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Edited by

Manas Chatterji and Chen Bo

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FOREWORD

The field of Peace Science was pioneered by Professor Walter Isard from the University of Pennsylvania. The growth of Peace Science as an interdisciplinary field integrates different fields such as Economics, Philosophy, Religious Studies, Spirituality, Political Science, Sociology, Psychology, Systems Science, etc. It addresses theoretical, mathematical and systems science approaches to peace research and public policy.

Peace Science borrows theories, methods and techniques from other social sciences and shows how co-operation rather than competition between individual decision making units can lead to the peaceful resolution of problems between individuals, communities, regional entities and governmental organizations. Some topics, such as Catastrophe Theory, Chaos Theory, Decision Science, Game Theory, and Coalition and Bargaining Theory, are widely used in this area. The tools of analysis in Peace Science usually involve probability theory and probability distributions, statistical inference, the analysis of variance and covariance, the non-parametric testing of hypotheses and the Chi-square test, multivariate distributions, and other tests of hypotheses.

Peace Economics is an important component of Peace Science, which addresses the subject from a purely economic point of view; for example, the macroeconomic impacts of reduced military expenditure. The research in Peace Economics involves numerous new approaches, including Macroeconomic Stability Analysis, Modern Growth Theory, Econometric Models, the Computable General Equilibrium Model (CGE), the Richardsonian Model of Action and Reaction in military expenditure, etc.

The study of conflict management involving mediation, negotiation, and arbitration often used in Industrial Relations is also important in Peace Economics. Conflict is different from purely having a dispute. Conflict can often exist without a specific focus. It may be expressed through a problem or a dispute. Sometimes, it may be difficult to eliminate conflict, but appropriate prevention and management techniques can lessen the negative impact of conflicts, such as turbulence and violence. Many theories in Psychology, Game Theory, the Cognitive Sciences, Sociology, the Stepwise Conflict Management Procedure, etc., have been used in Conflict Management.

Peace Science and Peace Economics are relatively new fields of study, which also use different methods and techniques of Management Science, such as Strategic Management, Marketing, Operations Research, as well as Information Systems. This area is a new discipline of the Social Sciences and is different from Peace Studies, where cases are discussed without the application of sophisticated mathematics and theoretical methods. The key areas of this journal include *Arms Control, Nuclear Proliferation, Peace Science Methodology and Theory, Democracy and Conflict, the Linkage between Internal and External Conflict, Ethnic Conflict, Coalition Politics, Environmental Conflicts and Global Warming, Globalization and Conflict, International Trade and Financial Crises, Disaster Management, Terrorism, Conflict Management, Energy and Water Conflict, Military Institutions and Sociology, Defense, the Economics of Conflict and War, the Economics of the Arms Trade, Procurement and Offsets, the Economics of Security, Globalization and the Restructuring of Multinational Corporations, Security Sector Reforms, Arm Races and Alliances, Intervention, etc.*

Manas K. Chatterji
Binghamton University—State University of New York
Chen Bo
Central University of Finance and Economics, China
—Editors

PREDICTING CRISES AND MONITORING THEIR EVOLUTION

URS LUTERBACHER*, THIERRY LORHO**
AND VALERIE FERT**
*PROFESSOR EMERITUS GRADUATE INSTITUTE
OF INTERNATIONAL AND DEVELOPMENT STUDIES,
GENEVA SWITZERLAND
**GMAP GROUP PARIS AND CHÂTEAU D'OEX SWITZERLAND

Abstract

All crises are not intense or global. Black swans (supposedly rare events), a term coined by the finance scholar Nassim Taleb refer to global and or intensive international crises (not necessarily financial), such as World War I or 9/11 or the Arab Spring with its ongoing civil wars, which are extremely difficult to predict. Thus the question: Is it possible to devise a methodology that is susceptible to help predict them and once they occur to monitor them by generating quantitative measurements of their evolution? This paper presents such a new perspective. The approach, which is embedded within an artificial intelligence system called Globe Expert, is based upon an analysis of textual data, available over the Internet, in the form of big quantities of machine-readable documents written in any language and also the notion that crises are generated through overconfident or optimistic behavior of agents, which then fosters instabilities. The idea is to try to extract a maximum of information from numerous written sources to uncover the existence of potential black swans in the form of potential crisis instability behavior of various agents and then to follow their evolution through time with the use of specific probabilistic indicators. The material is analyzed via a Bayesian algorithm called **dbacl**, which looks at the concatenation of various words and concepts in a text. These are then evaluated statistically according to their probabilities of occurrence and the relationships that link them to each other. In this way the information content of each word and sequence of

words can be assessed based upon Shannon's information theory. The methodology can be applied to attempt to predict singular events as well as occurrences that evolve through time as a result of these (such as the Syrian Civil War for instance). Runs carried out with Globe Expert indicate successful results at prediction as well as calculating plausible time sequences, which correlate well with other quantitative economic or political indicators.

The work presented here was partially funded through a grant from SNIS Geneva. This help is gratefully acknowledged.

Crises, be they financial or political, are hard to predict let alone apprehend. Not all crises, however, are intense and global. Black swans[1] (supposedly extremely rare events)—a term introduced by the finance scholar and professor Nassim Nicholas Taleb (2007)—refer to global and intensive crises (not necessarily financial), such as World War I, 9/11, or the Arab Spring with its ongoing civil wars, which are extremely difficult to predict.[2] The 1929 and 2008 financial crises would qualify as black swans. Since Taleb's work, the economist and probability theorist Graciela Chichilnisky (2010) has attempted to take these issues into account by developing a new axiomatic system that can deal with extreme or unusual events (i.e. black swans) in order to account for attitudes in decision making involving the fear of catastrophes. She has, in particular, been able to show that her new axiomatic is capable of accounting for both normal and unusual events in a single analytical framework. A similar approach is taken in the so-called Rank Dependent Expected Utility Theory, originally conceived by Quiggin (1982), but then developed by Chateauneuf, Cohen, and Meilijson (2005), among others. The idea here is to assume that certain types of distortions occur in terms of probability perceptions within decision-making processes.

These then lead to unusual types of behavior whose cumulative or mass effects may lead into crises either in the form of market bubbles, which then burst, or generalized conflicts. In both cases, agents are excessively optimistic about the bubble continuing or about their chances of prevailing

[1] In some senses, the term "black swan" is euro-centric or euro-American-centric, since black swans do exist in Australia.

[2] In our discussion, we exclude rare events due to non-human causes, i.e. purely natural disasters such as earthquakes, meteorite impacts and volcanic eruptions.

in a conflict.[3] Such behavior is enhanced by bilateral and multilateral bargaining. It can be shown (Arcand and Luterbacher 2014) that it is sufficient for one party to show optimism/risk preferences for all the other parties to eventually do the same: here, optimism is contagious, a factor that heightens either bubbles or crisis escalation. Moreover, the state of optimism or pessimism involves a certain degree of indeterminacy, since an optimist can only figure out that his opponent in a bargaining situation is an optimist or a pessimist by trying to extract more concessions from him. Before asking for more concessions, a bargainer does not know the true state of his opponent.[4] Asking for more can turn a pessimist into an optimist. One-sided risk preference leads to emotional behavior and particularly to fear on the part of the other side, which also leads to risk preference, even if it originally had risk averse or risk neutral attitudes.[5] As we will see below, this type of effect is essential for the understanding of our methodology. What is the rationale for this type of behavior? Why are some agents optimists? Experimental psychology and behavioral neuroscience provide us with the beginnings of an explanation: Optimism gives agents short-term advantages over the other side (Goette et al. 2015). This is confirmed to some extent by a computer simulation of agents using competing strategies, which involve overconfidence or the absence of it; when overconfidence prevails: “populations tend to become overconfident, as long as benefits from contested resources are sufficiently large compared with the cost of competition” (Johnson and Fowler 2011: 317). This implies that when the costs of competition are greater than the benefits from the contested resources, overconfidence should dwindle. Unfortunately, this is often not the case in the real world as bloody wars or domestic conflicts persist, even though they are largely costlier than any reward that can be gained from victory.[6] Moreover, historical records show that overconfident war initiators frequently end up on the losing

[3] Clearly such a process was occurring in the crisis that preceded World War I: All the parties involved were far too optimistic about their chances of winning, since the expectation that the war would be over by Christmas 1914 was widespread. This point is also recognized by Johnson and Fowler (2011: 317).

[4] In some senses, neuroscience research confirms this uncertainty but in reverse: In an experiment, stress made high anxiety subjects less optimistic whereas it made low anxiety individuals more so. However, the experiment does not measure the long-term dynamic effects of stress, which could again lead to a reversion (Goette et al. 2015).

[5] For a demonstration of all these properties, refer back to Arcand and Luterbacher (2014).

[6] This is illustrated by the dollar auction game imagined by Shubik (1971), which implies that a costly conflict equilibrium may obtain.

side.[7] In any case, the possibility of such long-term conflict equilibria and of Keynesian long-term unemployment equilibria again suggest the necessity of trying to anticipate black swans.

Thus, the question: Is it possible to devise a methodology that is able to help predict black swan type crises, and, once they occur, to monitor them by generating quantitative measurements of their evolution? If we return to the topic of economic crises, it is striking to see how some people were able to predict them while most analysts missed them. In the 2007-2008 financial crisis, traditional doomsday sayers such as Peter Schiff, Mark Faber, and Nouriel Roubini, but also some seasoned economists such as Joseph Stiglitz, Robert Schiller and Martin Feldstein, predicted an imminent crash, but again most others did not. This reveals, if nothing else, an ambiguity in the signals that can be picked up from various information sources, whether textual or numerical. Now the question: Is it possible to do better? Can one tease more knowledge out of sources that are around and available?

We intend to accomplish this with the help of a specific artificial intelligence system, to be outlined in this chapter, called Globe Expert. Before we can go into the details of how Globe Expert handles information, we need to present the general perspective in which the system is imbedded.

Entropy of a Text

As mentioned above, information is available roughly in two forms: textual and numerical. Information available in other formats, such as pictorial or sound, can eventually be reduced to numerical elements. We will first discuss the case of textual information. There is now an enormous amount of textual material available over the Internet, ranging from the serious to the more frivolous. This content is given in several languages. Could one tease out information from it that would eventually give us some valuable insight into the possible occurrence of an event? We want to show that this is actually possible with the help of information theory. Classical information theory was developed by Shannon (1948) in connection with the then early development of computer technology. To understand it, start with the model of tossing a fair coin, where each side

[7] As the examples of both Napoleons (I and III), Germany in World War I and Hitler in World War II clearly show.

has a probability of ½. One question with one answer will give information about the result of the toss being heads or tail. We can now introduce the concept of **entropy**, which constitutes a measure of the uncertainty associated with an experiment that provides information, in our case here, the tossing of a coin. Entropy in this case will be maximal and worth 1 or 1 bit, because only one question has to be asked with one answer, which is completely unknown before the experiment. We can now generalize from this: if 3 questions with 3 answers are necessary, the entropy or information will be worth 3 bits. In mathematical terms, we end up with the following function:

$$H(X) = -\sum_{i=1}^{n} p_i \log_2 p_i$$

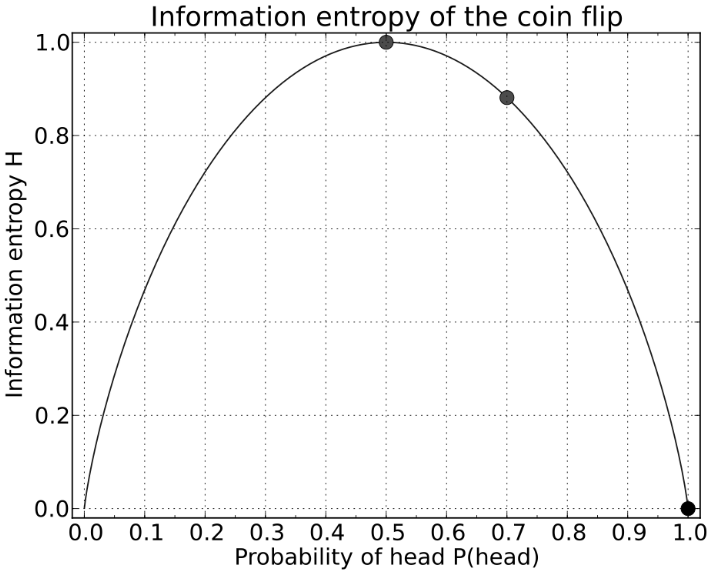
which measures entropy or information. It is easy to see that entropy is maximized when the probabilities are uniformly spread, as in a fair die, for instance, so that:

$$H_{max}(X) = -\sum_{i=1}^{n} \frac{1}{n} \log_2 \frac{1}{n}$$

And thus we have:

$$H_{max}(X) = \log_2 n$$

We can thus establish the information-entropy probability space of a coin flip from fair to unfair:



These properties can now be applied to textual material. For a text made up of words, similar principles to the ones presented above are applied.

For each word and for each combination of words, it is possible to determine a probability space. By extension, each document composed of texts and each set of documents can be represented in this way, which will constitute an exact representation of the information structure contained in them. The AI system used here works on the basis of dbacl, a digramic Bayesian classifier for text documents. dbacl computes maximum (relative) entropy models for text corpora and can compute the Bayesian posterior distribution for a given document in terms of any number of previously computed models.

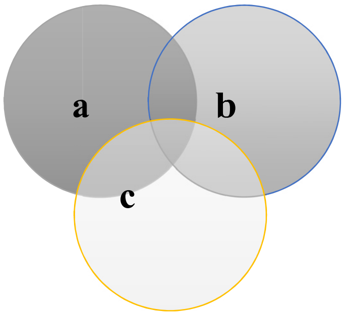
Start by computing the entropy of a letter, a or b or c, etc. which we will call x (generic, not the letter x). Its probability of appearing, if it is in a text of length L letters p_x times, will be p_x/L. If the text is made up of letters that appear purely randomly, then its probability of appearing is 1/26 (in English, but also in French) with an entropy of 4.7 bits. But then the probability of letters will depend on the sequence defined by the word in which they appear: given sequences of letters are more probable after a first letter, for instance. This allows for the use of Bayesian conditional probabilities in calculating the sequences of letters defining words. Thus we can compute the entropy of a generic letter x as $-\log(p_x)$. The entropy of a word is:

$$\sum_{x=1}^{n} p_x \log_2 p_x$$

Now, if one moves from word to text, Shannon has demonstrated that one needs at least $H = -n\sum_{i=1}^{n} p_i \log_2 p_i$ bits to store a complete text, where now i may refer to a generic letter or to a generic word. The value H will obviously differ depending on the language. One identifies n-grams within a language group of n letters or n words.

Entropy of a Segment, Divergence, and, Cross-Entropy between Segments

We will imagine three sets which we will call segments containing information **a**, **b**, and **c.** We can also define **U**, the union of **a**, **b**, and **c**, and represent these segments in the following way:



All of these segments can be represented by probability spaces. These segments are partially overlapping. One can measure the information shared by these three segments through the following indicators, which are measures of **entropy**, **divergence** and **cross-entropy**. What has been established so far enables the measurement of the entropy of each segment. The information difference between segments can be evaluated via the Kullback-Leibler (KL) (1951) divergence measure between sets, say **a** and **b**, in terms of their probability spaces **P** and **Q** but relative to **a** (thus it is asymmetric since one can do something similar, but not identical, relative to **b**) which is:

$$D_{KL}(a\|b) = \sum_{i=1}^{n} p(i)\log_2 \frac{P(i)}{Q(i)}$$

The cross-entropy is then simply the entropy of each segment plus the KL divergence between them:

$$H(a,b) = H(a) + D_{KL}(a\|b)$$

Cross-entropy is thus also asymmetric.

Uncertainty, Information Content and Predictability Measurements

Entropy, divergence and cross-entropy allow us now to define other types of indicators which will allow us to progress toward the goal of evaluating the likelihood of rare events or even sequences of such rare events. So, the **uncertainty measure** evaluates the increase in entropy resulting from the addition of the information of segment **b** to that of segment **a** (knowing their respective entropies): H(**a**+**b**) ≤ H(**a**) + H(**b**) has to obtain. In case of equality, there would be no information sharing between **a** and **b**.

Practically this amounts to evaluating:

$$\frac{H(a+b)}{H(a)} - 1$$

The above expression assesses this difference in percentages, which can be positive or negative.

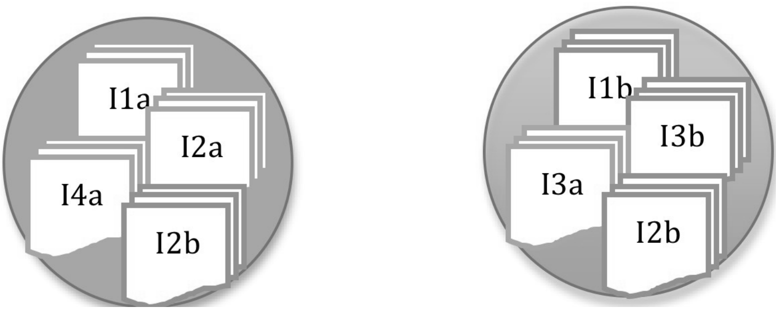
In terms of **information content**, the KL divergence measure allows for the evaluation of the gain resulting from the use of a different probability space than the one used initially. This can be achieved if one evaluates the variations in the distance between the KL divergence of the probability spaces of sets **a** and **U** (the universal set) and the KL divergence of the probability spaces of sets **a**+**b** and, again, **U**. Here, **U** is the set against which the gain mentioned above is measured. Predictability measures the quantity of information shared by segments **a** and **b**. It allows one to determine *a posteriori* if it is likely that an information set might belong to another set, hence the measurement here of the predictability (or respectively unpredictability) of the information. Here, one measures the variation in percentage of H(**a**, **b**) with respect to H(**U**), the universal set, so:

$$\frac{H(a,b)}{H(\mathcal{U})}-1$$

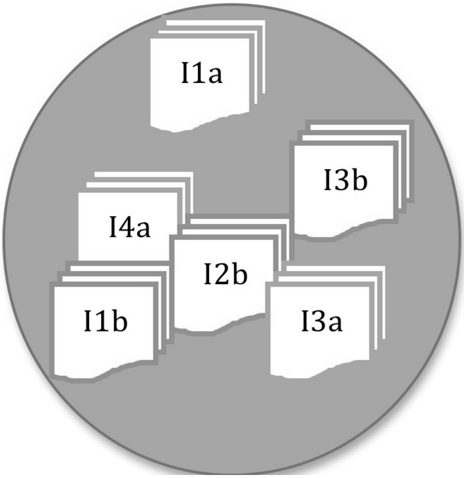
Again, this expression can be positive or negative.

Detecting Rare Events, i.e. “Black Swans”

The detection of a unique black swan from the probability space associated with the set where it might nest is obviously impossible. However, if information about it is contained within other segments, then it might be possible to very closely circumscribe the whereabouts of a black swan. To illustrate this methodology let us consider two segments:



For segment a, we have the information 11**a**, 12**a**, 14**a** and information from segment **b**, namely 12**b.** For segment b, we have information 11**b**, 12**b**, and 13**b**, and then information 13**a**. This is interesting since the information concerns **a**, but it is not within **a** and thus, in a way, not known by **a**, although it should concern **a.** One can now make a sum of all the information within a and b to get:



What can we say now, once this addition of information is achieved, concerning their uncertainty, information content and predictability?

If we want to assess the uncertainty, information content, and predictability of the new set, we will proceed in the following way: If a black swan nests within **a** but is relatively hidden, then any information coming from outside the segment (here 13a) that concerns it should significantly increase the certainty level. The **uncertainty reduction** as a result of the addition should thus be detected and measured. If there is a black swan in **a**, then any addition of outside information should be significantly different from what is in **a**; in other words, **the KL divergence should increase**. From the point of view of **a**, this new information is unpredictable and thus the **predictability of the new segment or set should diminish**. If one carries out these analyses, a black swan will not necessarily be detected, but a web of relationships between sets or segments will be discovered which will generate a network of presumptions about possible major disequilibria. Here, a major disequilibrium means that information is available, but that this information (usually a forewarning of the coming difficulties) is not taken into account. A black swan deviates significantly with respect to a norm and thus such an imbalance can point to one.

It has to be noted here that the methodology developed thus far is based on the same assumptions as the decision theories evoked in our introductory section. The distortions in terms of probability perceptions can clearly lead, on the parts of decision-makers, to either excess pessimism, but more often to excess optimism, which as stated above generates bubbles or conflict type escalations and crises. This is consonant with the notion of imbalance or disequilibrium which was evoked in the previous paragraph.

Path to results

What happens now if we want to analyze the likelihood of (black swan) events, such as, for instance, the 2007-2008 financial crisis followed by the great recession, the effects of which are still with us somewhat, or the Syrian crisis and then the civil war following the "Arab Spring" episodes of 2011? To answer this question, we will have to conduct multiple investigations of textual material according to the principles developed so far. The results of these, to be presented here, are calculated as mentioned via the AI system Globe Expert. This system can manipulate classical and quantum probabilities with the help of a Bayesian digramic algorithm, which seeks maximum entropy for each information sample (for more about dbacl, refer to Berger, Della Pietra and Della Pietra 1996 and to Breyer 2004).

Indeed, next to Shannon's classical information theory, a quantum version has been developed which adds the superposition principle to the classical version: "The superposition principle states that a quantum particle can be in a linear combination state, or superposed state, of any two other allowable states" (Wilde 2013:23). In other words, if one refers back to the coin tossing experiment described above, it can result in either a Head or a Tail, or a superposition of these two states.[8] Information from performing the experiment will thus have the value of a quantum bit or qbit as opposed to a bit in the classical theory. It might seem strange to invoke these quantum notions in a social and political context; however, there are plenty of examples where these superpositions might occur. So often in a social setting, observing a type of behavior and letting this observation be known can induce an individual to change it. Moreover, a voter who is indifferent between two candidates and decides just when he is casting his vote, or a decision-maker who uses a mixed strategy, can also be seen as examples of superpositions. Finally, referring back to the remarks made

[8] There is an analogy here with the famous Schrödinger's cat: The cat is in a box where the radioactive decay of an atom triggers the emission of a cyanide gas that kills the cat. Since radioactive decay is a quantum type phenomenon, one can only find out if the cat is dead or alive once one opens the box. Before that, the cat is to some extent both alive and dead in superposition.

above about optimism and pessimism, and the difficulty in a bargaining situation in evaluating if the opponent displays either one of these two characteristics, leads us also to a superposition perspective.

Results achieved through the dbacl analysis are assumed to follow a normal distribution. This distribution, as can easily be understood, maximizes entropy among distributions depending on two parameters. Before engaging in the actual analysis, one or several "referentials" have to be constructed. These consist of a list of segments, which contain in turn an enumeration of key words, which refer to a particular universe of cases and thus limit the field of textual information analysis.

For instance, for the financial crisis of 2007-2008, several "referentials" were constructed with the help of specialists in finance or banking. To each referential, the query "Financial Crisis" is associated. The resulting association query referential then corresponds to a universe. Three distinct periods were analyzed: 1995-2000, 2002-2006, and 2007-2013 (2001 is excluded because of the peculiar situation generated by 9/11). Here, we show the results concerning one universe in detail—"Vision American Financial Markets". Another referential's results, "Vision European Central Bank", will be briefly commented upon later. The universe is chosen for one temporal sequence: 2002-2006. Other temporal sequences will be analysed afterwards.

The referential "Vision American Financial Markets" for the period 2002-2006 was decomposed into annual queries. The year-by-year observation of potential disequilibria corresponds to what one can get if the period is taken as a whole. The system was checked for a possible significant informational bias for the universe **U** by carrying out the same queries and research for another universe, which was defined by a different referential (macroeconomic type). The two universes were then merged and the query research compared: No significant divergence obtained. So the chosen universe **U** can be considered a representative and unbiased sample of the "true" informational universe. This referential (Vision American Financial Markets) is presented in detail in the Appendix. With the referential as a point of reference, we can then easily compare different combinations. The referential constitutes the learning space of the AI system. For each segment within it, a probability space can be determined and its maximal entropy can be calculated, which provides the information content of a segment (here, we can refer back to the fair/unfair coin example). A query is then raised for the AI system. Here, the query is simply: "Financial crisis" associated with each segment in their embedded key words. The system then seeks all of the information connected with that query before the crisis i.e. 2002–31 December 2006. The AI system evaluates the characteristics of each set of calculated results with respect to the segment of reference, which thus provides the probability space for these. For instance, for the query Fannie Mae+ Financial Crisis, the IA system verifies if the calculated results don't diverge with respect to the corresponding probability space. To achieve this, the entropy of the calculated results, the divergence with respect to the referential probability space, and the cross entropy are evaluated. In this case, the entropy of the universe **U** is 10.57. The procedure will now consist of crossing segment dyads in order to assess whether or not the addition of outside information has an impact on the receiving segment:

Dyadic Analysis

	Entropy	Variation of entropy Uncertainty	Distance	Variation of distance Information Content	Cross-entropy	cross-entropy variation Unpredicatbility
Segma segment 🡐 receives information from b segment	**H(x)**	**% H(a+b)/H(a)**	**D_{KL}(a+b||U)**	**%D_{KL}(a+b||U) / D_{KL}(a ||U)**	**H(a,b)**	**%H(a,b) / H(u)**
ECONOMY Fannie Mae <== ECONOMY Instability	10,44	1,36%	0,3	-30,23%	10,85	2,84%
ECONOMY Fannie Mae <== ECONOMY Opacity	10,31	0,10%	0,24	-44,19%	10,79	2,27%
ECONOMY Fannie Mae <== ECONOMY Unemployment	10,42	1,17%	0,34	-20,93%	10,89	3,22%
ECONOMY Fannie Mae <== FINANCIAL WORLD Financial Engineering	10,53	2,23%	0,26	-39,53%	10,81	2,46%
ECONOMY Fannie Mae <== FINANCIAL WORLD Financial Guarantees	10,4	0,97%	0,27	-37,21%	10,82	2,56%
ECONOMY Fannie Mae <== FINANCIAL WORLD Financial Institutions	10,36	0,58%	0,27	-37,21%	10,82	2,56%
ECONOMY Fannie Mae <== FINANCIAL WORLD Financial Markets	10,47	1,65%	0,16	-62,79%	10,71	1,52%
ECONOMY Fannie Mae <== FINANCIAL WORLD Incentive	10,65	3,40%	0,26	-39,53%	10,81	2,46%
ECONOMY Fannie Mae <== FINANCIAL WORLD Mortgage Brokers	10,28	-0,19%	0,31	-27,91%	10,86	2,94%
ECONOMY Fannie Mae <== FINANCIAL WORLD Rating Agencies	10,3	0,00%	0,29	-32,56%	10,84	2,75%
ECONOMY Fannie Mae <== FINANCIAL WORLD Securitization	10,5	1,94%	0,26	-39,53%	10,81	2,46%
ECONOMY Fannie Mae <== POLITICS Alan Greenspan	10,23	-0,68%	0,26	-39,53%	10,81	2,46%
ECONOMY Fannie Mae <== POLITICS Bipartisan Congress	10,08	-2,14%	0,28	-34,88%	10,83	2,65%
ECONOMY Fannie Mae <== POLITICS FED	10,53	2,23%	0,2	-53,49%	10,75	1,90%
ECONOMY Fannie Mae <== SOCIETY American Dream	10,5	1,94%	0,39	-9,30%	10,94	3,70%
ECONOMY Fannie Mae <== SOCIETY Mortgage	10,43	1,26%	0,26	-39,53%	10,81	2,46%
ECONOMY Fannie Mae <== SOCIETY Real Estate	9,4	-8,74%	0,52	20,93%	11,07	4,93%

95% confidence intervals for all the measurements can then be calculated:

Confidence Interval	Entropy Variation Uncertainty	Distance Variation Information Content	Cross-Entropy Variation Unpredictability
Higher End	1.24%	-34.55%	2.43%
Lower End	2.40%	-29.43%	2.66%

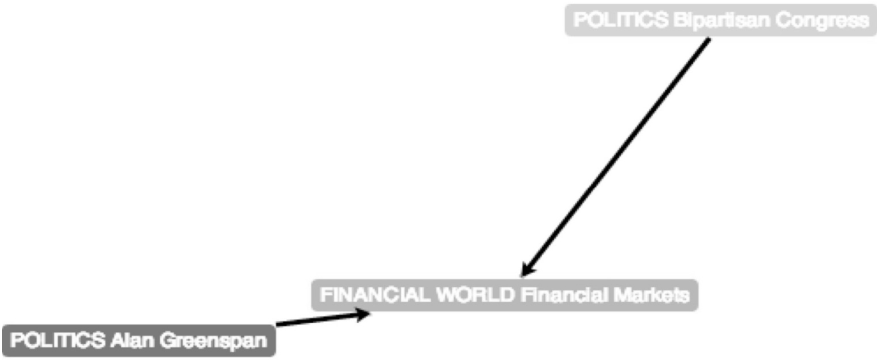
According to our criteria, the following combinations of segments should be retained:

- Uncertainty: all combinations below 1.24%
- Information content: all combinations above -29.43
- Predictability: all combinations below 2.43

This will allow us to select sequences of segments, as in the following.

POLITICS Alan Greenspan <== FINANCIAL WORLD Mortgage Brokers	10, 12	0,80%	0,25	-16,67%	10,8	2,37%
POLITICS FED <== ECONOMY Fannie Mae	10, 53	0,29%	0,2	-13,04%	10,7 5	1,90%
POLITICS FED <== ECONOMY Instability	10, 52	0,19%	0,22	-4,35%	10,7 7	2,09%
POLITICS FED <== ECONOMY Unemployment	10, 5	0,00%	0,24	0,043478 3	10,7 9	2,27%
POLITICS FED <== FINANCIAL WORLD Financial Engineering	10, 55	0,48%	0,21	-8,70%	10,7 6	1,99%
POLITICS FED <== FINANCIAL WORLD Financial Guarantees	10, 51	0,10%	0,19	-0,173913	10,7 4	1,80%
POLITICS FED <== FINANCIAL WORLD Financial Institutions	10, 47	-0,29%	0,21	-8,70%	10,7 6	1,99%
POLITICS FED <== FINANCIAL WORLD Rating Agencies	10, 49	-0,10%	0,17	-26,09%	10,7 2	1,61%
POLITICS FED <== FINANCIAL WORLD Securitization	10, 56	0,57%	0,19	-17,39%	10,7 4	1,80%
POLITICS FED <== SOCIETY American Dream	10, 59	0,86%	0,21	-8,70%	10,7 6	1,99%

We will now calculate the rank of each of these sequences with respect to the criteria of Uncertainty/Certainty, Predictability, and Information Content, when compared to all other sequences. If the rank in all of these (in percentages) remains below 50%, then no major breaking point is likely. However, if these are above 50%, then major risks of breaking points (disequilibria) appear: Here, again, a major risk means that information is available but that this information (usually announcing what is called "bad news") is not taken into account.[9] These rank limits help one to select particular relationships. The higher the rank threshold, the higher the major risks. For instance, for an 85% threshold, we only get the following relationships:



We can now refine the analysis of the relationship. Each segment that influences another segment can ultimately be decomposed into more sub-segments, as can the segment being influenced. So the segment Allan Greenspan→ Financial Markets eventually leads one to take into account an 85% threshold leading to:

Capital_AND_Market←Weak_AND_Oversight

Loss_AND_OF_AND_Confidence←Weak_AND_Oversight

OverTheCounterTrading ←Weak_AND_Oversight

[9] We already made this point about disequilibria earlier when we pointed out the role of optimism versus pessimism in generating crises. Here, we are looking for a prevalence of optimistic decision-making.

It has to be noticed that the OverTheCounter derivative trade contributed significantly to the demise of Lehman Brothers.

Now what makes a segment a black swan? To identify a black swan, we will now investigate not only the rank but also the **mean** of each segment, again with respect to Certainty/Uncertainty, Information Content, and Predictability. Below 50%, a segment does not point to any particular risk. Above 50%, the risk will become significant. The higher it is, the greater the risk of encountering a black swan. Combined with the risk of breaking points (treated above), we should now be able to identify a black swan. A statistical analysis of type I and II errors shows us that in order to get a significant black swan prediction result, all three indicators have to be higher than 60.[10] What are the black swans for the period 2002-2006; in other words, the precursors of the bubble? Our analysis shows that the combination of rank and mean analysis lead to two black swan segments:

- FINANCIAL WORLD Financial Markets
- POLITICS FED

The segments: "Financial Engineering" and "Incentives" are significant only with respect to Uncertainty, but the values of the other two factors are not sufficient in order to characterize them as black swans (<60). "Securitization" is significant for Uncertainty and Information Content, but not for Unpredictability. This can be seen in the following table:

[10] Here, the null hypothesis is the absence of a black swan. It is possible that the 60% threshold could also be justified in terms of quantum information theory. This number guaranties, then, that the rare event has more than a 50% chance of occurring.

	Uncertainty	Information Content	Unpredictability
(Financial World) FINANCIAL ENGINEERING	67.66	51.41	55.17
(Financial World) FINANCIAL MARKETS	67.09	88.24	92.25
(Financial World) INCENTIVES	83.1	52.15	56.32
(Financial World) SECURITIZATION	71.19	61.39	58.17
(Politics) FED	72.10	75.29	84.46

Now that we have established the likelihood of a black swan on the basis of a given time period, the question is: when will it unfold in the next period? The IA system will then seek how much time it will take for a global equilibrium to emerge between segments, treated as "agents", which will maximize their benefits and minimize their costs. This global equilibrium obtains after 4.72 years. Beyond it, no additional information can be extracted.

Now, a simple formula allows one to calculate the time span for the likely black swan to emerge here for Financial Markets:

> $t_{1,2} = t_0 + 4.72*2*$(1-**m**ean **i**nformation **c**ontent value)* m (Uncertainty Margin) where t_0 is the reference year
> - $t_1= t_0+4.72*2*(1\text{-mic})*m$ (lower bound) while
> - $t_2=t_0 +4.72*2*(1\text{-mic})/m$ (upper bound)

The mean information content here is 0.891 and m is 0.67, so that we finally have **2007.69 < t < 2008.54**.

We can now perform some simple checks. Clearly, if the black swan appears at a given period under the presented form, it should not occur earlier or later. This seems to be the case, since for neither the period 1995-2000 (predicting to 2003-2004) nor for the period 2007-2013 (predicting to 2017) are our three indicators above 60%. In fact, two out of three are below 50%. This simple analysis thus confirms our main result. It also seems to imply that a major event will not be happening in this category soon. We can further verify these conclusions by performing a more advanced error analysis. We first verify that our sample referential is representative of the “true” referential, which we take as “balanced” with a mean of 50. We can see that such a balanced referential lies within the confidence intervals of the observed referential (the last two rows of the table below):

M Observed	**Uncertainty**	**Information**	**Unpredictability**
M0	50	50	50
Absolute Standard Deviation	29.12	29.07	29.47
Case Numbers	306	306	306
Type I Error	0.01	0.01	0.01
Type II Error	0.98979	0.98821	0.87229
Power of the Test	1.02%	1.18%	12.77%
Cohen’s d	**0.43%**	**1.25%**	**8.24%**
Relative Standard Error	1.66778	1.66468	1.68761
Lower Bound	45.83	45.35	48.08
Upper Bound	54.42	53.93	56.77

The Cohen’s d is usually significant above 0.8. It measures the influence of an indicator. We then examine the results of the error analysis, which we will report only for the segments, which turned out to be significant in terms of black swan occurrence. Here, we want to recall that we analyze two types of errors in standard statistical fashion, which are defined with respect to a null hypothesis. Here, the null hypothesis refers to the absence of a black swan (or crisis or bubble) prediction. Classically, our error is of type I if the null hypothesis is accepted, even though it is incorrect, and of type II if the null hypothesis is rejected, even though it is accurate. We present the result of the error investigation below: