# Model risk: a novel approach using a category-oriented framework[+]

Paulo Cacella[*]

## Abstract

Amidst today's rapidly changing business environment, most government entities and private enterprises support their decision-making process with data, projections and analyses using reality-based models. Misuse, model errors and a misunderstanding of model limitations, however, can lead to huge losses and strategical misdirection. This paper presents an innovative way to reduce model risks, proposing a framework based on categories that allow for diversifying risks and, importantly, grant decision-makers the ability to adjust models in line with the changing environment. The main objective of this work is to establish a viable framework for a holistic view of model risk and explain how it can be applied to strategic decision-making.

Keywords: model, model risk, risk management.

[+] The views, thoughts and opinions expressed in this paper are those of its author and do not necessarily reflect those of the Central Bank of Brazil or its members.

[*] Corporate Risk Dept, Banco Central do Brasil, Brasília, DF, Brazil; Corresponding email: paulo.cacella@bcb.gov.br

# 1. Introduction

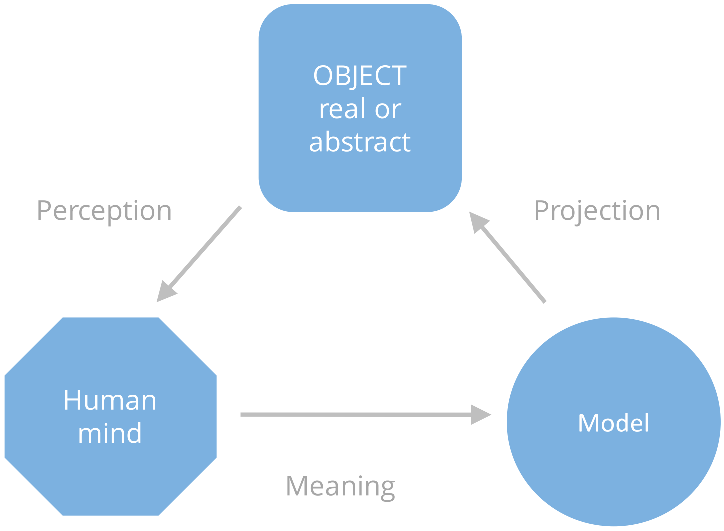
A model is defined by Merrian-Webster (2019) as: "a simplified representation of an object; a system of postulates, data and inferences presented as a mathematical description of an entity or state of affairs". Models capture a wide variety of representations and world views, and are used frequently in finance, decision-making, risk and resource allocation.

In this paper, and using Merrian-Webster as a foundation, I simplify the meaning of a model as "a human construct that represents a view of the world".

As a human construction, we often try to explain possible relationships among objects, the human mind and the model. We try to define categories based on models' shared characteristics. Models, in this sense, are representations of an object: real or abstract, that may have a meaning and must be projected from our minds into reality. Figure 1 shows a pictorial representation of the definition of model as an entity, ie as a conceptual reality.

In such a representation, the existence of an object, real or abstract, is accepted, as is the human mind as a processor that obtains data from its senses before building explanatory models of the object. This is done through perception, which maps sensory input data to environmental awareness. This awareness is subjective and high in entropy. To make things understandable, ie capable of generating objective and rational actions, we search for a meaning. Then we build models that can be projected into our conceptual reality. The reasons for designing a model are to forecast future events, comprehend past ones and to allow a rational view of the world with cause-and-effect relationships.

Model as an entity — Figure 1




Source: Author's elaboration.

## 1.1. Epistemic model categories

To better understand the role of models in our connection with reality, I introduce them as abstract entities that can be grouped into epistemic categories. These categories represent the object's nature itself, in contrast to applied categories, which are oriented to techniques targeting the problem-solution format. I propose an approach where each of the following epistemic model categories is related to an object type that we intend to replicate or understand:

**Pure abstract model:** a model based on an abstract conception of the world. The model's projection represents an abstract object, eg pure algebraic mathematical models. It is not intended to forecast real quantities or future events; it is a framework rather than an imitation of a real object.

**Natural model**: a model based on an understanding of how nature works, eg physical sciences models. The model's projection represents a real object. It is intended to forecast future events and other data through a rational view of the world. This model relies heavily on empirical sensory data.

**Emergent model**: a model based on emergent sciences linked to behaviour or emergent phenomena, eg social sciences. The model's projection may represent abstract or real objects. It is intended to forecast future events and data, or to mirror rational perspectives of the world and/or an ideology.

## 1.2. Understanding the problem of model risk

The scope of model risk is usually limited to the model itself and not to the whole framework and set of models. Model risk is mainly related to validation aspects such as an incorrectly designed model, insufficient or flawed input data, a misunderstanding of model limitations etc. This process is called model validation, and though it is present in almost all large organisations worldwide, it lacks in several important aspects related to the construction of a model.

Firstly, a model is designed to represent a schematic, partial and limited view of an object. It has an inherent error that it will lead to an approximate representation of the reality. In the case of an emergent epistemic category, like sociology and economics, a model is usually prone to generating misconceptions and misrepresentations as the external environment changes. A practical example is the use of value-at-risk (VaR) and credit risk ratings during and after the 2008 Great Financial Crisis. At the time, standard models that relied solely on historical data collapsed as the economic and financial system moved to a new equilibrium. A crisis can be explained in a systems engineering perspective as a transitional phase between two equilibria plateaus. In this way, environmental conditions are real and important factors to consider when managing model risks.

Another relevant aspect to consider is that even if a complete set of alternative or complementary models exist, they lack the synergy needed to be used as a single strategy in the decision-making process. This is because a preferred model usually deprecates older models, concentrating risks as it is used as a single model of reality. A thorough interpretation of the breadth of model risk clearly goes beyond the analysis of each single model. However, it is nevertheless necessary to have a holistic view, ie a connecting framework among models, to reduce misuse and enhance the quality of decision-making.

Modelling practice is strongly related to the amount of data and processing power available. Natural epistemic models, in general, due to their stability in time and the low number of significant explaining variables, are the easiest to implement with limited data and processing, adding to the fact that they are easy to comprehend. These models are based on the assumptions that nature has no teleological basis, that reality behaves as in the so-called "A Series [1]" (McTaggart (1908)) and that models' structures remain stable even if parameters change. That is why they are used as an initial approach to solve problems that are related to emergent epistemic models such as those in social sciences. Because emergent phenomena are from a distinct nature, with the human factor as a central issue, we understand that this approach of using only a natural epistemic model set is inadequate, imprecise and may lead to ideology manipulation and calibration/time window bias.

With the recent availability of big data and cheap processing power, new opportunities are arising to tackle complex problems related to social sciences and behaviour. A new revolution of computer-based models using artificial intelligence, new statistical models and a less comprehensible but more precise view of the world is what will set new standards in our era. The handling of human-based, decision-making models is also, somewhat, put in a distinct basket, creating an opportunity for us to redesign the way we see and use models in an organisation. A new approach is necessary to tackle the problem of model management and model risk. This is the idea I propose and discuss in this paper.

## 2. Discussion

Risk is often discussed in terms of taking preventative actions or making course-changing decisions that could minimise losses or amplify opportunities. In terms of loss control, model risk offers a procedure known as model validation, ie a model risk mitigation tool that is usually implemented in every model in an effort to address several sources of model risk.

In this paper, I present a novel approach on how to handle model management and model risk within an organisation. I begin by outlining the current view on model risk, followed by my proposal, which includes an abstract framework, decision-making support and, finally, governance.

[1] "A Series" are series that allow the existence of past, present and future, in contrast with "B Series" where flow of time is an illusion.

## 2.1. Model risk

Model risk can generally be defined as a loss that an organisation may incur as a result of decisions made based on errors in internal models (KPMG (2016)). It is usually considered a subset of operational risk. Even if this can be accepted conceptually, I consider this classification to be inadequate, as operational risk is strongly related to a business's process control activities, while model risk can be strongly impacted by non-control elements, such as changes in the external environment and intersubjectivity of players. Also, model risk has a higher impact on strategic decisions than on operational ones. Because the main nature of models is to support decision-making, it is also, to a high degree, related to strategic actions and strategic risks. In this sense, model risk is better managed when viewed outside an operational risk framework and distinctively from any other major type of risk. Thus, it must be considered in the highest levels of an enterprise's risk framework.

## 2.2. Sources of model risk

Model risks may have internal and external factors that can be analysed during model validation, such as the following:

*Internal sources*

- incorrect implementation
- incorrect model specification
- misunderstanding of model limitations
- flawed input data
- errors in calibration
- inaccurate numerical approach
- weakness in backtesting

*External sources*

- changes in the environment that affect the world model explanation
- advances in technology

## 2.3. Regulatory initiatives

Although the proposed framework is not related to any one specific activity, the following example from the financial sector provides insight into model risk validation.

Several regulatory initiatives arose after the 2008 Great Financial Crisis with the objective of minimising model risks and its nefarious consequences for the decision-making process. The US Federal Reserve and the Office of Comptroller of the Currency published in 2011 supervisory guidance on model risk management with reference SR 11-7 (Federal Reserve (2019)). This turned into a regulatory standard for model risk management. The focus of the guidance is to challenge models using a thorough understanding of all relevant sources of model risk and mitigation initiatives covering the end-to-end model lifecycle. The United Kingdom and the European Central Bank (ECB) also have in place regulatory initiatives on model risk. The ECB released the *Guide for the Targeted Review of Internal Models* (TRIM) in 2017 (ECB (2017)).

One key aspect in all regulatory frameworks is that models are viewed as an inventory and that model validation is individually managed.

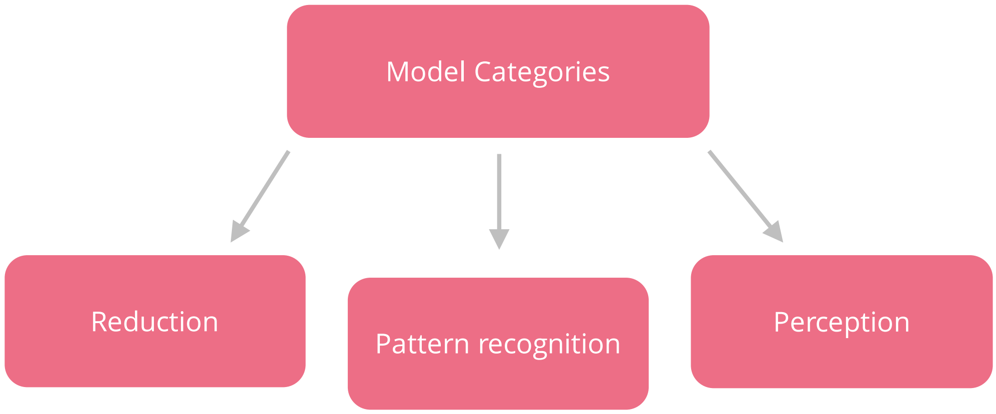
## 2.4. Applied categories

In order to build a workable, comprehensive model risk framework as an effective support for decision-making, I argue that it is not sufficient to handle models as an inventory and manage model validation individually. My belief is grounded in the following key aspects:

- big data and processing power are available in staggering volumes nowadays;
- models have different categories that must be handled distinctly; and
- decision-making processes must be fed with more structured data to allow decision-makers to select models that best match the present environment and/or adapt to changing conditions.

To solve this conundrum, I propose a set of categories that are applied to model implementation and diversification. Specifically, I recommend three applied categories based on a model as an entity that represents distinct views of the world: reduction, pattern recognition and perception (see Figure 2).

Model-applied categories — Figure 2




Source: Author's elaboration.

This setup matches perfectly with the concepts of meaning, projection and perception as shown in Figure 1 (ie the definition of a model), covering all aspects of its epistemological classes.

### 2.4.1. Reduction models

Reduction models aim at capturing a meaning represented by a small number of representative variables that express, in a simplified way, how the object behaves. The model is usually an equation or a set of equations with variables that could explain future events and the behaviour of the object at a significant level. Reduction models are oriented to meaning. Natural science models are usually of this kind. The modelling formalism can be defined as in system theory, using differential equations, difference equations and discrete events and/or dates (Zeigler et al (2019)). A classic example in economics is the dynamic stochastics general equilibrium (DSGE) model types. In finance, the Black-Scholes equation is another classic example. Reduction models may or may not be deterministic, being frequentist or Bayesian, but certainly they can be understood and are defined by a manageable and comprehensible set of explanation variables.

### 2.4.2. Pattern recognition models

Pattern recognition is a scientific discipline whose goal is the classification of objects into a number of categories or classes (Tolk (2013)). A pattern recognition model is agnostic to a specific world view defined by a small set of understandable variables. This type of model is used when you cannot get a meaning from observations in a simplified way. In several circumstances the problem is so complex that each variable, individually, explains very little of the whole system behaviour. Worse than that, they usually are not understandable together, putting the modeller in a tentative position to reduce the model and possibly rendering it worthless. In cases like this, it is necessary to use computational power to find patterns that could be used to forecast observations, even if these patterns cannot be comprehended as a whole or in parts. These models are oriented to projection. Principal component analysis and machine learning, supervised or unsupervised, are examples of pattern recognition models. They frequently need a large amount of data and processing power.

The question of inadequacy of a numerical model regarding low predictive power, overfitting and other regression diseases is related to the validation process of the specific model under study. The decision-making process requires necessary information including the confidence level and the type of environment where it can be used securely.

### 2.4.3. Perception models

Perception models are oriented, as expected, to human perception. We, as a biological species, are very complex information processors. We absorb an enormous amount of information through our senses and process it in a way that the most complex computers in the world cannot yet handle. Also, human beings have objectives, some of which are hidden from others. Pattern recognition and reduction models are dependent on past observations and pre-conceived world views, respectively. They are not efficient during changing environmental conditions, like a crisis, which represents a transient step between two equilibria plateaus.

Perception models use real time information in a much more effective way when there is a rupture in system behaviour and the regime change generates a transient response. Perception models are more adaptable to a changing environment. Consensus methodologies like Delphi (Brown (1968)) and expert elicitation (Colson and Cooke (2018)), and others briefly explained below, are examples of perception models. Because they are pivotal in this proposal and not used often in organisations, I will discuss some of them in more detail.

**Delphi**: a technique used or the elicitation of opinions with the object of obtaining a group response of a panel of experts (Brown (1968)). The main idea behind this technique is to replace confrontation and brainstorming with a planned sequence of questionnaires among a panel of experts. This process may be repeated several times until a consensus among the group is reached on how to address all problems raised. The opinions are anonymous and questionnaires are conducted individually. The selected panel (usually totalling five to 20 people) are experts in the respective areas under review. An interesting approach to Delphi is the technique Real-time Delphi, which tries to speed up the process and is well suited for fast financial decision-making (Gordon and Pease (2006)).

**Expert elicitation**: a systematic approach to synthesise subjective judgments of experts on a subject where there is uncertainty due to insufficient data, ie when such data is unattainable because of physical constraints or lack of resources (Slotje et al (2008)). This method relies on subjective statistical distributions agreed upon by experts and considers lagged observables when taking into account delayed effects. As Morgan (2014) stated: "We humans are not equipped with a competent mental statistical processor. Rather, in making judgments in the face of uncertainty, we unconsciously use a variety of cognitive heuristics. As a consequence, when asked to make probabilistic judgments, either in a formal elicitation or in any less formal setting, people's judgments are often biased. Two of the cognitive heuristics that are most relevant to expert elicitation are called "availability" and "anchoring and adjustment.""

**The Analytic Hierarchy Process (AHP)**: a general theory of measurement. The AHP is used to derive ratio scales from both discrete and continuous paired comparisons in multi-level hierarchic structures. These comparisons may be taken from actual measurements or from a fundamental scale that reflects the relative strength of preferences and feelings. The AHP has a special focus on departures from consistency and the measurement of those departures, as well as with dependence within and between the groups of elements of its structure. It has found its widest applications in multi-criteria decision-making, in planning and resource allocation and in conflict resolution" (Saaty and Vargas (2001)). The main objective of the technique is to reach a goal using the best group information focused in the problem's objective. It can be used to attach actions to strategies, which is a paramount step in the decision-making process.

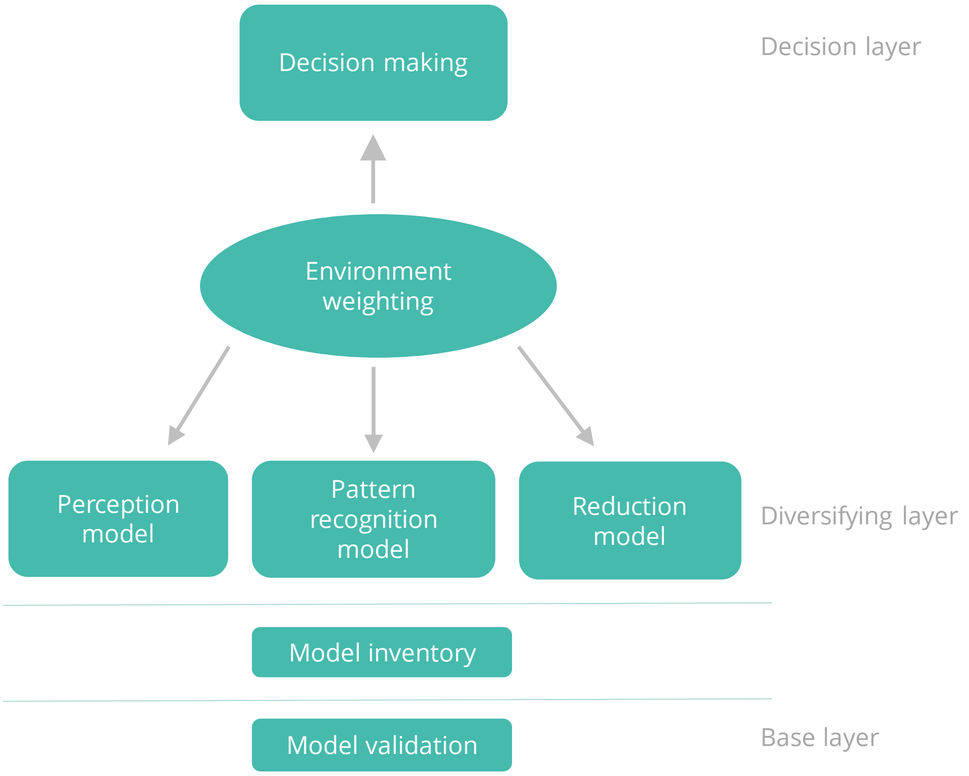
**Multiple-criteria decision-making (MCDM):** a subfield of operations research that has been succinctly defined as making decisions in the face of multiple conflicting objectives (Ramanathan et al (2017)). Where there are multiple objectives with the possibility of one optimal solution to the problem, a performance measure needs to be defined and an MCMD optimisation implemented. There are several distinct heuristic approaches to a problem like genetic algorithms. Applications in finance can solve complex problems that go beyond simple convex optimisations (Cacella et al (2010)). The main challenge of this methodology is defining the performance function. However, another important aspect is that because the solution will be a Pareto frontier, usually the decision-maker is not limited by a single choice and can select the solution that has the best probability of reaching the specific goal.

## 2.5. Proposing a model risk governance

Figure 3 highlights a proposed model risk governance that covers all model-applied categories, which can also be applied when working with emergent models like social models (economics, sociological, financial etc) or other models involving the use of human behaviour.

The base layer is already well developed in current model risk frameworks. Usually, model validation is applied to individual models in the inventory. The innovative approach here is to create a diversifying layer that incorporates, for each decision-making process, a set of models covering, if possible, all three categories: perception, pattern recognition and reduction.

Model risk governance Figure 3




Source: Author's elaboration.

### 2.5.1. Diversifying layer

In emergent models related to social sciences, the human behaviour is the game-changing variable. In natural models like those for classic physics, we can be sure that certain events will happen – such as an eclipse or lightning – regardless of human behaviour. Even when dealing with complex problems like a delayed-choice double slit quantum experiment or deterministic chaotic dynamic systems, there is no human behaviour factor. In emergent models of social sciences, however, everything may change without warning. Belief, will, compassion and other human attributes can change in the blink of an eye. The complexity is so high that we cannot simplify the explanation of the phenomena in a meaningful way. Precisely because the changing environment is associated with the impossibility of reducing complexity, it is important that all three categories of models can be used simultaneously. In this case, the decision-makers can state, subjectively, the weight of each model in their decision-making according to the environment.

One might ask if such weighting is a superimposed perception model over the diversifying layer. The answer is both yes and no. The very nature of the human decision-making process is a perception model. However, there are some subtle differences regarding approach in the cases at hand. The perception model in the diversifying layer is setup to minimise personal bias and preferences and to collect filtered information from experts in each field. The decision-making process, in another way, relates to a small number of people, like those comprising a board, who usually are not technical experts in each specific field and are more prone to be affected by a principal-agent problem. It is not easy to impose at this level, without strong governance, the correct incentives for a sound decision-making process. However, I believe the availability of a set of models that can show aspects of the same problem in distinct viewpoints may be a restraint regarding agent behaviour.

The diversifying layer has the objective of mitigating risks associated with a single viewpoint/solution for a problem. By contrast, in model validation, mitigation is usually restricted to factors like uncertainties in estimates, inadequate model use, lack of data etc.

One additional advantage of the proposed model is that it is designed to embed the treatment of emerging risks. The most dangerous emerging risks are those that may occur in the transient phases of regime changes. These kind of risks are poorly assessed with models that use historical data as a single source of information. The diversifying layer provides a way to tackle these risks through a sound decision-making process.

### 2.5.2. Decision-making process

Decision rules under uncertainty is a classical problem in decision theory. One of the key aspects regarding human decision-making is that human bias may render a process inefficient or even ineffective. This was pointed out in a simple way in prospect theory (Tversky and Kahneman (1974)). Beyond techniques like decision trees, decision matrices and others, we consider multi-objective trade-off analysis (Haimes (2009)) as an important reference point to consider when designing a model risk framework in an organisation. Multi-objective methods largely depend on a subjective assessment of weights that will generate a Pareto frontier of available solutions. Even if there is scepticism in using models as a tool to generate final answers in a decision-making process, it is reasonable to use them, at a minimum, to guarantee that decision-makers' perceptions and available information are not self-contradictory, which would lead to inefficiencies in the process of mapping intentions to actions.

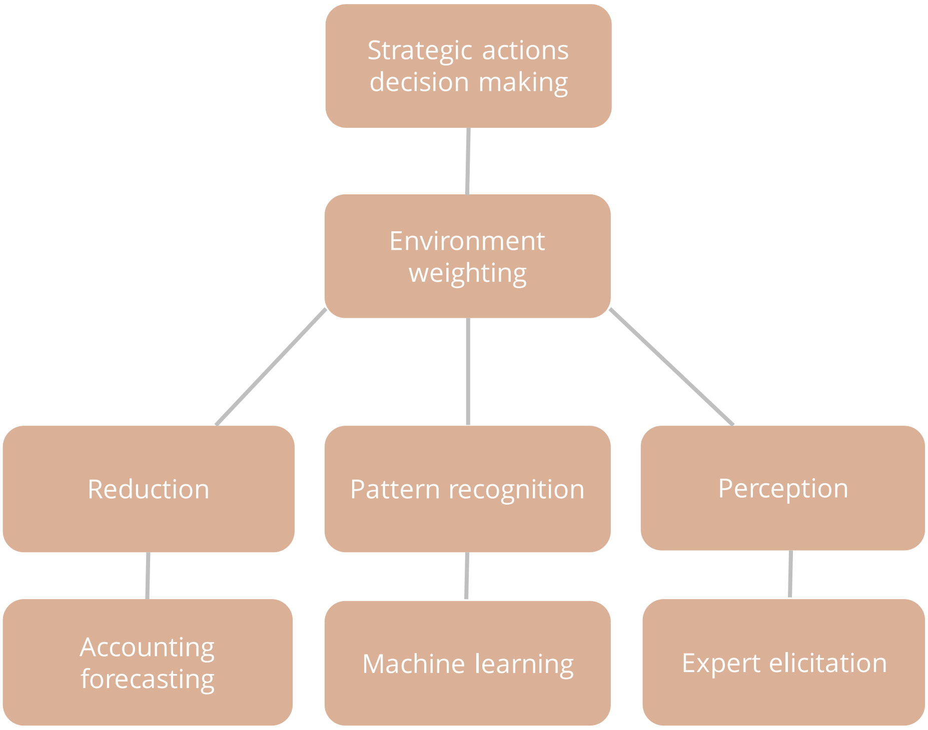
One further factor to consider when using models that have inputs from other models is the uncertainty propagation. Special care must be taken to control these effects in order to avoid presenting incorrect or biased data to the decision-makers.

Finally, although automated decision-making is a very convenient approach to some operational and repetitive processes, it is not adequate for strategic decisions, where human factors, bias and preferences are not yet mapped to support the changing environment.

## 3. Framework in practice

To exemplify the theoretical approach of the proposal, I present a practical implementation of the framework. A standard case is used as a hypothetic example: decision-making on strategic actions in a company (see Figure 4).

Framework in practice Figure 4




Source: Author's elaboration.

The environmental conditions include:

- changing economic environment, with huge uncertainties in profits and geopolitical aspects; and
- a company with budget restrictions in information technology.

The models available include:

- a reduction model based on historical data forecasting earnings and cashflow behaviour in the next year;
- a pattern recognition model based on machine learning with some sentiment analysis showing that the market is set to grow; and
- a perception model based on an expert elicitation round with the main executives of the company requesting a shift on the main product line.

With the information of all three model categories and the environmental conditions, the decision-makers set actions based on their trust of each model output and the applicability to the specific situation. This process is subjective by nature and cannot be automated.

In our sample case, the decision-makers, based on environment data, decided to begin a speedup study on shifting the product line, do not trust in machine learning because of changing environment and are conservative about earnings for the next year based on the same reason.

## 4. Conclusions

I have outlined how the current framework of model risk is oriented to model inventories and individual model validation practices, and how my proposed framework tries to take advantage of modern technologies, perception models and big data to enhance the strategic decision-making process in emergent phenomena like social sciences. I also introduced the concept of model-applied categories and environmental weighting. I believe this approach brings more flexibility, accuracy and precision in supporting the decision-making process of an enterprise.

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