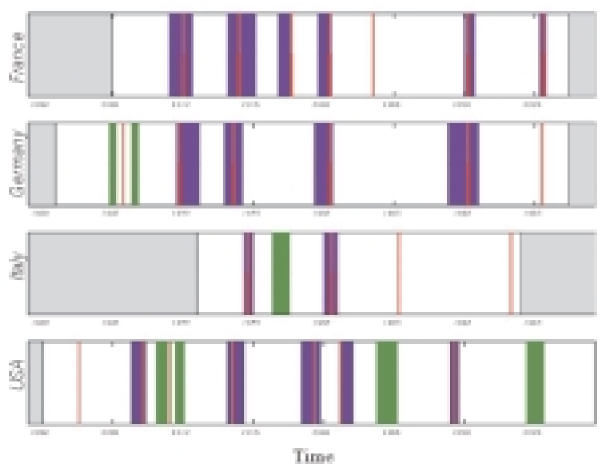

Figure 9. Prediction of fast acceleration of unemployment (*FAU*). Precursor is the steep rise of three national macroeconomic indicators. Red vertical lines – moments of FAU. Blue bars – periods of alarms. Green bars – false alarms. Gray areas on both sides – periods, for which the economic indicators were unavailable.