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ABSTRACT

Enterprise risk management has moved from an event based view of risk to a holistic, systems based approach. Risk systems that involve human interaction are classified and behave as complex adaptive systems and evolve over time. An understanding of the evolution of an enterprise's risk system should reveal the nature of risk relatedness, future likely emergence of risks and be able to identify risk characteristics that are systemic to that specific enterprise. In order to operationalise such an approach, a methodology has been developed that draws on phylogenetic approaches that have been successfully developed for biological and language evolution studies. The technique and process provides an insight into the lineage, pace and impact of external conditions on the evolution of risks. It also provides a unique and rational classification of risk in an enterprise which can be used to optimize risk management resources. An example of a fictitious insurance company is used to illustrate the approach.

1. INTRODUCTION

The authors introduce a novel approach to risk analysis and management that is grounded on three interconnected principles:

1. Risks behave as complex adaptive systems, not as an aggregation of events, (Allan and Davis, 2006). This concept extends beyond the principle 'the whole is greater than the sum of the parts' to include Angyal's modification that, 'aggregation and whole formation are processes of an entirely different order' (Angyal, 1941).

2. Evolution is a signature of complex adaptive systems (Mitleton-Kelly, 2003) and (Morel and Ramanujam, 1999); and hence risks, should by definition, evolve and follow evolutionary principles. This also applies to companies and economies (Arthur, 1997).

3. Connectivity is a fundamental property of any system (Newman, 2010), (Mason, 2005), Barabasi and Albert, (2002) and (Checkland and Scholes, 1990).

There is a trend, that in modern society and its organisations, risks have become more complex and interdependent (Beck, 1992, and 2004). This has been borne out by the recent systemic crisis in the financial sector, where banks were lending and trading with each other and the impacts of their losses relating to their mis-priced mortgage books, are felt throughout the broader economy and society as a whole. Indeed, it is suggested that connectivity is the third dimension of risk (Allan, Yun and Cantle, 2008) to be added to the two-factor risk paradigm of probability and impact. Moreover, Mitleton-Kelly (2003) argued that the interconnected nature of the elements in a system enables both the system and its parts to evolve.

Using evolutionary theory, and specifically phylogenetic techniques developed to study the evolution of biological systems, it will be demonstrated, using a case study, that:

1. Risks can be understood to have a unique characteristic sequence, very much like a DNA to a biological entity.

2. The history of the evolutionary path (path-dependency) is an important aspect of a risk; this is of course already well known to financial and insurance professionals. The point here is to understand what the parent risk is and when a risk characteristic combines or separates to form a new lineage. It is possible to identify systemic characteristics that are highly influential in the forming of risks in a system.

3. Taking into account the unique evolutionary history of an organisation's risk system it is possible to determine the likely future trajectories or emergence of new or evolving risks.

4. Lastly the paper demonstrates that the evolutionary analysis provides a unique and powerful way of classifying risks that is independent of traditional organisational boundaries and risk taxonomy structures such as are imposed through capital standards. The technique can show the most interdependent risks – that is the risks that could have a significant influence on a cascading failure of the enterprise. This can aid effectiveness and efficiencies in managing risks and allocating risk related resources or capital.

Before embarking on the case study it is necessary to first explain the background to phylogenetics and its principles so as to appreciate how the approach has been adapted to analysing risks.

2. HISTORY AND DESCRIPTION OF PHYLOGENETIC ANALYSIS

In the eighteenth century, Linnaeus pioneered the classification practice by grouping organisms in accordance to their similarities and differences (Wheeler, 2005). Linnaeus' work, much like traditional risk management, can be described as systematic, instead of evolutionary, as the objective was to place all known organisms into a hierarchical structure. Phylogeny on the other hand, being inspired by Darwin's evolutionary approach, (Brown, 2007) not only indicates the similarities and differences between species, but also illustrates their evolutionary relationships (Pagel, 1999).

With the advances in computational capabilities and molecular knowledge, the study of classification and evolution has entered a new era. Phylogenetic analysis[1] utilises molecular information, i.e. DNA, to meet the data requirements, and assigns equal weights to characters (Mishler, 2005). By doing so, the approach is less subjective – 'rather than making assumptions about which characters are important, phylogenetic analysis demands that the evolutionary relevance of individual characters be defined' (Brown, 2007).

The outputs from phylogenetic analysis are tree-like shapes, often called 'evolution trees', 'phylogenetic trees' or 'cladograms' – see figure 1 for a high-level cladogram of the tree of life. A phylogenetic tree is essentially a connected graph that is composed of nodes and branches and does not contain any closed structures. The nodes symbolise the organisms under investigation, whereas the branches that connect all the nodes represent the relationships among different organisms, in terms of their ancestry and descent relationships. Epistemologically, a node is an entity that is homogenous and comparable to other entities being studied and its informative character states are always subject to change as knowledge of characters progresses (Albert, 2005). Therefore, the application of the phylogenetic trees, which is composed of nodes and branches that link nodes, is not restricted to organisms. Indeed all individual entities

[1] The terminology 'phylogenetic analysis' and 'cladistic analysis' are often interchangeable in contemporary usages and this paper does not discriminate between the two.

with taxonomic characters, such as species, populations, individuals, genes, or even organisations (McCarthy et al., 2000), can be analysed with this method.

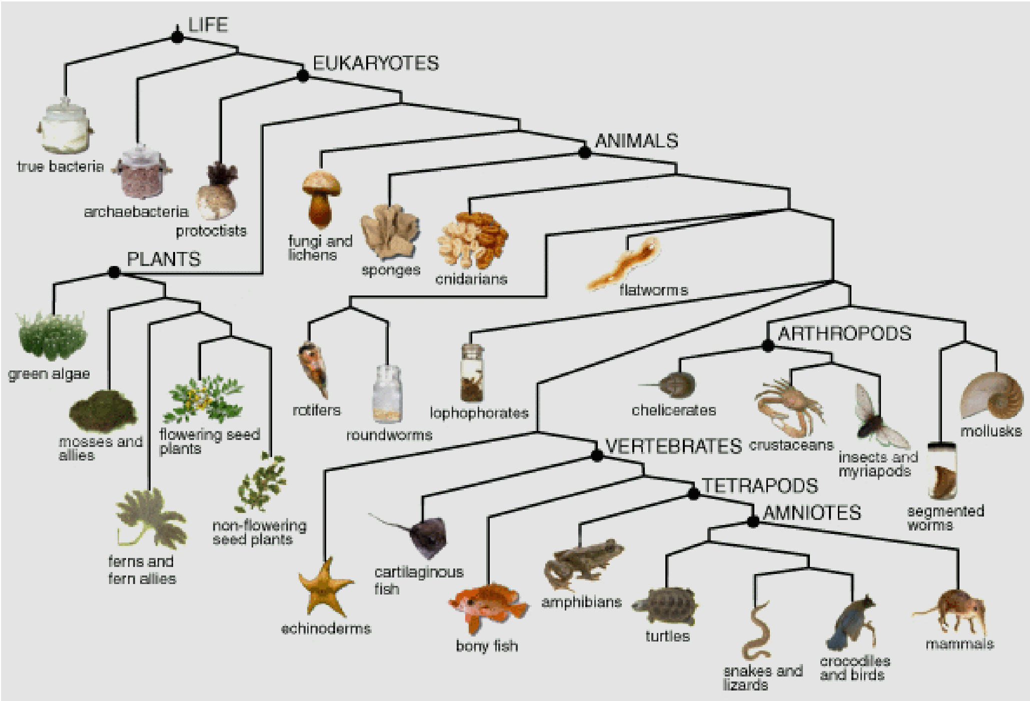


Figure 1 – Cladogram example of the tree of life. We can apply this to the example of risk by substituting risk events or losses for the "species". We can then explore the relationships in order to understand how certain characteristics are evolving over time to generate new emergent risks.

All phylogenetic trees can provide the same basic information, including a historical pattern of ancestry, divergence, and descent, all of which can be interpreted from their structure (Lecointre and Le Guyader, 2007). Basically, the nodes of a tree can be categorised as external or internal, according to their relevant positions. That is, nodes at the terminal tips of a tree are called the external nodes (Mishler, 2005), whilst the rest are termed the internal nodes and these are the ancestors of the former. In other words, external nodes are descendants of connected internal nodes. The links between the nodes are called the branches and the lengths of these are proportional either to the evolutionary time or the number of mutations occurring along that branch (Li et al., 2000). Evolution occurs independently along the branches emanating from each internal node and the overall structure of nodes and branches represents a given entity set's degree of diversity.

2.2 *DIFFERENT PHYLOGENETIC ALGORITHMS*

Li et al. conducted a survey of how scientists construct phylogenetic trees and concluded that there are three major methods and algorithms employed (Li, 2000):

- distance matrix;
- maximum likelihood;
- parsimony.

In practice, these different tree constructing algorithms need to be applied with care, particularly in the context of risk analysis. For example, the distance matrix algorithm, though computationally efficient, can produce inaccurate inferences under certain conditions (Pagel, 1999). The maximum likelihood method and other Bayesian methods rely more on statistical models to describe the mutation process at a molecular level (Kishino et al., 1990). This sort of model is not easy to obtain for risk analysis, and the results can be difficult to interpret.

Methods based on the principle of maximum parsimony have been by far the most widely used, because they are probably the most logical and intuitive to apply. The principle behind the parsimony approach is that '*a tree is more preferable if it involves fewer evolutionary changes*' (Lin et al., 2007). In other words, the one with the fewest evolution changes is termed a parsimonious tree, as the term 'parsimony' implies as few changes as possible (Sneath and Sokal, 1973). However, Sober notes that the parsimony algorithm does make assumptions about evolution but that those assumptions are modest and unproblematic and that the most-parsimonious tree is better supported than the others, (Sober, 2005). After considering the advantages and drawbacks of each algorithm and their experience of applying and interpreting the resulting trees in a risk context, the authors conclude that the parsimony method is the most suitable for risk analysis.

3.0 Techniques for viewing and interpreting the Trees and data

A risk tree is studied from left to right. As we move to the right, the tree branches to indicate points where the risk characteristics are separating in evolutionary terms. The evolution risk trees show the origin on the left hand side with the branches separating at bifurcation points caused by a change of common risk characteristics.

Figure 2 below shows a section of a tree with two legs representing risks A & B 'lost intellectual property rights' and 'claims infringement of intellectual property rights', respectively. The risk characteristics are indicated by the numbers on the branches: 22 – 'inadequate legal framework; 7 – 'crime' and 25 – 'human error or incompetence'. This tree shows there was an earlier risk with hazard 22 from which emerged the two new risks, A & B, with additional characteristics, 7 and 25 respectively.

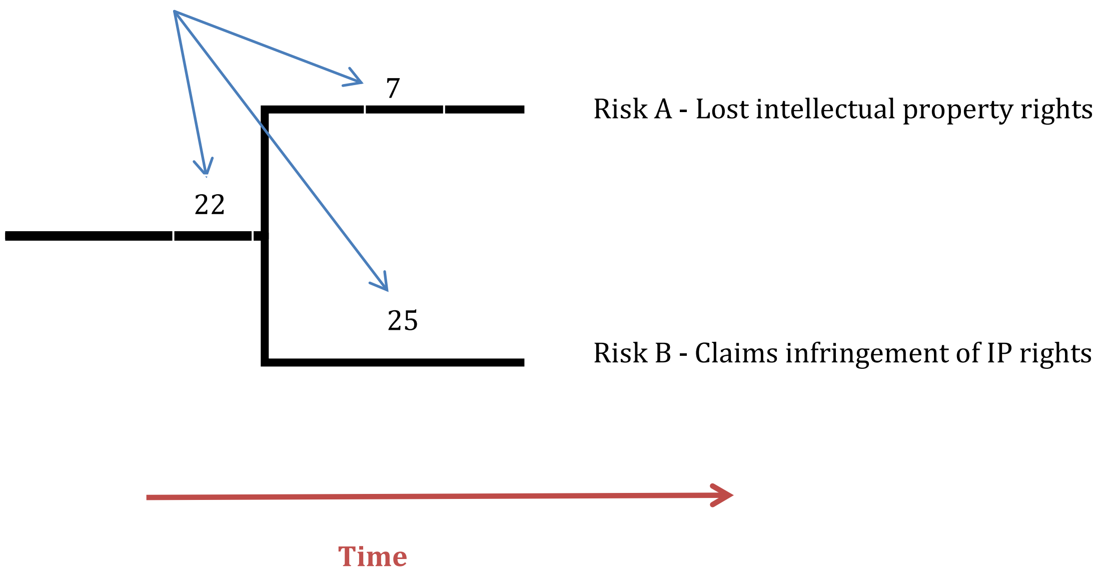
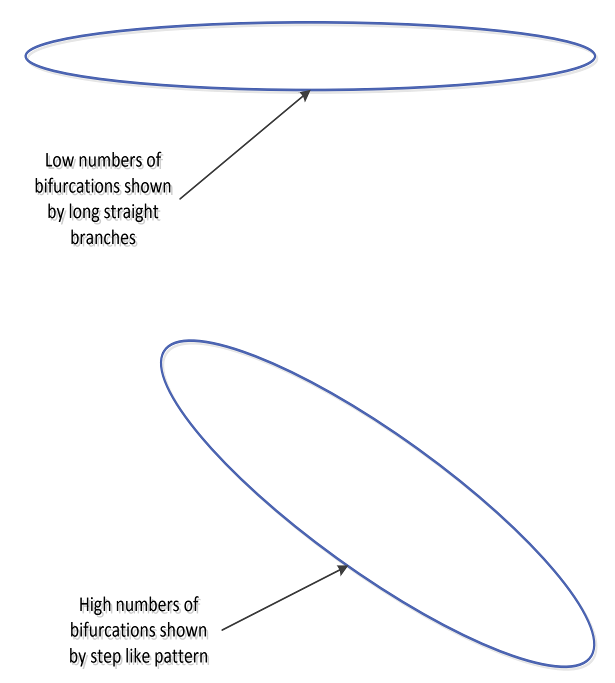
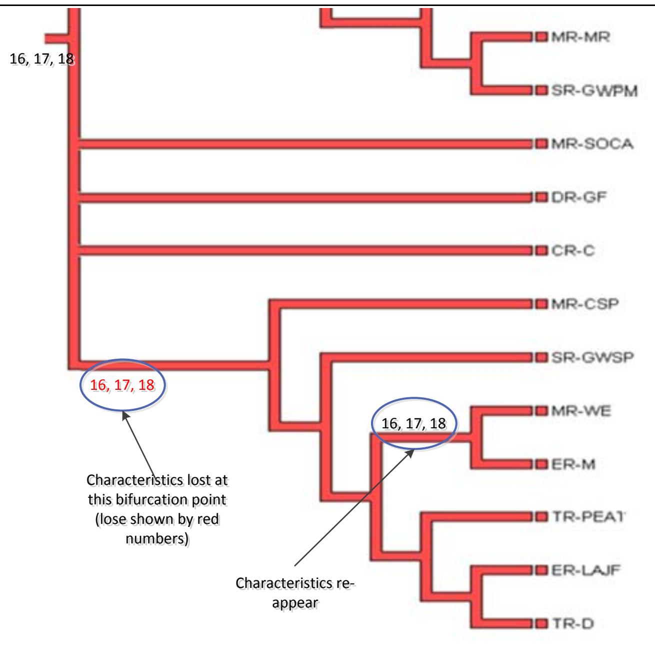


Figure 2 above shows a section of a tree with two risks. The characteristics are indicated by the numbers on the branches: 22 – 'inadequate legal framework; 7 – 'crime' and 25 – 'human error/ incompetence'.

There are many patterns formed within the trees which indicate where evolution is most likely, thus helping with the monitoring and prioritisation of risk mitigations. These common patterns are captured in the Table 1 below:

<table>
<tr><th>Characteristic</th><th>Example evolution tree</th></tr>
<tr><td>Low Bifurcation:
Low numbers of bifurcations, shown by long straight branches, indicate areas of limited emergence. These areas are stable and independent from other risks. They possess few characteristics and can be more easily tracked.</td><td rowspan="2"></td></tr>
<tr><td>High Bifurcation:
High numbers of bifurcations indicate areas of high complexity where risks are more likely to evolve from. This is shown by many branches on the evolutionary tree. Character patterns in these highly active regions can often be identified, creating a warning system.</td></tr>
<tr><td>Lost and Gained Characteristics:
Where Characteristics are lost and later regained indicates an interesting evolutionary path. This case may be because of a change in the environment and is worthy of further investigation.</td><td></td></tr>
</table>

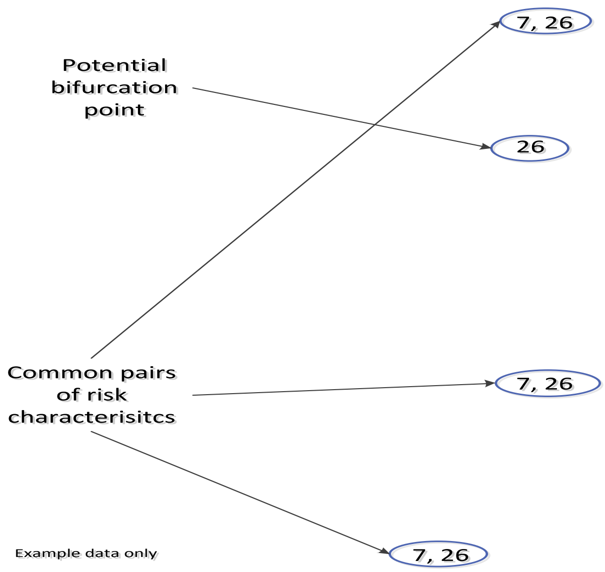
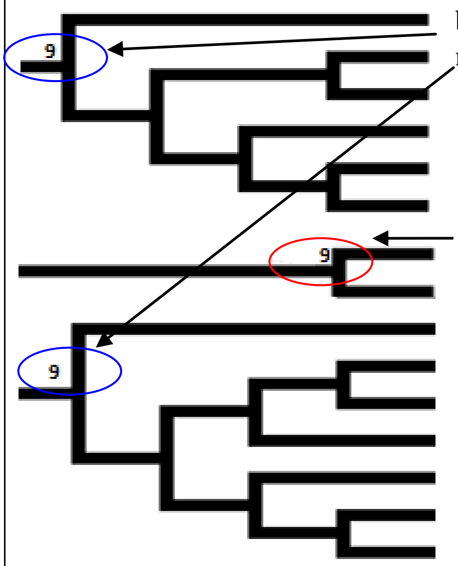
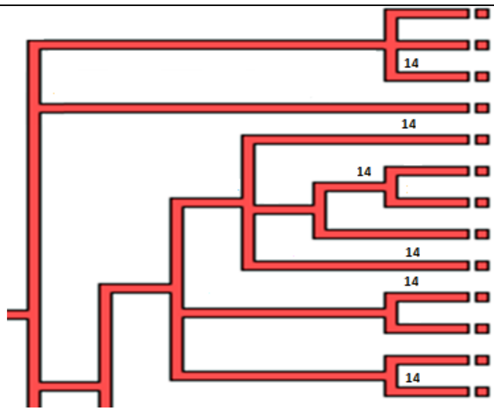
Patterns: Pattern spotting between sets. As an example, pairs of common characteristics appearing in multiple locations can be used to identify potential locations for emerging risks. The emerging risks occur where one of the pair of characteristics exist. It is possible that these single characteristic locations may evolve into the common pair. Pair spotting (and other character pattern spotting) can be used to make predictions or scenarios about future risks.	
Key character Change: Key characters can indicate a change to the stability of the system and their presence can warn of sudden changes and further emerging risks.	 Twice the character 9 has been shown to result in many emerging risks The character 9 has evolved into these risks. This should be of great concern and requires particular attention as new risks are more likely to emerge
Sudden Character Emergence: The same character in multiple risk locations indicates something is changing fast. If character '14' was 'government', for example, why is it suddenly affecting so many risks and what will the consequences of this be?	

Table 1: Patterns in evolution trees

3. CASE STUDY

3.1 *APPLYING PHYLOGENETIC ANALYSIS TO RISKS*

A detailed methodology of the phylogenetic analysis and techniques used in this paper is given in Allan, et al., (2013) so is not repeated here.

3.2 *BACKGROUND INFORMATION FOR THE CASE STUDY*

In order to demonstrate this technique, we have applied it to operational losses associated with derivatives. We have leveraged the work produced by Coleman (2011) who mapped a range of relevant characteristics to a number of major derivative loss events. The loss events are shown in Figure 3 below.

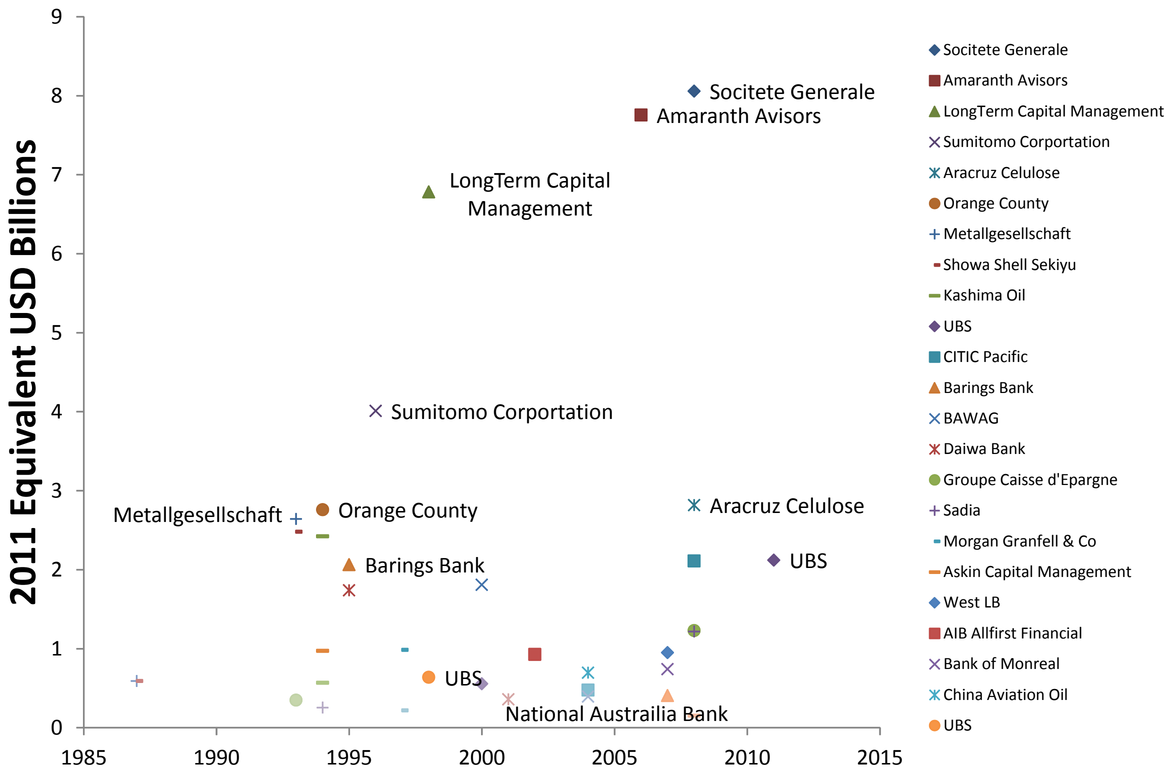


Figure 3 - Selection of Large Derivative Trading Losses (2011 USD equivalent figures)

The characteristics these risk events have been mapped to are:

1. Involves Fraud
2. Involving Fraudulent trading
3. To cover up a problem
4. Normal trading activity gone wrong
5. Trading in excess of limits

6. Primary activity financial or investing
7. Failure to segregate functions
8. Lax management / risk control problem
9. Long-term accumulated losses > 3 years
10. Single Person
11. Physicals
12. Futures
13. Options
14. Derivatives

We have taken this mapping data at face value from Coleman (2011), with the exception of aggregating some of the finer levels of granularity on the security type. These characteristics are somewhat subjective, and clearly it would be possible to define additional characteristics, but they are sufficient for our purposes to demonstrate this technique.

The following Figure 4 shows the cladogram of this mapping.

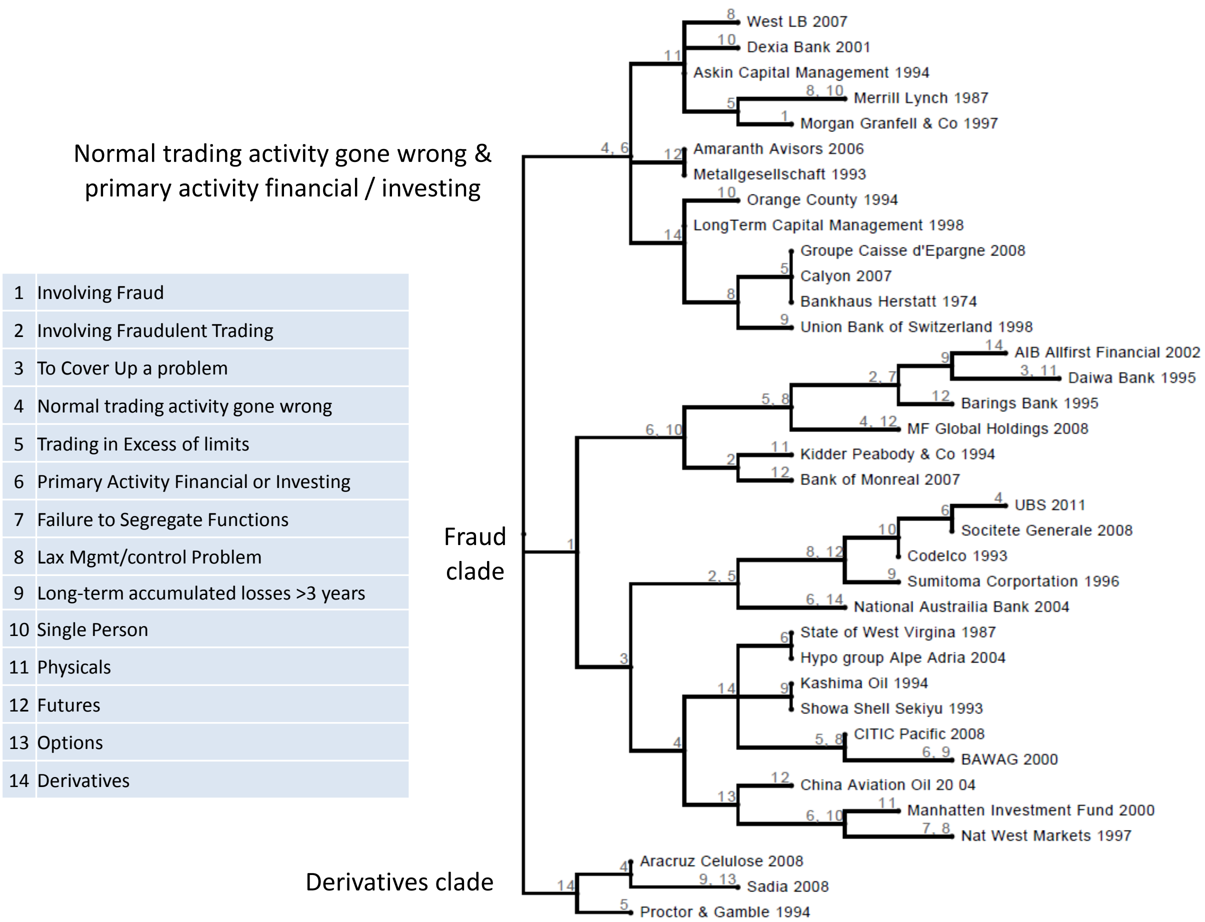


Figure 4 - Cladogram of Large Derivative Loss Events and Characteristics[2]

Each branch in the above Cladogram ends in a specific event. Each branching point is defined by a split in the characteristics as identified by the numbers that are common to all members of the sub-branches. The length of the branch represents the number of characteristics that "evolved" to define that branch, with more characteristics leading the longer branches.

These diagrams are very useful in helping to visually identify patterns of interest. The first thing that is noticeable in this cladogram is the division into three major clades or groups:

- normal activity gone wrong
- fraudulent activity
- collection of "simple" events characterised by the use of a range of derivatives

These can be considered the fundamental risk elements. Essentially the presence or absence of fraud defines the first major break in lineage. We can then analyse which event types are more evolved than others by analysing the branch length as shown in Figure 5 below.

[2] Cladograms produced using Evolutionary Risk Analysis software available from www.systemicconsult.com

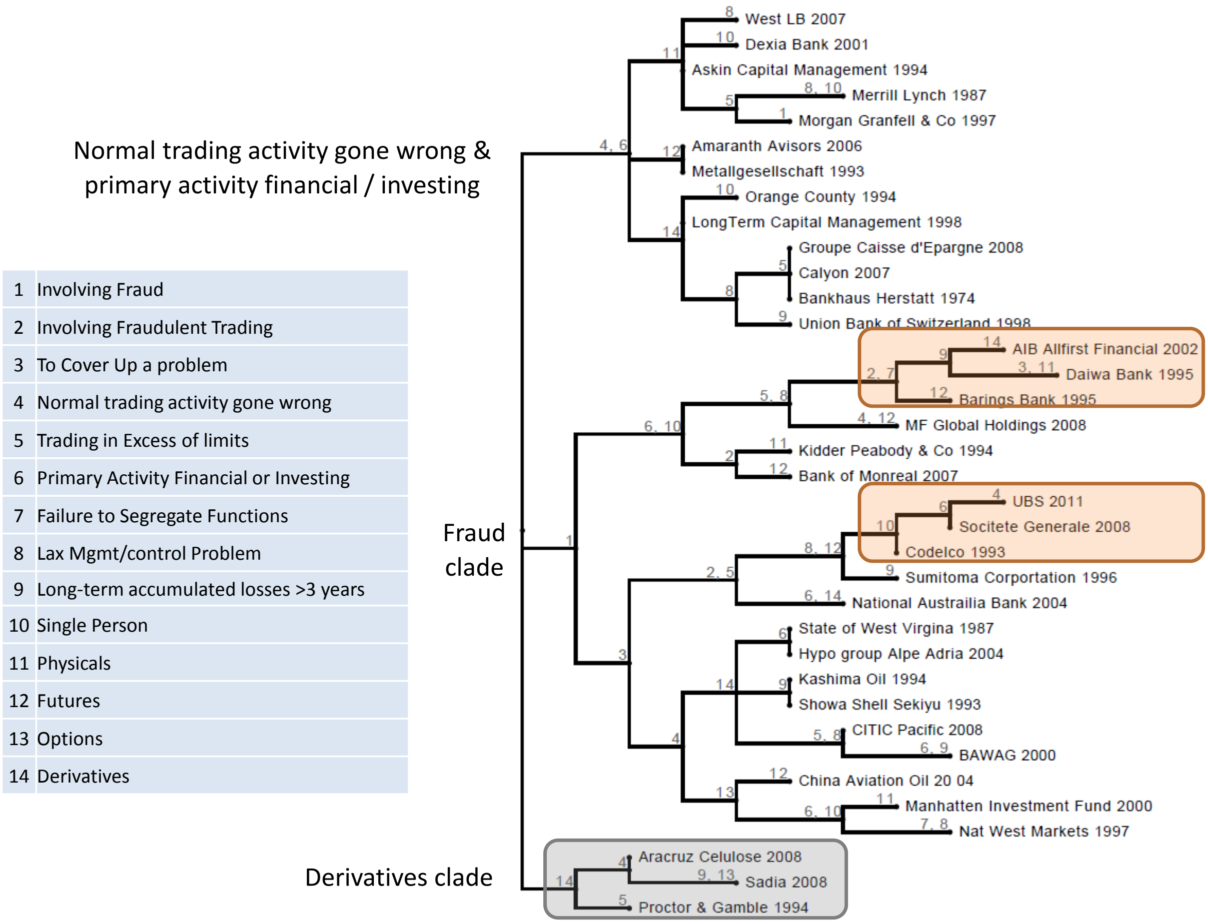
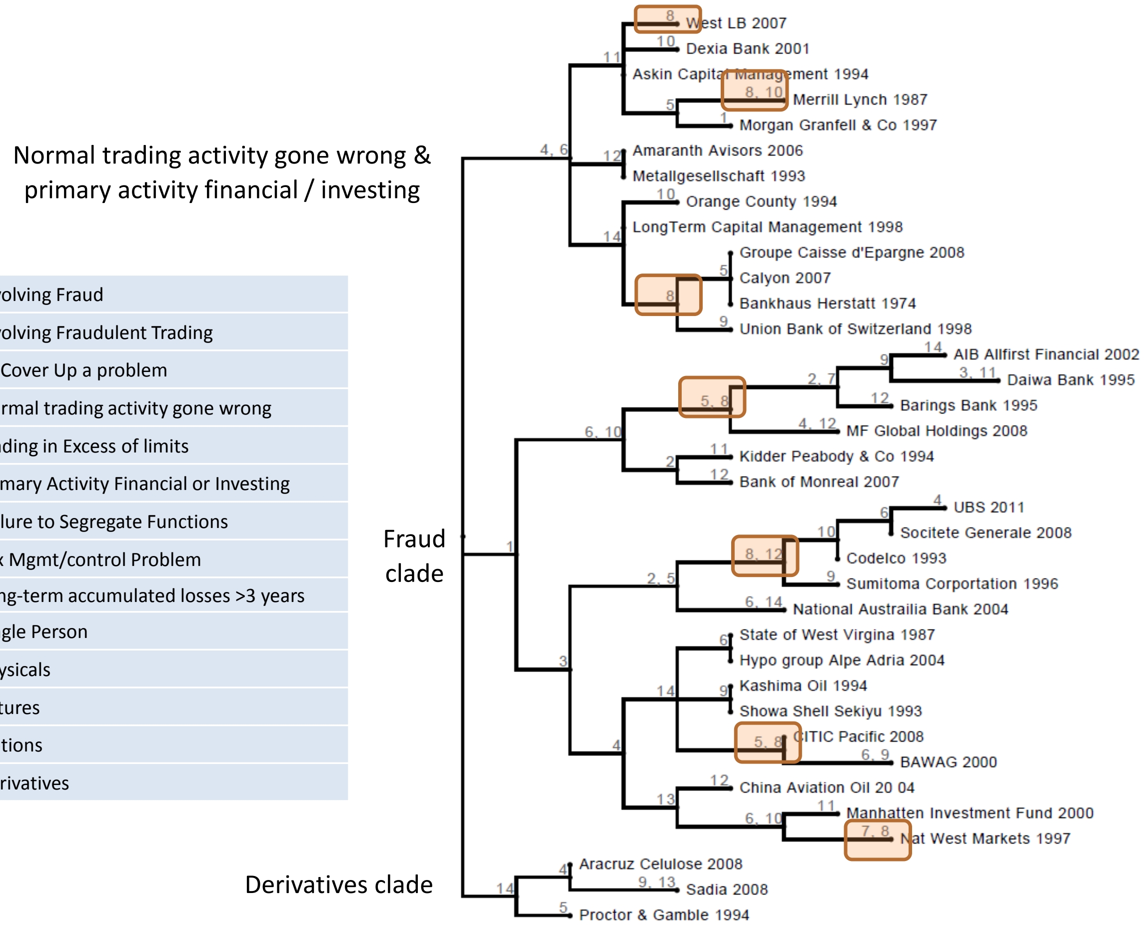


Figure 5 - Cladogram of Large Derivative Loss Events and Characteristics – Evolutionary Events

The bottom highlighted group, the derivatives clade, shows very little evolutionary process. These events can be considered to be relatively stable and unchanging in nature. These are the crocodiles of the risk world – they have reached their evolutionary peak and show little sign of emergent behaviour.

In contrast to these events, the two most evolved groups in the fraud clade show significant evolution through a large number of bifurcations in characteristics. They can be considered to be highly evolved risk events, essentially derivatives of earlier risk events that occur back up along the branch path. These types of events should be studied in detail, as they are likely to give us greater insight into the types of events that are more likely to be subject to evolutionary forces in the future. Companies with similar characteristics to these events are more likely to be subject to emerging risk. Furthermore, we would generally expect to see an increased complexity in the new risks that evolve in these highly active areas.

Figure 6 below now looks at the characteristics that are defining the evolutionary process.



1	Involving Fraud
2	Involving Fraudulent Trading
3	To Cover Up a problem
4	Normal trading activity gone wrong
5	Trading in Excess of limits
6	Primary Activity Financial or Investing
7	Failure to Segregate Functions
8	Lax Mgmt/control Problem
9	Long-term accumulated losses >3 years
10	Single Person
11	Physicals
12	Futures
13	Options
14	Derivatives

Figure 6 - Cladogram of Large Derivative Loss Events and Characteristics – Characteristics

Characters that appear frequently are more likely to appear in the future. The sequence of characters can also be important, as some characteristics tend to occur towards the end of branches rather than at the beginning. For example, characteristic 9 (Long-term accumulated losses in excess of 3 years) always occurs at the end of a branch structure, indicating that it could readily jump across to another branch to define a new emerging risk characteristic.

We have highlighted bifurcations involving characteristic number 8, Lax Management, Control Problem. This is a very common characteristic as it is evident in almost all branches / events. In many cases, it is also evolving jointly along with a number of other characteristics such as:

- 10: Single person
- 5: Trading in excess of limits
- 12: Physicals
- 7: Failure to segregate functions

Characters 8 and 5 (Trading in excess of limits) in particular seem to be very closely related in evolutionary terms. Note that this seems somewhat logical in hindsight, but we arrived at this conclusion through an objective analysis based purely upon a rich classification dataset. This could be very important information as it provides clues as to what characteristics emerging risk events might have in the future. From this we can then ask more focused questions such as:

- What would the next West LB (very top) or NatWest Markets (near bottom) events look like, if they evolved to contain a 5 characteristic (trading in excess of limits) as they already have an 8 characteristic?
- What would this event possibly look like if it happened at my organisation?

3.3 Implications

This emerging operational risk framework has a number of implications.

The first is that risk can be viewed as an evolutionary process that gives rise to emerging risks. This will be the case whenever the underlying system is a complex adaptive one, rather than a static or chaotic one. Investigating the evolving characteristics of system events in the past can provide insight into our understanding of how emerging risks might occur in the future.

The second is that it is important to capture multiple characteristics of risk events, both in terms of realised historic events, as well as forward looking events. Valuable information may be lost if risks are forced to be assigned to only single categories or characteristics, which may be the case if risk register software constraints exist, if a prescriptive risk classification framework is narrowly defined, or if the emerging risk identification approach is biased from the outset to focus on single processes or risk silos. The quality and completeness of loss data collection and classification processes become critical activities in the emerging risk process.

The third is that the risk taxonomy can be determined objectively from the data, rather than being defined prescriptively in an ex-ante sense. Risk taxonomies are almost always defined on the latter basis, resulting in linear structures, which is appropriate whenever system complexity is low. However humans tend to overly simplify situations where there is complexity, losing valuable information in the process. By defining the risk taxonomy objectively through this framework, we are able to map the interrelationships and connectivity between different risk branches, to gain insight into how risk events are truly related.

This is closely related to the discussion on the boundary between risk classes. Whilst it is a natural human response to try to carve everything up neatly into independent risk silos, with risks such as operational risk, it is not quite as appropriate to do so because of the high degree of interaction with other risk types. The Société Générale rogue trading event is a good example here, as there are clearly elements of market risk, operational risk and liquidity risk involved in the generation of the final loss amount. We suggest that it is necessary to move beyond the traditional silo view to understand and ultimately to manage risks that span multiple silos.

The final implication is that the above framework provides a structured way of addressing emerging risk. It is another lens through which we can possibly gain insight into future emerging risk events that we haven't yet seen and when we are not sure exactly what we should be looking for.

5. DISCUSSIONS

Whilst risk is considered by many to be just a social construct, it can be argued that, like money, risk is treated as though it exists, grows, interacts and has value. Risk is essentially real and alive; people act and make decisions on it, and it evolves.

One claimed merit of a phylogenetic analysis is that it provides a unique, unambiguous and objective classification solution (McCarthy et al., 2000). Ridley argued that '*Cladism is theoretically the best justified system of classification… and has a deep philosophic justification…* (Ridley, 1993)'.

Our phylogenetic approach to risk analysis described here satisfies the objectivity criteria in social research, which requires that different rational people would obtain the same result under independent investigations (Bryman, 2008). There is a possibility of people obtaining diverging results if they cannot agree on the characters of risks in their original inputs for the analysis. Secondly, applying inappropriate algorithms and not testing the model's robustness can lead to the dissimilarities between entities being identified within a cladistic classification. However, we believe the approach can effectively present data in an unbiased way that is accessible to a wider range of potential users, thereby bringing greater transparency to decision-making processes (McCarthy et al., 2000).

The structure of cladograms and the associated sub trees have significant implications for both scientific and practical risk management. Once risks are positioned in a cladogram, the comparisons of their characters are established so that people can identify the common properties and distinguish individual attributes, thereby allowing for reasonable hypotheses to be made (Andreatta and Ribeiro, 2002). Phylogenetic analysis reveals reliable evolutionary information. Without this form of analysis, evolution studies are more or less based on pure predictions (Gould, 1999). With phylogenetic risk knowledge, people can understand the order, rate, direction, and diversity of risk evolution and hence obtain greater insight into their risk system. Additionally, this type of analysis can articulate a robust roadmap of evolution. As pointed out by Mitleton-Kelly, the evolution behaviours of a complex adaptive system make the system path and history dependent (Mitleton-Kelly, 2003). In other words, phylogenetic analysis demonstrates how individual risks have reached their current state and indicates potential ways in which risks and the risk system will evolve.

Risk management often encounters a new risk with very limited information. In this case, people are likely to use heuristic knowledge to make estimations, leading to possible biased judgements (Goodwin, 2004). With the help of phylogenetic analysis, such a problem can be relieved, to some extent, because cladograms are based on a binary description of an organism's characters and such characters can be utilised to gain a comprehension of the new risk. As a consequence, a new risk cladogram can be constructed which contains this risk. The properties of the new entry are supposed to be similar, although not necessarily identical, to its neighbours and hence this will allow for more rational predictions of how this risk behaves.

6. CONCLUSION

In the ever increasing complexity and interrelatedness of the business environment it is unhelpful and even misleading, to manage risks as a collection of isolated events. The interconnected nature of risks should be addressed holistically in risk management analysis, particularly in enterprise risk management (ERM). Management approaches should actively try to understand the whole system of risks, not the aggregated sum of the risks. The authors of this paper endeavoured to solve this problem by looking at evolutionary analysis methods from biology.

Traditional risk methods invariably require the classification of risks according to a single dominant characteristic. This immediate loss of information makes the subsequent analysis of risk behaviour problematic, and significantly less useful. By retaining the richness of multi-characteristic classification the authors have shown that phylogenetic analysis provides a more appropriate scientific basis for understanding risk development, consistent with the view of risk as the emergent property of a complex adaptive system.

Risks, like organisms, can be classified in accordance with their evolutionary relationships to obtain insight and knowledge regarding the patterns that emerge through phylogenetic analysis. A risk DNA can be achieved and as in biology it could start to unlock some of the deep interconnected secrets of complex risk behaviour, and our perceptions of it. The authors have reviewed relevant bioinformatics literature and recommended the parsimony algorithm. A real world case study has been carried out with the aim of explaining the process and inviting discussions. The case study demonstrates the process of classification and how emerging risks may evolve and adapt. There are issues with data quality in the risk arena and computational efficiency of large risk matrices, validation and interpretation of complex trees. Further research is needed in these areas and close attention to developments from biological sciences may provide some partial solutions to these concerns.

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