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Prediction of Extreme Events in Socio-economic Systems

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1. INTRODUCTION

At stake in the development of accurate and reliable methods of prediction for social systems is the capacity of scientific reason to improve the human condition. Today's civilization is highly vulnerable to crises arising from extreme events generated by complex and poorly understood systems. Examples include external and civil wars, terrorist attacks, crime waves, economic downturns, and famines, to name just a few. Yet more subtle effects threaten modern society, such as the inability of democratic systems to produce policies responsive to challenges such as climate change, global poverty, and resource depletion.

Our capacity to predict the course of events in complex social systems is inherently limited. However, there is a new and promising approach to predicting and understanding complex systems that has emerged through the integration of studies in the social sciences and the mathematics of prediction. This entry describes and analyzes that approach and its real-world applications. These include algorithmic prediction of electoral fortunes of incumbent parties, economic recessions, surges of unemployment, and outbursts of crimes. This leads to important inferences for averting and responding to impending crises and for improving the functioning of modern democratic societies.

That approach was successfully applied also to natural disasters such as earthquakes. Ultimately, improved prediction methods enhance our capacity for understanding the world and for protecting and sustaining our civilization.

Extreme events. Hierarchical complex systems persistently generate extreme events – the rare fast changes that have a strong impact on the system. Depending on connotation they are also known as critical phenomena, disasters, catastrophes, and crises. This study examines the development and application of the algorithmic prediction of extreme socio-economic and political events.

1.1 The Prediction Problem

The problem is formulated as follows:

given are time series that describe dynamics of the system up to the current moment of time t and contain potential precursors of an extreme event;

to predict whether an extreme event will or will not occur during the subsequent time period $(t, t + \tau)$; if the answer is "yes", this will be the "*period of alarm.*"

As the time goes by, predictions form a discrete sequence of alarms. The possible outcomes of such a prediction are shown in Fig. 1. The actual outcome is determined unambiguously, since the extreme events are identified independently of the prediction either by the actual happening (e.g. by an election result) or by a separate algorithm (e.g. homicide surge) after they occur.

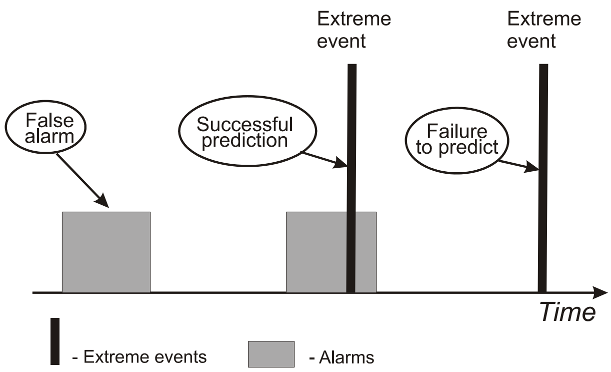

Figure 1 Possible outcomes of prediction

Such “yes or no” prediction is aimed not at analyzing the whole dynamics of the system, but only at identifying the occurrence of rare extreme events. In a broad field of prediction studies this prediction is different from and complementary to the classical Kolmogoroff – Wiener prediction of continuous functions, and to traditional cause-and-effect analysis.

The problem includes estimating the predictions’ accuracy: the rates of false alarms and failures to predict, and the total duration of alarms in % to the total time considered. These characteristics represent the inevitable *probabilistic component* of prediction; they provide for statistical validation of a prediction algorithm and for optimizing preparedness to predicted events (e.g. recessions or crime surges).

Twofold importance. Prediction problem is pivotal in two areas:

-- *Fundamental understanding of complex systems*. Prediction algorithms quantitatively define phenomena that anticipate extreme events. Such quantitative definition is pivotal for fundamental understanding of a complex system where these events occur, including the intertwined mechanisms of system’s development and its basic features, e. g. multiple scaling, correlation range, clustering, fragmentation etc. The understanding of complex systems remains a major unsolved problem of modern science, tantamount to transforming our understanding of the natural and human world.

-- *Disaster preparedness*. On the practical side prediction is pivotal for coping with a variety of disasters, commonly recognized as major threats to the survival and sustainability of our civilization (e.g. Keilis-Borok and Sorondo, 2000; Davis et al., 2010). The reliable advance prediction of extreme events can save lives, contribute to social and economic stability, and to improving the governing of modern societies.

1.2 Holistic Approach

Holistic approach (Farmer and Sidorowich, 1987; Ma et al., 1990; Kravtsov, 1993; Gell-Mann, 1994; Holland, 1995; Kadanoff, 1976; Crutchfield et al., 1986) is needed to reach predictability for complex systems. Natural science had for many centuries regarded the Universe as a completely predictable machine. As Pierre Simon de Laplace wrote in 1776, "…if we knew exactly the laws of nature and the situation of the universe at the initial moment, we could predict exactly the situation of the same universe at a succeeding moment." However, at the turn of the 20th century (1905) Jules Henry Poincare discovered, that "... this is not always so. It may happen that small differences in the initial conditions will produce very great ones in the final phenomena. Prediction becomes impossible".

This instability of initial conditions is indeed a definitive attribute of complex systems. Nonetheless, through the robust integral description of such systems, it is possible to discover their regular behavior patterns transcending the inherent complexity. For that reason studying complexity requires the holistic approach that proceeds from the whole to details, as opposed to the reductionism approach that proceeds from details to the whole. It is in principle not possible “to understand a complex system by breaking it apart” (Crutchfield et al, 1986).

Among the regular behavior patterns of complex systems are “premonitory” ones that emerge more frequently as an extreme event approaches. These premonitory patterns make complex systems predictable. The accuracy of predictions, however, is inevitably limited due to the systems’ complexity and observational errors.

Premonitory patterns and extreme events are consecutive manifestations of a system’s dynamics. These patterns may not trigger extreme events but merely signal the growth of instability, making the system ripe for the emergence of extreme events.

1.3 Methodology

The prediction algorithms described here are based on discovering premonitory patterns. The development of the algorithms requires the integration of complementary methods:

- theoretical and numerical modelling of complex systems; this includes "universal"models considered in statistical physics and non-linear dynamics (e.g. Burridge and Knopoff, 1967; Gell-Mann, 1994; Newman et al., 1994; Allègre et al., 1995; Holland, 1995; Blanter et al., 1997; Gabrielov et al., 2000a; Keilis-Borok and Soloviev, 2003), and system-specific models, if available;
- exploratory data analysis;
- statistical analysis of limited samples, which is relevant since the prediction targets are by definition rare;
- practical expertise, even if it is intuitive;
- risk analysis and theory of optimal control for optimizing prediction strategy along with disaster preparedness.

Pattern recognition of rare events. This methodology provides an efficient framework for integrating diverse information into prediction algorithms (Bongard et al., 1966; Gelfand et al., 1976; Keilis-Borok and Press, 1980). This methodology has been developed by the artificial intelligence school of I. Gelfand for the study of rare phenomena of a highly complex origin. In terminology of pattern recognition, the "object of recognition" is the time moment *t*. The problem is to recognize whether it belongs to the period of alarm, i.e. to a time interval Δ preceding an extreme event. An alarm starts when certain combinations of premonitory emerges.

Several features of that methodology are important for predicting extreme events in the absence of a complete closed theory that would unambiguously define a prediction algorithm. First, this kind of pattern recognition relies on simple, robust parameters that overcome the bane of complexity analysis – incomplete of the system's causal mechanisms and chronic imperfections in the available data. In its efficient robustness, pattern recognition of rare events is akin to exploratory data analysis as developed by J. Tukey (1977). Second, unlike other statistical methods, e. g. regression analysis, that methodology can be used for small samples such as presidential elections or economic recessions. Also, it integrates quantitative and judgmental parameters and thereby more fully capture the full dimensions of the prediction problem than procedures that rely strictly on quantitative variables.

Summing up, the methodology described here "can help forecasters when there are (1) many causal variables, (2) good domain knowledge about which variables are important, and (3) limited amounts of data" (Armstrong and Cuzan, 2005).

Besides societal predictions, pattern recognition of rare events has been successfully applied in seismology and earthquake predictions (e.g. Press and Briggs, 1975; Gelfand et al., 1976; Keilis-Borok and Press, 1980; Press and Allen, 1995; Keilis-Borok and Soloviev, 2003), geological prospecting (e.g. Press and Briggs, 1977) and in many other fields.

Validation of prediction algorithms. The algorithms include many adjustable elements, from selecting the data and defining the prediction targets, to specifying numerical parameters involved. In lieu of theory that would unambiguously determine these elements they have to be developed retrospectively, by "predicting" past extreme events. The application of the methodology to known events creates the danger of self-deceptive data-fitting: As J. Von Neumann put it "*with four exponents I can fit an elephant*". The proper validation of the prediction algorithms requires three consecutive tests:

- *sensitivity analysis*: testing whether predictions are sensitive to variations of adjustable elements;

- *out of sample analysis*: application of an algorithm to past data that has not been used in the algorithm's development; the test is considered successful if algorithm retains its accuracy;
- *predicting future events* – the only decisive test of a prediction algorithm.

A highly efficient tool for such tests is the error diagram, showing major characteristics of prediction accuracy (Molchan, 1990, 1991, 1994, 1997, 2003; Mason, 2003; Molchan and Keilis-Borok, 2008). Exhaustive sets of these tests are described in Gelfand et al. (1976), Gabrielov et al. (2000b), Zaliapin et al. (2003), Keilis-Borok and Soloviev (2003).

2. COMMON ELEMENTS OF DATA ANALYSIS

Methodology discussed above was used for predicting various kinds of extreme events, as illustrated in the next four Sections. Naturally, from case to case this methodology was used in different ways, according to specifics of phenomena considered. However in all cases data analysis has essential common elements described below.

Sequence of analysis comprises four stages: (i) defining prediction targets; (ii) choosing the data (time series), where premonitory patterns will be looked for and summing up a priory constrains on these patterns; (iii) formulating hypothetical definition of these patterns and developing prediction algorithm; determining the error diagram; (iv) validating and optimising that algorithm.

Preliminary transformation of raw data*.* In predicting recessions (Sect. III), fast acceleration of unemployment (Sect. IV) and crime surges (Sect. V) raw data were time series of relevant monthly indicators, hypothetically containing premonitory patterns. Let $f(m)$ be such an indicator, with integer m showing time in months. Premonitory behaviour of some indicators is better captured by their linear trends.

Let $W^{f}(l/q,p)$ be the local linear least-squares regression of a function $f(m)$ within the sliding time window (q, p):

$$W^{f}(l/q,p) = K^{f}(q,p)l + B^{f}(q,p),\ q \le l \le p, \tag{1}$$

where integers l, q, and p stand for time in months.

Premonitory behavior of most indicators was captured by two following two functions.

-- The trend of $f(m)$ in the s months long window, $(m\text{-}s+1,\ m)$. For brevity we denote

$$K^{f}(m/s) = K^{f}(m\text{-}s+1,m) \tag{2}$$

-- The deviation of $f(m)$ from extrapolation of its long-term regression (i.e. regression on a long time window $(q,\ m-1)$):

$$R^{f}(m/q) = f(m) - W^{f}(m/q,m\text{-}1). \tag{3}$$

Both functions can be used for prediction since their values do not depend on the information about the future (after the month m) which would be anathema in prediction.

Discretization. Values of functions used in a prediction algorithm are identified on the lowest level of resolution, 1 or 0, distinguishing only the values of each function $F(m)$ above and below a threshold $T(Q)$. This threshold is defined as a percentile of a level Q, that is, by the condition that $F(m)$ exceeds $T(Q)$ during $Q\%$ of the months considered. The discretization ensures robustness of analysis and the objects of recognition are described after it by binary vectors of the same length.

Simple algorithm called Hamming distance is used for classification of binary vectors in applications considered here (Gvishiani and Kossobokov, 1981; Lichtman and Keilis-Borok, 1989; Keilis-Borok and Soloviev, 2003). Each vector is either premonitory or not. Analyzing the samples of vectors of each class ("the learning material"), the algorithm determines a reference binary vector ("kernel") with components typical for premonitory vector. Let D be the Hamming distance of a vector from the kernel (the number of non-coinciding binary components). The given vector is recognised as premonitory class, if D is below a certain threshold D^*. This criterion takes advantage of the clustering of precursors in time.

Summing up, these elements of pattern recognition approach are common for its numerous applications, their diversity notwithstanding. Experience in the specific applications is described in Sections III – VI. Conceptual summary of the accumulated experience is given in the final Sect. VII.

3. ECONOMIC RECESSIONS IN THE U.S.

US National Bureau of Economic Research (NBER) has identified the seven recessions that occurred in the US since 1960 (Table 1). The starting points of a recession and of the recovery from it follow the months marked by a peak and a trough of economic activity, respectively.

Table 1. Economic Recessions in the U.S. since 1960

#	Peaks	Troughs
1	April 1960	February 1961
2	December 1969	November 1970
3	November 1973	March 1975
4	January 1980	July 1980
5	July 1981	November 1982
6	July 1990	March 1991
7	March 2001	November 2001
8	December 2007	June 2009

A peak indicates the last month before a recession, and a trough -- the last month of a recession.

Prediction targets considered are the first month after the peak and after the trough ("the turns to the worst and to the best", respectively). The start of the first recession, in 1960, is not among the targets, since the data do not cover a sufficient period of time preceding the recession.

The data used for prediction comprise the time series, consisting of monthly values of the following leading macroeconomic indicators (mnemonics in bold are the same as in the data sources).

IP Industrial Production, total: indicator of real (constant dollars, dimensionless) output in the entire economy. This represents mainly manufacturing because of the difficulties in measuring the quantity of output in services (services include travel agents, banking, etc.). At the beginning of the recession studies (Keilis-Borok et al., 2000) we used the Stock-Watson indicator of overall monthly economic activity (**XCI**) defined by Stock and Watson (Stock and Watson, 1989). But at the present time this indicator is not published and we have replaced **XCI** by **IP**. Our analysis shows that the results are not sensible in this replacement. It is explained by the fact that the indicator **XCI** is calculated mainly on the basis of **IP**.

INVMTQ. Total inventories in manufacturing and trade, in real dollars that includes intermediate inventories (for example held by manufacturers, ready to be sent to retailers) and final goods inventories (goods on shelves in stores).

LHELL. Indicator of "help wanted" advertising. This is put together by a private publishing company that measures the amount of job advertising (column-inches) in a number of major newspapers.

LUINC. Average weekly number of people claiming unemployment insurance.

FYGM3. Interest rate on 90-day U.S. treasury bills at an annual rate (in percent).

G10FF = FYGT10 – FYFF. Difference between interest rate on 10-year U.S. Treasury bonds, and federal funds interest rate, on an annual basis.

The first four indicators concern the economy, while the two others concern the financial market. These indicators were already known (Stock and Watson, 1989, 1993), as those that correlate with a recession's approach.

3.1 Prediction of a Recession Start

The problem of prediction of a recession start was considered by Keilis-Borok et al. (2000). The purpose was to develop an algorithm that could predict retrospectively starts of recessions ## 2-6 from Table 1.

Prediction targets considered are the first months after the peaks. The start of the first recession, in 1960, is not among the targets, since the data do not cover a sufficient period of time preceding the recession.

Single indicators exhibit the following premonitory patterns:

IP: the deviation from the long-term trend $R^{IP}(m/48)$ (3) is below the threshold $T(Q)$, $Q = 75\%$;

INVMTQ: the deviation from the long-term trend $R^{INVMTQ}(m/48)$ (3) is below the threshold $T(Q)$, $Q = 25\%$;

LHELL: the short-term trend $K^{LHELL}(m/5)$ (2) is below the threshold $T(Q)$, $Q = 67\%$;

LUINC: the short-term trend $K^{LUINC}(m/10)$ (2) is above the threshold $T(Q)$, $Q = 17\%$;

FYGM3: the deviation from the long-term trend $R^{FYGM3}(m/48)$ (3) is above the threshold $T(Q)$, $Q = 25\%$;

G10FF: the value of **G10FF** is below the threshold $T(Q)$, $Q = 90\%$.

Only months belonging to periods between recessions are used for determining the discretization thresholds $T(Q)$.

Prediction algorithm triggers an alarm after a month when at least 4 patterns emerge simultaneously. It lasts 3 months and can be extended by the same rule, if premonitory patterns keep emerging. Description of the algorithm can be found in Keilis-Borok et al. (2000) along with its validation by sensitivity and out-of-sample analyses.

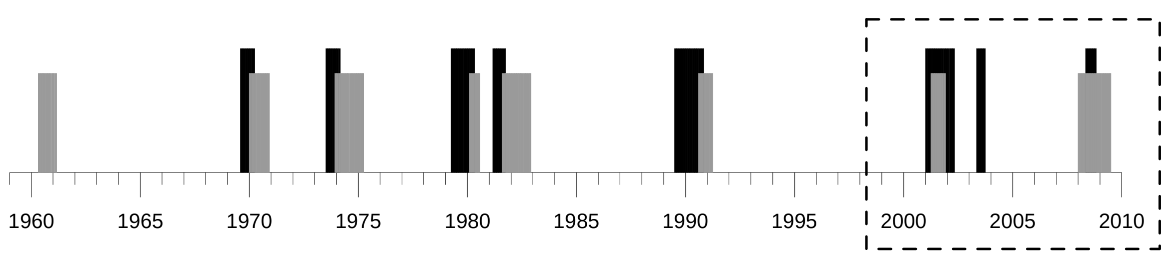

Figure 2 Alarms (black bars) obtained by the algorithm for prediction of a recession start and recessions (grey bars)

Alarms and recessions are juxtaposed in Fig. 2. We see that five recessions occurring between 1961 and 2000 were predicted retrospectively by alarms. These retrospective alarms have been detected within 6 to 14 month before each of the five recessions and at no other time. Total duration of these alarms is 38 months, or 13.6 % of the whole time interval between recessions considered. Recession in 2001 was predicted in advance, a false alarm was obtained in 2003. For the last recession the algorithm detected an alarm on May 2008, four months later than it started according to NBER. Note that the NBER announcement about this recession was issued in December 2008.

3.2 Prediction of a Recession End

Prediction targets are the starting points of recovery from recessions (the first months after the troughs listed in Table 1).

The data comprise the same six indicators that are used to indicate the approach of a recession start (see Sect. 3.1); they are analysed only within the recessions' periods. It has been found (Keilis-Borok et al., 2008) that single indicators exhibit the following premonitory patterns:

IP: the deviation from the long-term trend $R^{IP}(m/48)$ (3) is below the threshold $T(Q)$, $Q = 75\%$;

INVMTQ: the deviation from the long-term trend $R^{INVMTQ}(m/48)$ (3) is below the threshold $T(Q)$, $Q = 50\%$;

LHELL: the short-term trend $K^{LHELL}(m/5)$ (2) is below the threshold $T(Q)$, $Q = 75\%$;

LUINC: the short-term trend $K^{LUINC}(m/10)$ (2) is above the threshold $T(Q)$, $Q = 50\%$;

FYGM3: the deviation from the long-term trend $R^{FYGM3}(m/48)$ (3) is below the threshold $T(Q)$, $Q = 50\%$;

G10FF: the value of **G10FF** is above the threshold $T(Q)$, $Q = 33\%$;

Only months belonging to recessions' periods are used for determining the discretization thresholds $T(Q)$.

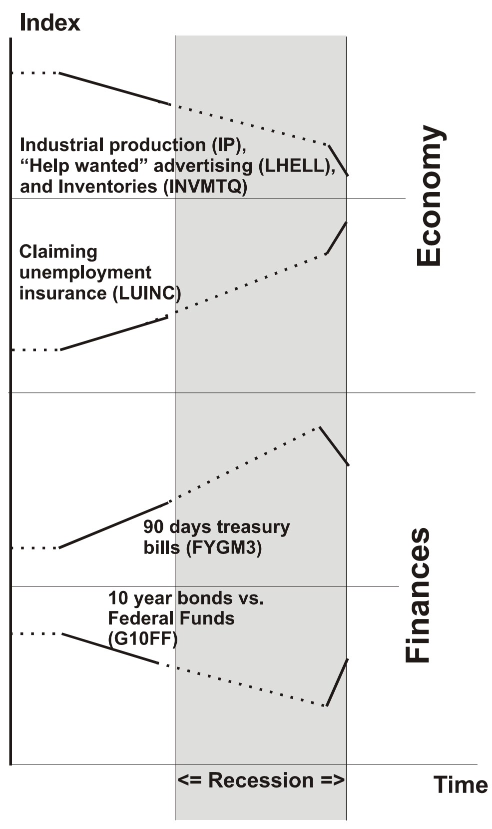

Figure 3 Premonitory changes of functions on indicators before of a recession start and before its end

Note that functions on financial indicators change in opposite directions before the recession and before the recovery. Functions on economic indicators change in the same direction before the recession and the recovery; but the change is stronger before the recovery, i.e., the economic situation is worse. The premonitory behaviour of functions on indicators before a recession start and before its end is shown schematically in Fig. 3.

Prediction algorithm is formulated as follows (Keilis-Borok et al., 2008): an alarm is triggered after *three* consecutive months when at least 3 premonitory patterns emerge simultaneously. As in the case of a recession start it lasts 3 months and can be extended by the same rule, if premonitory patterns keep emerging. Alarms and prediction targets are juxtaposed in Fig. 4. Duration of a single alarm is one to eight months. There are neither false alarms nor failures to predict. The algorithm has been developed using the data on the first six recessions occurred in 1960-1991. Total duration of alarms for these recessions is 16 months, which is 22% of time covered by the recessions.

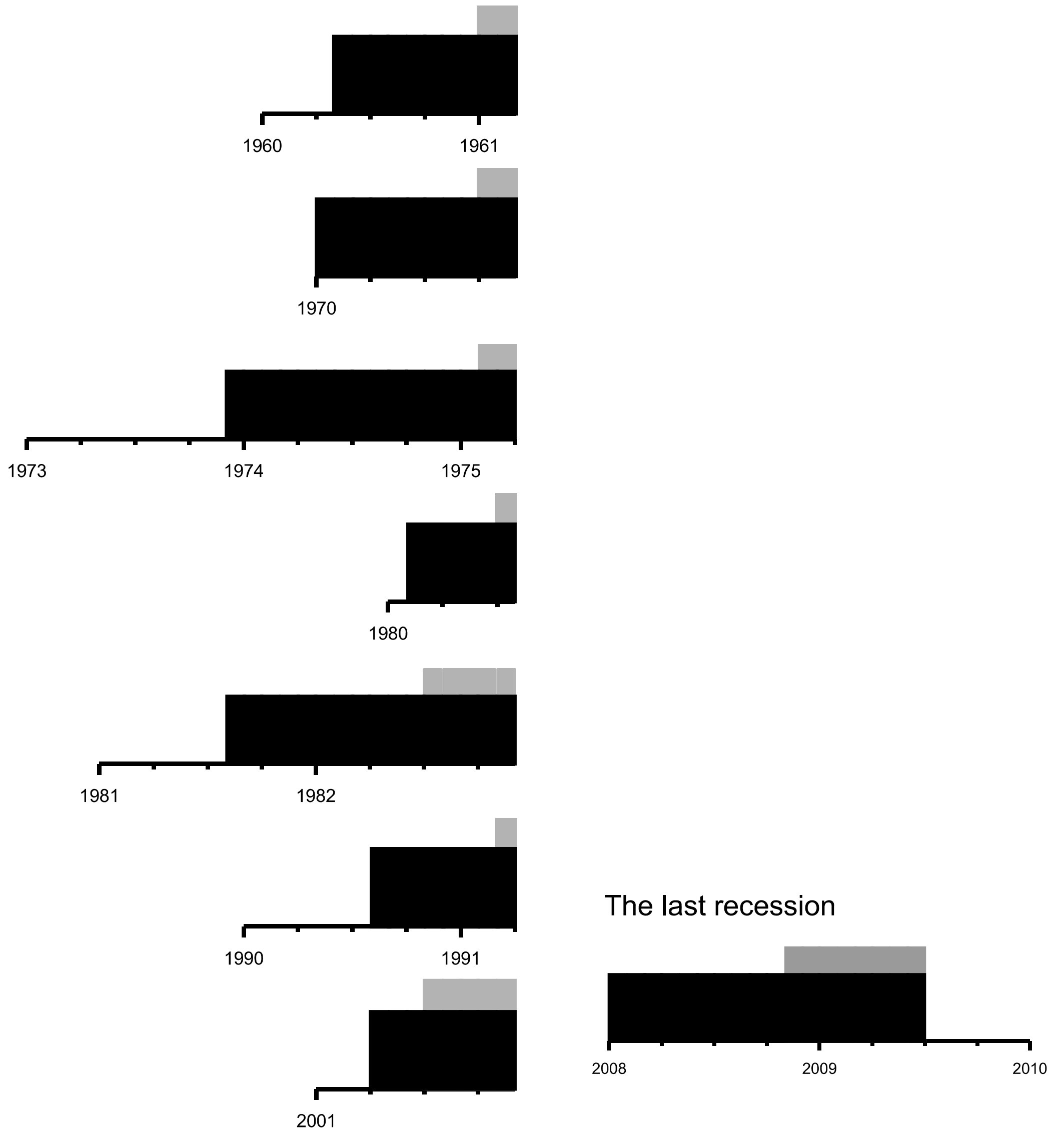

Figure 4 Prediction of a recession end; black bars – periods of recessions, gray bars – alarms preceding a recession end

4. UNEMPLOYMENT

A specific phenomenon in the dynamics of unemployment – episodes of a sharp increase in the in the rate of unemployment growth is considered (Keilis-Borok et al., 2005). It is called here "Fast Acceleration of Unemployment" (*FAU*). The goal is to identify by an analysis of macroeconomic indicators a robust and rigidly defined prediction algorithm of the *"yes or no"* variety indicating at any time moment, whether a *FAU* should be expected or not within the subsequent months. Considering unemployment in France between 1962 and 1997, we have found a specific "premonitory" pattern of three macroeconomic indicators that may be used for algorithmic prediction of *FAU*s. Among seven *FAU*s identified within these years six are preceded within 12 months by this pattern that appears at no other time. The application of this algorithm to Germany, Italy and the USA yields similar results. Such predictability reflects the fact that the economy, like other complex systems, exhibits regular collective behavior patterns. The final test, as in any prediction research, should be advance prediction. The first such predictions, for the USA in 2000 and 2006, have been correct.

4.1 Prediction Target

In the case of France the unemployment is characterized by the monthly number of unemployed $u(m)$, including seasonal variations. Seasonal variations are smoothed away by substituting $u(m)$ by its linear regression (1) $U(m) = W^u(m/m\text{-}6, m{+}6)$ over the year-long sliding time interval $(m - 6, m + 6)$. A prediction target is schematically illustrated in Fig. 5 where the thick curve shows $U(m)$. The arrow indicates a sharp upward bend of this curve. The moment of that bend is the prediction target. It is called by the acronym *FAU*, for "Fast Acceleration of Unemployment."

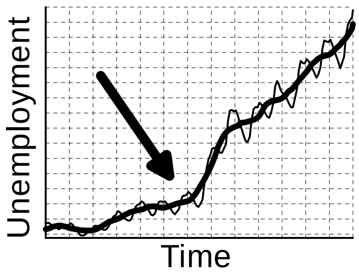

Figure 5 Fast acceleration of unemployment (*FAU*): schematic definition; thin line – monthly unemployment; with seasonal variations $u(m)$, thick line – monthly unemployment, with seasonal variations smoothed away $U(m)$. The arrow indicates a *FAU* – the sharp bend of the smoothed curve. The moment of a *FAU* is the target of prediction.

A natural robust measure of unemployment acceleration at the time m is the bend of the linear trend of $U(m)$; in notations (1) this is the function $F(m/s) = K^U(m{+}s, m) - K^U(m, m\text{-}s)$. This function with s = 24 months $F(m) = F(m/24)$ is used as a coarse measure of unemployment acceleration. The *FAU*s are identified by the local maxima of $F(m)$ exceeding a certain threshold $\boldsymbol{F}$. The time m^* and the height F^* of such a maximum are, respectively, the time and the magnitude of a *FAU*. Subsequent local minimum of $F(m)$ identifies the month m_e when acceleration ends. Fig. 6 shows thus defined *FAU*s for France.

4.2 The Data

The analysis has been initially made for France and three groups of data have been analyzed.

-- Composite macroeconomic indicators of national economy

1. **IP**: Industrial production indicator, composed of weighted production levels in numerous sectors of the economy, in % relative to the index for 1990.
2. **L**: Long-term interest rate on 10-year government bonds, in %.
3. **S**: Short-term interest rate on 3-month bills, in %.

-- *Characteristics of more narrow areas of French economy*

4. **NC**: The number of new passenger car registrations, in thousands of units.
5. **EI**: Expected prospects for the national industrial sector.
6. **EP**: Expected prospects for manufacturers.
7. **EO**: Estimated volume of current orders.

Indicators 5-7 distinguish only "good" and "bad" expectations determined polling 2 500 manufacturers, with the expectations weighted by the size of their businesses.

-- *Indicators related to US economy.*

8. **FF/$**: Value of U.S. dollar in French francs.
9. **AR**: The state of the American economy: is it close to a recession or not? This indicator shows the presence or absence of a current pre-recession alarm (see Sect. 3.1).

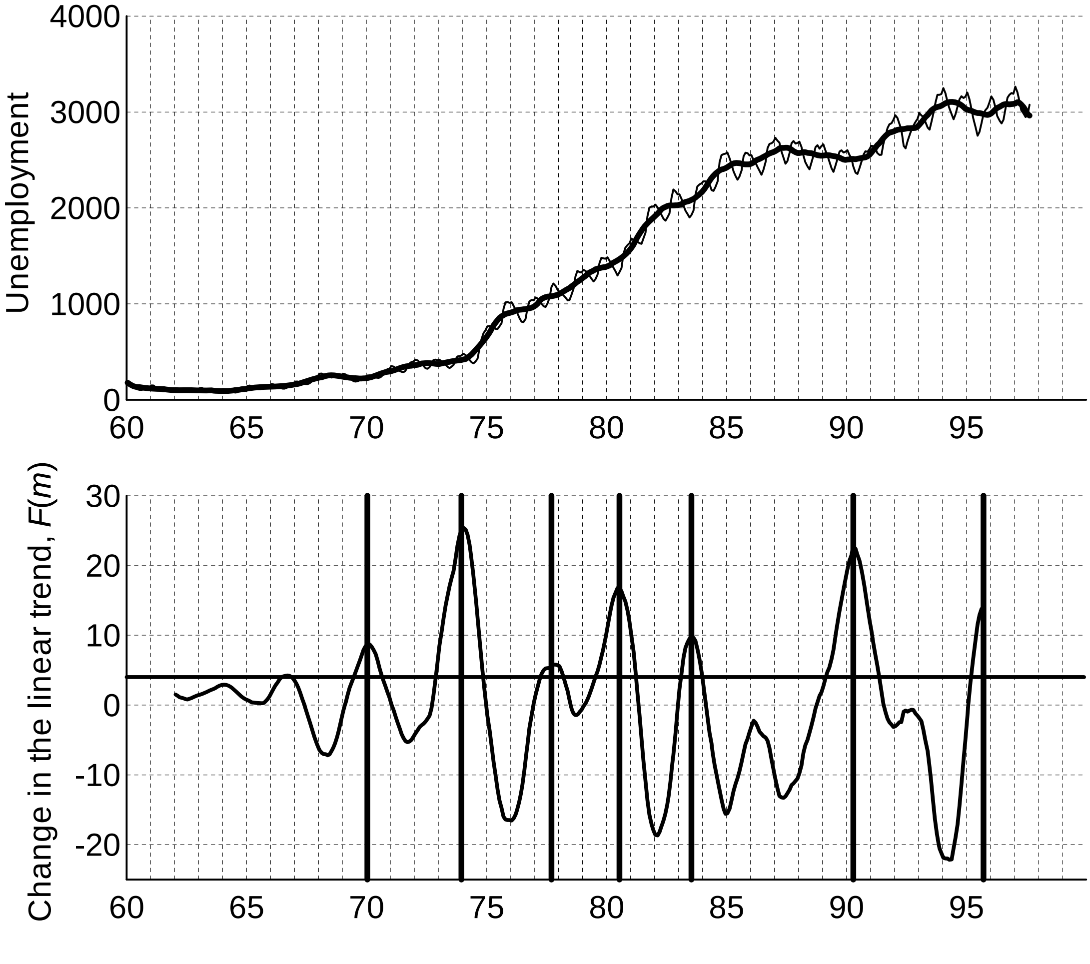

Figure 6 Unemployment in France.
Top: Monthly unemployment, thousands of people. Thin line: $u(m)$, data from the OECD database; note the seasonal variations. Thick line: $U(m)$, data smoothed over one year.
Bottom: Determination of *FAU*s. $F(m)$ shows the change in the linear trend of unemployment $U(m)$. *FAU*s are attributed to the local maxima of $F(m)$ exceeding threshold $\boldsymbol{F} = 4.0$ shown by horizontal line. The thick vertical lines show moments of the *FAU*s.

The data bases with above indicators for Europe are issued by the Organization for Economic Cooperation and Development (OECD, 1997) and the International Monetary Fund (IMF, 1997).

American analogues of indicators **IP**, **L**, and **S** are described in Sect. 3 under abbreviations **IP**, **FYGM3** and **FYGT10** respectively.

4.3 Prediction

Single indicators exhibit the following premonitory behaviour.

-- Steep upward trends of composite indicators (## 1 – 3). This behaviour reflects “overheating” of the economy and may sound counterintuitive for industrial production (#1), since the rise of production is supposed to create more jobs. However, a particularly steep rise may create oversupply.

-- Steep downward trends of economic expectations by general public (# 4) and business community (##5 – 8).

-- Proximity of an American recession (#9). Before analysis was made such and opposite precursors might be expected for equally plausible reasons, so that this finding, if further confirmed, does provide a constraint on understanding unemployment’s dynamics.

Among different combinations of indicators the macroeconomic ones (## 1 – 3) jointly give relatively better predictions, with smallest rates of errors and highest stability in sensitivity tests. Premonitory patterns that they exhibit are described formally as follows.

IP: the short-term trend $K^{IP}(m/12)$ (2) is above the threshold $T(Q)$, $Q = 50\%$;

L: the short-term trend $K^{L}(m/12)$ (2) is above the threshold $T(Q)$, $Q = 33\%$;

S: the short-term trend $K^{S}(m/12)$ (2) is above the threshold $T(Q)$, $Q = 25\%$.

Prediction algorithm (Keilis-Borok et al., 2005) triggers an alarm after a month when all three patterns emerge simultaneously. It lasts 6 months and can be extended by the same rule, if premonitory patterns keep emerging. Being robust and self-adjusting to regional conditions, this algorithm was applied retrospectively without any changes to the four countries considered here. Error diagram in Fig. 7 shows quality of prediction for different countries.

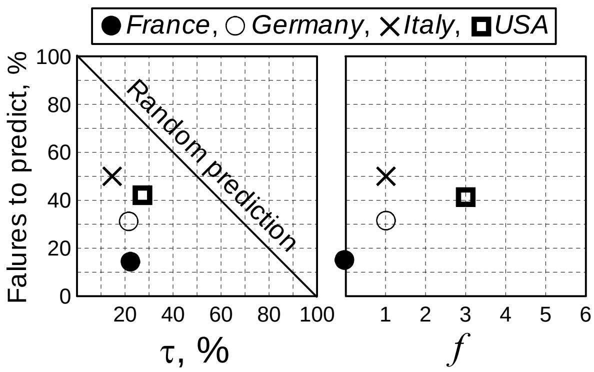

Figure 7 Error diagram for prediction of *FAU*s in different countries;
τ is total duration of alarms in % to the time interval considered,
f – total number of false alarms.

4.4 Application to the U.S.

We use the data on monthly unemployment rates for the U.S. civilian labor force, as given by U.S. Department of Labor. Unemployment rate in USA had no general trend during the years considered. One can see this in Fig. 8. The *FAU*s are the times when unemployment started to rise, that are the local minima of the unemployment rate. They are formally defined as follows. Let $R(m)$ be the smoothed monthly unemployment rate in a month m. Then $R(m)$ has the local minima in a month m^* if for j = 1, 2, 3, 4 $R(m^*-j) \geq R(m^*)$ and $R(m^*+j) > R(m^*)$. Seven such minima are identified within the period 1960-1999 in 1962:08 (9), 1967:03 (3), 1969:02 (28), 1973:07 (24), 1979:05 (19), 1981:03 (21), and 1989:05 (38). The duration of the unemployment rise is given in brackets after the corresponding months m^*, which are the targets of our prediction.

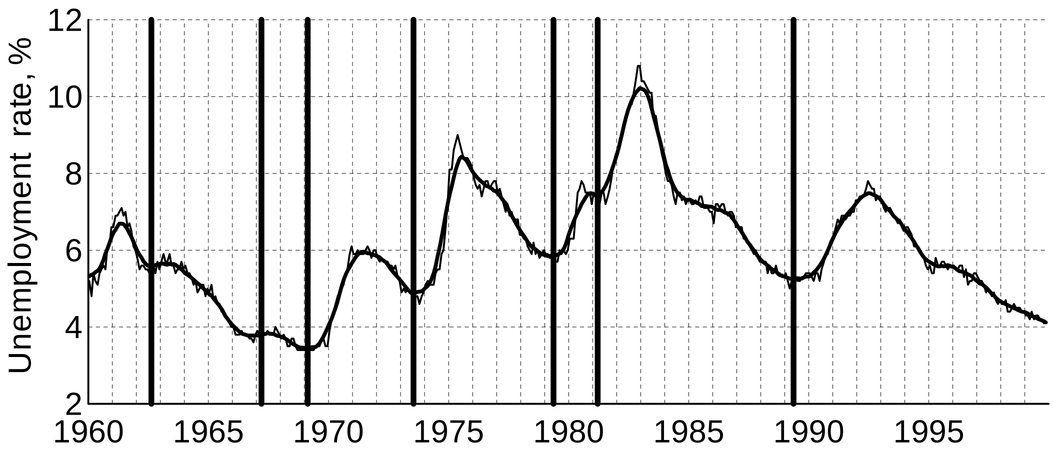

Figure 8 Unemployment rates in the U.S.; thin line: $r(m)$, original data; thick line: $R(m)$, data after smoothing out the seasonal variations; the thick vertical lines show the moments when unemployment started to rise (local minima of smoothed unemployment rate).

In the retrospective application of the algorithm 4 out of 7 *FAU*s are captured by alarms; three *FAU*s, in 1962, 1969, and 1981, are missed; and there are three false alarms, in 1968, 1983, and 1994 (Fig. 9). The alarms within the periods of unemployment growth are not regarded as false ones. Total count of errors for the *USA* is given in Fig 7. It is worse that for European countries, though still better than random. Note, that this is a rigorous count, giving lower estimate for the algorithm's performance. Such an estimate is necessary for some purposes, e.g. evaluation of statistical significance of predictions, but for other purposes it might be misleading. Next we discuss a more practical estimate.

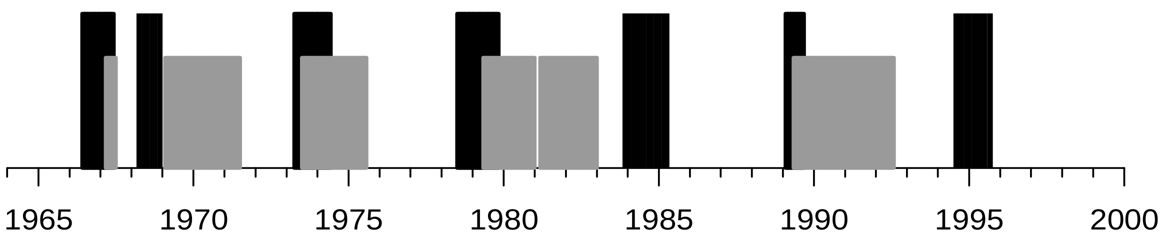

Figure 9 Alarms (black bars) obtained by the algorithm for prediction of FAUs in the U.S. and periods of the unemployment rise (grey bars)

Information for a potential end user. Let us consider our count of errors from a disaster preparedness point of view. One of the alarms ended in 1968:12, a month before the *FAU*; we counted it as a false alarm and the subsequent *FAU* – as missed by prediction. Similarly, we counted as missed the *FAU* in 1981:03, while it was followed by an alarm a month later. Since a *FAU* is a starting point of a long rise in unemployment, lasting about 20 months, a one month difference is not necessary important for a decision-maker, responding to a prediction. Moreover, this difference is within the accuracy of *FAU*s, since they are determined after considerable smoothing of the unemployment rate. Accordingly, for the end user only the three errors might be worth counting: the failure to predict in 1962 and the false alarms in 1983 and 1994.

***Prediction* of the future *FAU*s** was launched for the U.S. in 1999 (Fig.10). The first prediction for early 2000 has been correct. The next alarm was obtained after April 2006 for the first time after 2000. This prediction was announced in September 2006 (Keilis-Borok et al., 2006) and has been confirmed by *FAU* that occurred in December 2006 (Fig. 10). There were no any alarms after that time.

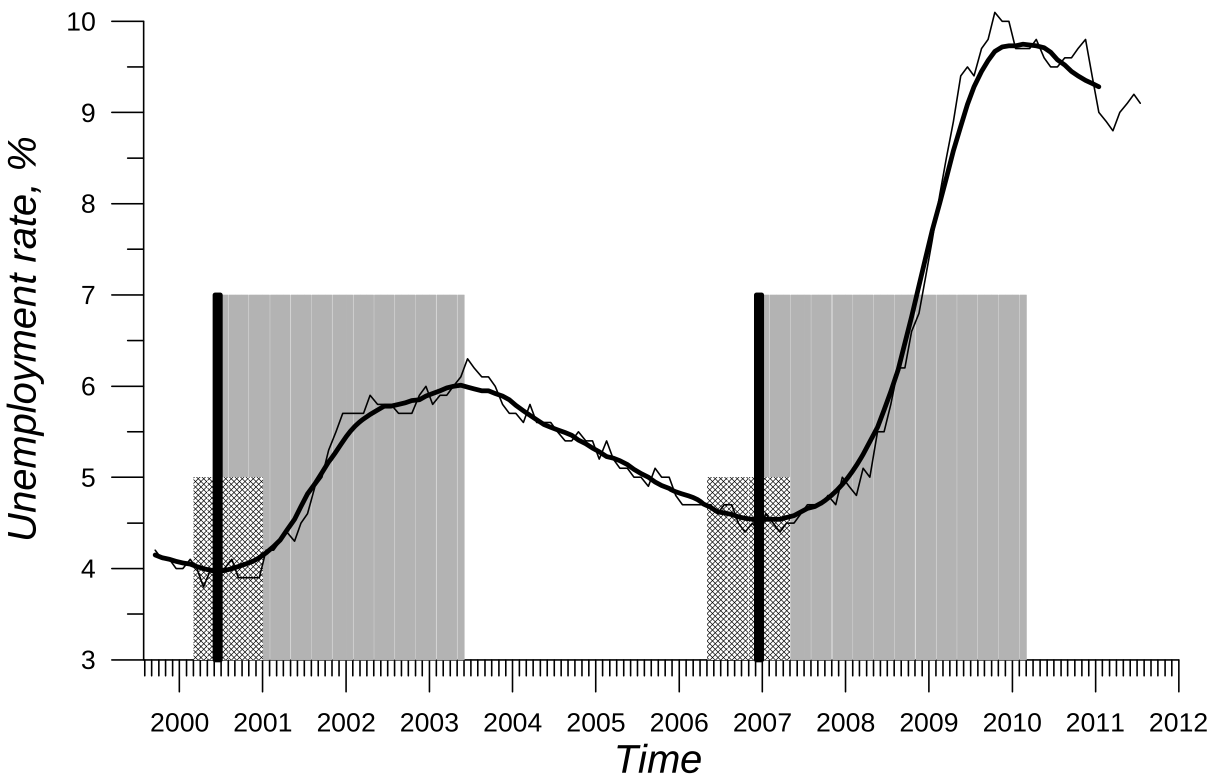

Figure 10 Unemployment rate in the U.S. in 1999-2011: thin curve shows the data of Bureau of Labor Statistics, U.S. Department of Labor (http://data.bls.gov), thick curve – the smoothed data. Checkered bars indicate the alarm periods obtained by the algorithm, vertical lines – moments of *FAU*, grey bars – periods of the unemployment rate growth.

Recessions and unemployment. Fig. 11 compares the periods of unemployment growth and recession in the U.S. We see that all eight American recessions during the time period under consideration, 1960-2011, did occur within the eight longest periods of unemployment growth. Therefore the prediction of unemployment could be useful for the prediction of recessions.

5. HOMICIDE SURGES

The prediction of homicide rates has been analyzed for an American megacity – Los Angeles, CA (Keilis-Borok et al., 2003).

5.1 Prediction target

*A prediction target is the start of a sharp and lasting acceleration of homicide rate; it is called by the acronym SHS, for "Start of the Homicide Surge." It is formally determined by the analysis of monthly homicides rat*es, with seasonal variations smoothed out, as described in Sect. 4.1. Prediction targets thus identified are shown by vertical lines in Figs 12 and 14 below.

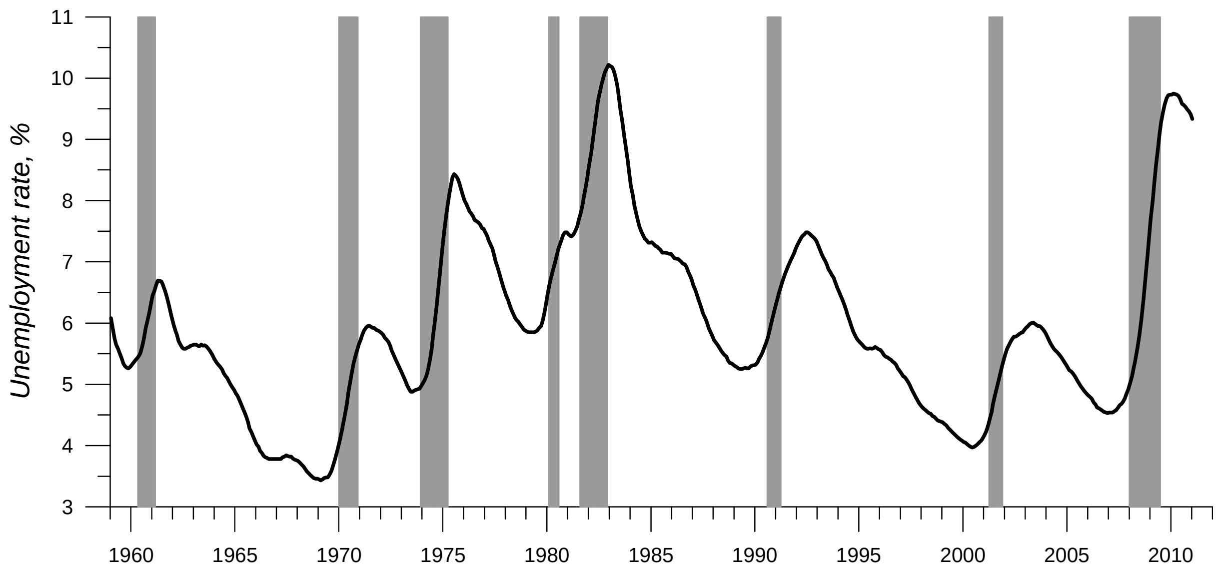

Figure 11 Unemployment rate and recessions in the U.S. in 1960-2011; gray bars indicate periods of recessions, a thick curve shows the smoothed data on unemployment rate.

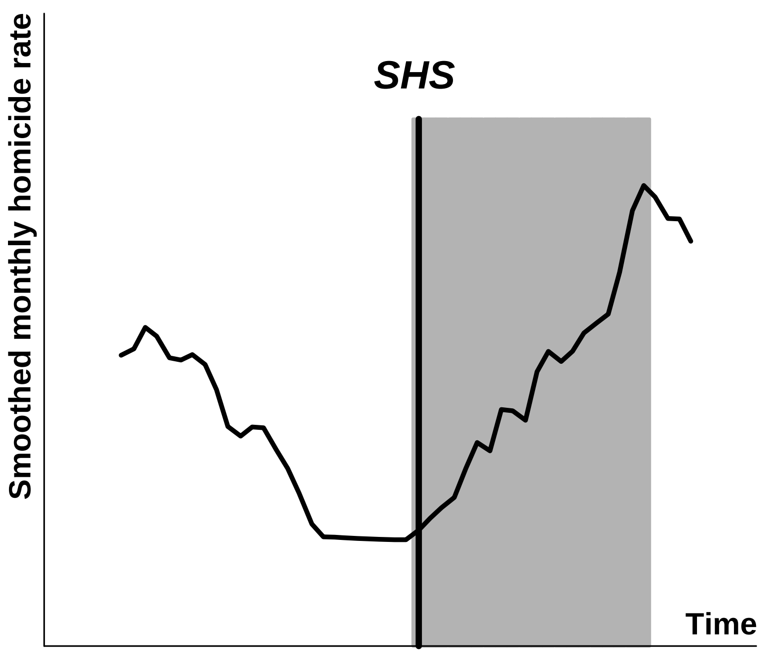

Figure 12 Target of prediction – the Start of the Homicide Surge ("*SHS*"); schematic definition. Gray bar marks the period of homicide surge.

5.2 The data

The analyzed data include monthly rates of the homicides and 11 types of lesser crimes, listed in Table 2. Definitions of these crimes are given in Carlson (1998).

The data are taken from two sources:

-- the National Archive of Criminal Justice Data, placed on the web site (NACJD), 1975 – 1993.

-- data bank of the Los Angeles Police Department (LAPD) Information Technology Division), 1990 – 2003.

The algorithm does not use socio-economic determinants of crime, or other data that might be also useful. The objective was to develop a simple, efficient prediction model; development of comprehensive causal model would be a complementary objective.

Table 2. Types of crimes considered
(after Carlson, 1998)

Homicide	**Robberies**	**Assaults**	**Burglaries**
❖ All (**H**)	❖ All (**Rob**) ❖ With firearms (**FRob**) ❖ With knife or cutting instrument (**KCIR**) ❖ With other dangerous weapon (**ODWR**) ❖ Strong-arm robberies (**SAR**)*	❖ All (**A**)* ❖ With firearms (**FA**) ❖ With knife or cutting instrument (**KCIA**) ❖ With other dangerous weapon (**ODWA**)* ❖ Aggravated injury assaults (**AIA**)*	❖ Unlawful not forcible entry (**UNFE**) ❖ Attempted forcible entry (**AFE**)*

* Analyzed in sensitivity tests only

5.3 Prediction

Premonitory patterns that were used in the prediction algorithm are described formally on the basis of seven indicators listed in Table 2 as follows.

Rob: the short-term trend $K^{\mathrm{Rob}}(m/12)$ (2) is below the threshold $T(Q)$, Q = 66.7%;
FRob: the short-term trend $K^{\mathrm{FRob}}(m/12)$ (2) is below the threshold $T(Q)$, Q = 66.7%;
KCIR: the short-term trend $K^{\mathrm{KCIR}}(m/12)$ (2) is below the threshold $T(Q)$, Q = 50%;
ODWR: the short-term trend $K^{\mathrm{ODWR}}(m/12)$ (2) is below the threshold $T(Q)$, Q = 87.5%;
FA: the short-term trend $K^{\mathrm{FA}}(m/12)$ (2) is above the threshold $T(Q)$, Q = 50%;
KCIA: the short-term trend $K^{\mathrm{KCIA}}(m/12)$ (2) is above the threshold $T(Q)$, Q = 50%;
UNFE: the short-term trend $K^{\mathrm{UNFE}}(m/12)$ (2) is above the threshold $T(Q)$, Q = 50%.

Other five indicators marked by * in Table 2 are used in sensitivity tests; and homicides rate is used for identification of targets *SHS*.

Premonitory behaviour of indicators is illustrated in Fig. 13. The first phase is characterized by an escalation of burglaries and assaults, but not of robberies. Later on, closer to a homicide surge, robberies also increase.

Prediction algorithm (Keilis-Borok et al., 2003) triggers an alarm after *two* consecutive months when at least 6 premonitory patterns emerge simultaneously. It lasts 9 months and can be extended by the same rule, if premonitory patterns keep emerging.

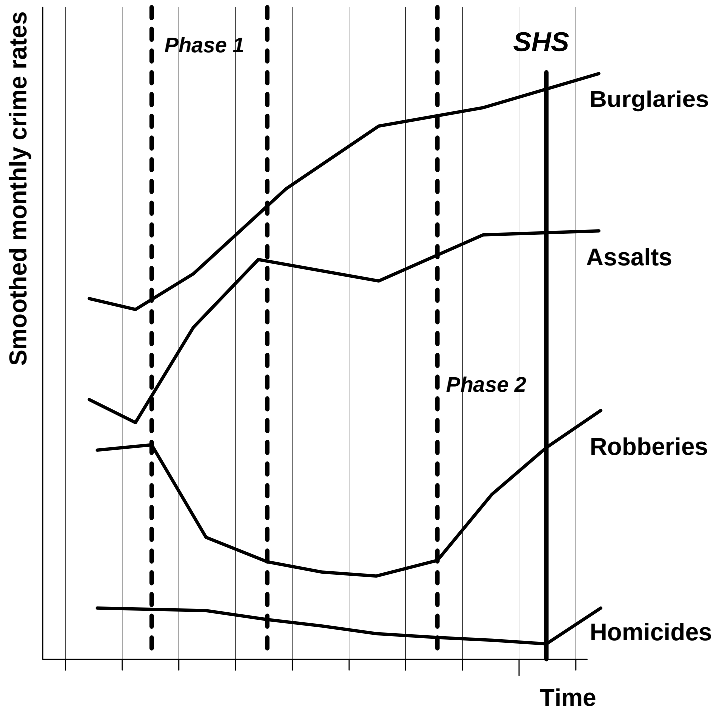

Figure 13 Scheme of premonitory changes in crime statistics.

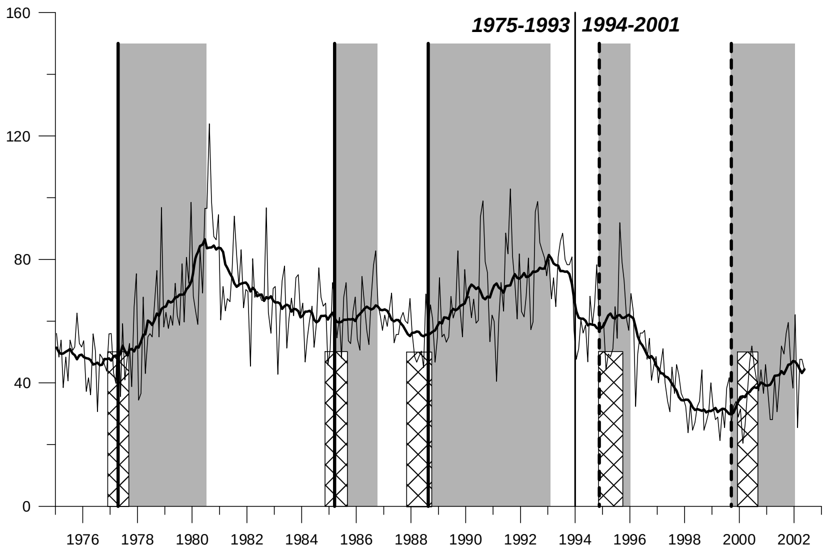

Figure 14 Performance of prediction algorithm through 1975-2002.
Thin curve – original time series, total monthly number of homicides in Los Angeles city, per 3,000,000 inhabitants. Data from (NACJD; Carlson, 1998) have been used for 1975 – 1993 and from the Data Bank of the Los Angeles Police Department (LAPD Information Technology Division) for subsequent 9 years.
Thick curve - smoothed series, with seasonal variations eliminated. Vertical lines show the targets of prediction – episodes of *SHS* (Sect. 5.1).
Gray bars show the periods of homicide surge. Checkered bars show the alarms declared by the prediction algorithm (Keilis-Borok et al., 2003).

*Alarms and homicide surges are juxtaposed in Fig. 14.*The *SHS* episode in November 1994 has occurred simultaneously with the corresponding alarm. It is captured by an alarm, which starts in the month of *SHS* without a lead time. Prediction missed the October 1999 episode: it occurred two months *before* the start of the corresponding alarm. Such delays should be taken into account for validating the algorithm. Note, however, that the last prediction did remain informative.

Altogether alarms occupy 15% of the time considered. During phase 2 (as defined in Fig. 13) this rate might be reduced (Keilis-Borok et al., 2003).

6. ELECTIONS

This Section describes algorithms for predicting the outcome of the US Presidential and mid-term Senatorial elections (Lichtman and Keilis-Borok, 1989; Lichtman, 1996, 2000, 2005) are described here.

Elections' time is set by the law as follows.

-- National elections are held every even-numbered year, on the first Tuesday after the first Monday in November (i.e., between November 2 and November 8, inclusively).

-- Presidential elections are held once every 4 years, i.e. on every other election day. People in each of the 50 states and District of Columbia are voting separately for "electors" pledged to one or another of the Presidential candidates. These electors make up the "Electoral College" which directly elects the President. Since 1860, when the present two-party system vas basically established, Electoral College reversed the decision of the popular vote only three times, in 1888, 1912, and 2000. Algorithmic prediction of such reversals is not developed so far.

-- A third of Senators are elected for a 6-year term every election day; "mid-term' elections held in the middle of a Presidential term are considered here.

6.1 Methodology

The prediction target is an electoral defeat of an "incumbent" party, i.e. the party holding the contested seat. Accordingly, the prediction problem is formulated as whether the incumbent party will retain this seat or lose it to the challenging party (*and not whether Republican or Democrat will win*).As is shown below, that formulation is crucial for predicting the outcomes of elections considered.

Table 3. Questionnaire for mid-term Senatorial Elections (Lichtman and Keilis-Borok, 1989)

1.	(Incumbency): The incumbent-party candidate is the sitting senator.
2.	(Stature): The incumbent-party candidate is a major national figure.
3.	(Contest): There was no serious contest for the incumbent-party nomination.
4.	(Party mandate): The incumbent party won the seat with 60% or more of the vote in the previous election.
5.	(Support): The incumbent-party candidate outspends the challenger by 10% or more.
6.	(Obscurity): The challenging-party candidate is not a major national figure or a past or present governor or member of Congress.
7.	(Opposition): The incumbent party is not the party of the President.
8.	(Contest): There is no serious contest for the challenging-party nomination (the nominee gains a majority of the votes cast in the first primary and beats the second-place finisher at least two to one).

Data. The pre-election situation is described by robust common sense parameters defined at the lowest (binary) level of resolution, as the *yes* or *no* answers to the questionnaires given below (Tables 3, 4). The questions are formulated in such a way that the answer *no* favors the victory of the challenging party. According to the Hamming distance analysis (Sect. III) the victory of the challenging party is predicted when the number *D* of answers *no* exceeds a threshold *D**.

Table 4. Questionnaire for Presidential elections (Lichtman, 1996, 2000)

KEY 1	(Party Mandate): After the midterm elections, the incumbent party holds more seats in the U.S. House of Representatives than it did after the previous midterm elections.
KEY 2	(Contest): There is no serious contest for the incumbent-party nomination.
KEY 3	(Incumbency): The incumbent-party candidate is the sitting president.
KEY 4	(Third party): There is significant third-party or independent campaign.
KEY 5	(Short-term economy): The economy is not in recession during the election campaign.
KEY 6	(Long-term economy): Real per-capita economic growth during the term equals or exceeds mean growth during the previous two terms.
KEY 7	(Policy change): The incumbent administration effects major changes in national policy.
KEY 8	(Social unrest): There is no sustained social unrest during the term.
KEY 9	(Scandal): The incumbent administration is unattained by a major scandal.
KEY 10	(Foreign/military failure): The incumbent administration suffers no major failure in foreign or military affairs.
KEY 11	(Foreign/military success}: The incumbent administration achieves a major success in foreign or military affairs.
KEY 12	(Incumbent charisma): The incumbent-party candidate is charismatic or a national hero.
KEY 13	(Challenger charisma): The challenging-party candidate is not charismatic or a national hero.

6.2 Mid-term Senatorial Elections

The prediction algorithm was developed by a retrospective analysis of the data on three elections, 1974, 1978, and 1982. The questionnaire is shown in Table 3. Victory of the challenger is predicted if the number of answers *no* is 5 or more (Lichtman and Keilis-Borok, 1989; Lichtman, 1996, 2000).

The meaning of these questions may be broader than their literal interpretation. For example, financial contributions (# 5) not only provide the resources required for an effective campaign, but may also constitute a poll in which the preferences are weighed by the money attached.

Predicting future elections. This algorithm (without any changes from year to year and from state to state) was applied in advance to the five subsequent elections, 1986 – 2002. Predictions are shown in Fig. 15. Altogether, 150 seats were put up for election. For each seat a separate prediction was made, 128 predictions were correct, and 22 – wrong.

Statistical significance of this score is 99.9%. In other words the probability to get such a score by chance is below 0.1% (Lichtman and Keilis-Borok, 1989; Lichtman, 1996, 2000). For some elections these predictions might be considered as trivial, since they coincide with prevailing expectation of experts. Such elections are identified by *Congressional Review.* Eliminating them from the score still results in 99% significance.

6. 3 Presidential Elections

The prediction algorithm was developed by a retrospective analysis of the data on the past 31 elections, 1860 – 1980; that covers the period between victories of A. Lincoln and R. Reagan inclusively. The questionnaire is shown in Table 4. Victory for the challenger is predicted if the number of answers *no* is 6 or more (Lichtman, 1996, 2000).

0	1	2	3	4	5	6	7
			OK98				
			CO98				
			FL98				
			GA98				
			HA98	TN02			
			ID98	SC02			
			MA98	NC02			
			ND98	NE02			
			PN98	KY02			
			SD98	IA02			
			UT98	CO02			
			FL94	AL02			
			HA94	AK98			
			IN94	CA98			
			MT94	CT98			
			NB94	NE98			
			NJ94	OR98			
			TX94	SC98			
			WA94	VT98			
		AS98	WV94	WA98			
		KA98	WI94	CT94			
		LA98	AK90	MD94			
		MI98	IN90	NV94			
		NH98	KN90	WY94			
		MS94	ME90	CO90			
	AL98	NM94	MA90	HA90			
	AZ98	ND94	MT90	KY90			
	IO98	RI94	NB90	MI90			
	DL94	VT94	NC90	AZ86			
	MA94	AS90	TX90	CO86			
	NY94	IO90	WY90	ID86			
	AL90	MS90	AR86	LA86			
	DE90	NM90	CA86	NY86			
	IL90	OR90	IL86	OK86	WI98	MN94	
	LA90	RI90	IN86	WI86	CA94	MO94	
	OK90	SD90	IA86	**NC86**	ID90	VA94	
	SC90	VA90	NH86	**WA86**	PA86	NH90	
	TN90	WV90	OR86	**MN90**	**IL98**	**IN98**	
	HI86	AK86	VT86	**OK94**	**ME94**	**OH98**	
	OH86	CT86	**TN94**	**PA94**	**AL86**	**MI94**	
UT94	SC86	KS86	**TX02**	**TN294**	**FL86**	**MD86**	**KY98**
GA90	UT86	KY86	**OK02**	**NC98**	**GA86**	**NV86**	**AZ94**
NJ90	**NH02**	**ND86**	**NJ02**	**NY98**	**MO86**	**SD86**	**OH94**
0	1	2	3	4	5	6	7

OK98 – incumbent won, **KY98** – challenger won, errors are highlighted.

Figure 15 Made-in-advance predictions of the mid-term senatorial elections (1986-2002). Each election is represented by the two-letter state abbreviation with the election year shown by two last digits. Each column shows elections with certain number D of answers "*no*" to the questionnaire given in Table 1 (such answers are favourable to challenging party). Value of D, indicated at the top, is the Hamming distance from the kernel).

Predicting of future elections. This algorithm (without any changes from year to year state) was applied in advance to the seven subsequent elections, 1984 – 2008. Predictions are shown in Fig. 16. All of them happened to be correct. In 2000 the decision of popular majority was reversed by the Electoral College; such reversals are not targeted by this algorithm (Lichtman, 1996, 2000).

D (number of answers NO)	0	1	2	3	4	5	6	7	8	9
Predictions published months in advance			*1984*	*1988*	*2004*	*2000** *1996*	1992	2008		
Learning	*1904*	*1956* *1936*	*1944* *1940* *1868*	*1964* *1928* *1916* *1908* *1900* *1872* *1864*	*1972* *1924* *1880*	*1948* *1888**	1912* 1892	1884 1860	1980 1976 1968 1952 1932 1920 1896	1960 1876*

1904 years when incumbent won popular vote
1892 years when challenger won popular vote
* years when popular vote was reversed by electoral vote

Figure 16 Division of presidential elections (1860 - 2008) by the number *D* of answers “*no*” to the questionnaire given in Table 4 (such answers are favourable to challenging party). *D* is the Hamming distance from the kernel)

6.4 Understanding elections

Collective behavior. The finding that aggregate-level parameters can reliably anticipate the outcome of both presidential and senatorial elections points to an electoral behavior highly integrated not only for the nation as a whole but also within the diverse American states.

-- A presidential election is determined by collective, integrated estimation of performance of incumbent administration during the previous four years.

-- In case of senatorial elections the electorate has more diffused expectations of performance but puts more importance on political experience and status than in the case of presidential elections. Senate incumbents, unlike presidential ones, do not suffer from a bad economy or benefit from a good one. (This suggests that rather than punishing the party holding a Senate seat for hard times, the voters may instead regard the incumbent party as a safe port in a storm).

Similarity. For each election year in all states the outcomes of elections follow the same pattern that transcends the diversities of the situations in each of the individual elections.

The same pattern of the choice of the US President prevails since 1860, i.e. since election of A. Lincoln, despite all the overwhelming changes in the electorate, the economy, the social order and the technology of politics during these 130 years. (For example, the electorate of 1860 did not include some of the groups, which constitute 3/4 of present electorate, such as women, African Americans, or most of the citizens of the Latin American, South European, Eastern European, and Jewish descent (Lichtman, 2000).

An alternative (and more traditional) concept of American elections focuses on the division of voters into interest and attitudinal groups. By this concept the goal of the contestants is to attract maximum number of voting blocks with minimal antagonism from other blocks. Electoral choice depends strongly on the factors irrelevant to the essence of the electoral dilemma (e.g. on the campaign tactics). The drawbacks of this concept are discussed in (Lichtman, 2000; Keilis-Borok and Lichtman, 1993). In sum, the work on presidential and senatorial elections described above suggests the following new ways of understanding American politics and perhaps the politics of other societies as well.

1. Fundamental shifts in the composition of the electorate, the technology of campaigning, the prevailing economic and social conditions, and the key issues of campaigns do not necessarily change the pragmatic basis on which voters choose their leaders.

2. It is governing not campaigning that counts in the outcomes of presidential elections.

3. Different factors may decide the outcome of executive as compared to legislative elections.

4. Conventional campaigning will not improve the prospects for candidates faced with an unfavorable combination of fundamental historical factors. Disadvantaged candidates have an incentive to adopt innovative campaigns that break the pattern of conventional politics.

5. All candidates would benefit from using campaigns to build a foundation for governing in the future.

7. SUMMARY: FINDINGS AND EMERGING POSSIBILITIES

The findings described above enhance predictive understanding of complexity indicate yet untapped possibilities for further R&D in that field.

7.1 Pattern recognition approach

Information extracted from the already available data is indeed increased by this approach. To each problem considered here one may apply the following conclusion of J. Stock, a leading expert in the field: “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 for recessions. It is striking that these models, in which the information in the data is reduced to binary indicators, have predictive contents comparable to or, in many cases, better than that of more conventional models.” Importantly, this is achieved by using not more detailed data and models, but more robust aggregate level (Sect. 1.2).

Partial “universality” of premonitory patterns is established by broad research in modelling and data analysis This includes common definition of the patterns, their self-adjustment, scaling, and similarity (Newman et al., 1994; Gabrielov et al, 2000b, 2007; Keilis-Borok and Soloviev, 2003; Keilis-Borok et al., 2007; see also references in Sections 3 – 6).

Relation to “cause and effect” analysis (*perpetrators or witnesses?*) Premonitory patterns might be either “perpetrators” contributing to causing extreme events, or the “witnesses” – parallel manifestations of the system’s development. The cause that triggered a specific extreme event is usually identified, at least in retrospect. It may be, for example, a certain governmental decision, a change in international situation, a natural disaster, depletion of natural resources etc. However an actual extreme event might materialize only if the system is destabilized and “ripe” for it. Patterns of each kind signal such a ripe situation.

-- *What premonitory patters to use for prediction?* Existing theories and experience reduce the number of such patterns, but too many of them remain hypothetically promising and have to be chosen by a trial and error procedure. Inevitably a prediction algorithm is using for a start a limited number of promising patterns. They should be sufficient for prediction, but other patterns may be equally or more useful and should be considered in further development of the algorithm. Most relevant "perpetrators" might be not the among most useful patterns (e.g. due to their sensitivity to too many factors).

Relation to policy-making: *prediction and disaster preparedness.* Reliable predictions of future extreme events in complex societal systems would allow policy-makers to take remedial action before rather than after the onset of such afflictions as economic disasters, crime surges, etc. As in case of military intelligence predictions would be useful if their accuracy is known, albeit not necessarily high. Analysis of error diagrams allows to regulate the tradeoff between the rates of failures to predict and false alarms according to the needs of decision-maker.

Relation to governing and campaigning. The findings presented here for the USA elections show that top elected officials would have better chances for reelection, if they focus on effective governing, and not on rhetoric, packaging and image-making. Candidates will have better chances in they run substantive campaigns that build a foundation for governing during the next term.

7.2 Further possibilities

A wealth of *yet untapped data and models* is readily available for the continuation of the kinds of studies described and analysed above. The following are some immediate possibilities.

-- *Continuing experiments in advance prediction*, for which the above findings set up a base. Successes and errors are equally important (Molchan, 1997, 2003).

-- *Incorporating other available data into the analysis.*

-- *Predicting the same kind of extreme events in different contexts.*

-- *Predicting the end of a crisis.*

-- *Multistage prediction with several lead times.*

Less imminent, but within reach are:

--*"Universal" scenarios of extreme development and low-parametric definition of an ensemble of premonitory patterns* (Turcotte et al., 2000; Zaliapin et al., 2003; Gabrielov et al., 2007).

--*Validation of an algorithm and joint optimization of prediction & preparedness strategy* (Molchan, 2003).

-- *Developing prediction algorithms for other types of extreme events.*

7.3 Generalizations

The problems considered here have the following common features:

-- *The absence of a closed theory* that would unambiguously determine prediction methodology. This leads to the need for intense intertwining of mathematics, statistical physics and non-linear dynamics, a range of societal sciences, and practical experience (Sect. 1.3). In reality this requires long-term collaboration of respective experts. As can be seen from the references to Sections 3 – 6 previous applications inevitably involved the teams of such experts.

-- *Predictions in advance* become the only final validation of the results obtained.

-- *The need for holistic analysis* driven to extreme robustness.

-- *Strong, albeit limited, universality* of the premonitory phenomena.

Two classical quotations shed the light on these features:

A. N. Kolmogoroff. "It became clear for me that it is unrealistic to have a hope for the creation of a pure theory [of the turbulent flows of fluids and gases] closed in itself. Due to the absence of such a theory we have to rely upon the hypotheses obtained by processing of the experimental data"

M. Gell-Mann: "…if the parts of a complex system or the various aspects of a complex situation, all defined in advance, are studied carefully by experts on those parts or aspects, and the results of their work are pooled, an adequate description of the whole system or situation does not usually emerge. …The reason, of course, is that these parts or aspects are typically entangled with one another. …We have to supplement the partial studies with a transdisciplinary crude look at the whole"

In the general scheme of things the problem considered belongs to a much wider field – the quest for universal theory of complex systems extended to predicting extreme events - the Holy Grail of complexity studies. This quest encompasses the natural and human-made complex systems that comprise what some analysts have called "the global village." It requires entirely new applications of modern science, such as algebraic geometry, combinatorics, and thermodynamics. As a means for anticipating, preventing and responding to natural and manmade disasters and for improving the outcomes of economic and political systems, the methods described here may hold one key for the survival and sustainability of our civilization.

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