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Pertinence of Predictive Models as Regards the Behavior of Observed Biological and Artificial Phenomena

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In this assessment, we have made an effort of synthesis on the role of theoretical and observational investigations in the analysis of the concepts and functioning of different natural biological and artificial phenomena. In this context, we pursued the objective of examining published works relating to the behavioral prediction of phenomena associated with its observation. We have examined examples from the literature concerning phenomena with known behaviors that associated to knowledge uncertainty as well as cases concerning phenomena with unknown and changing random behaviors linked to random uncertainty. The concerned cases are relative to brain functioning in neuroscience, modern smart industrial devices, and health care predictive endemic protocols. As predictive modeling is very concerned by the problematics relative to uncertainties that depend on the degree of matching in the link prediction-observation, we investigated first how to improve the model to match better the observation. Thus, we considered the case when the observed behavior and its model are contrasting, that implies the development of revised or amended models. Then we studied the case concerning the practice of modeling for the prediction of future behaviors of a phenomenon that is well known, and owning identified behavior. For such case, we illustrated the situation of prediction matched to observation operated in two cases. These are the Bayesian Brain theory in neuroscience and the Digital Twins industrial concept. The last investigated circumstance concerns the use of modeling for the prediction of future behaviors of a phenomenon that is not well known, or owning behavior varying arbitrary. For this situation, we studied contagion infections with an unknown mutant virus where the prediction task is very complicated and would be constrained only to adjust the principal clinical observation protocol.

Keywords: *prediction, observation, Bayesian, neuroscience, brain functioning, mutant virus*

Introduction

The practice of modeling for the prediction of future behavior of a scientific phenomenon is frequently used in different situations. The use of prediction is often associated with observational approaches in a matching or mimic procedure. The prediction activity associated with observation is one of the firstborn natural duties in the world. The couple prediction-observation could be encountered in natural inherent occurrences or artificial procedures. The most popular theory explaining the brain functioning named Bayesian Brain corresponds to a typical natural manifestation, while the Digital Twins industrial concept is a representative example of artificial procedures. The link prediction-observation plays almost the same role in these two episodes. Both are using predictions associated with sensorial observations and historical ones data. The whole association is assisted

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by sensing connections as well as matching and/or mimic links.

In the practice of the link prediction-observation, we can meet different situations regarding the character of the link itself, as well as the nature of the concerned phenomenon and its behavior. The prediction concept is practiced to resolve difficulties regarding the problematics of uncertainties. Uncertainty is affiliated to different notions for instance unpredictability, imprecision and variability. Generally, uncertainties can be classified into aleatory or epistemic ones. The first is associated with arbitrary modifications, existing in natural variability, happening in the world or owning external nature, while epistemic uncertainty is concomitant with an unknown, resulting from deficit of knowledge, appearing in the mind or owning an internal character (see for example, Baecher and Christian 2003). Thus, epistemic or knowledge uncertainty can be diminished with gathering further data or by upgrading models established on enhanced comprehending of the concerned objects. In contrast, aleatory uncertainty or natural variation cannot be reduced by the disposal of extra information.

Therefore, regarding the character of the link prediction-observation, the observed behavior and its model are conventionally fitted. When the observed behavior and its model are contrasting, we are in front of a problem of knowledge uncertainty. This is a kind of model uncertainty that indicates the degree how mathematical model accuracy mimics the reality. This is generally for the reason that the model is deliberated idealized. In such a case, it is necessary to amend the model to move toward reality.

Regarding the concerned phenomenon, it is supposed that it is well known and owning identified behavior. In the event of an unknown phenomenon with unidentified (random) behavior, we are in presence of a problem of an aleatory uncertainty; the practice of the prediction-observation link could be problematic and will be restricted. In such a case, the prediction side will be handicapped due to the total inexperience of the observed object in addition to its random behavior. Observation will be the main task in the connection and prediction can only help predisposition. This could be based on an approximate model (the real is unknown) and a probabilistic behavior (the real is random).

To apprehend the nature of the link modeling-observation, we need to examine each of the two sides of this link. Generally, the theoretical and the observation topics could be used for the evaluation of the functioning of a given system or procedure. A real entity that is observable behaves according to environmental occurrences that are observable. We can designate the model of this entity involved in its environment, through the supply and the result of its observed behavior. This dominance is generally related to a science or a scientific occurrence. The investigation of an entity and its behavior accounting for the environmental events, could be performed by observation and/or modeling. Observation or modeling can be autonomous in the domains of assessment that we habitually hold practically idyllic. In the everyday condition of authentic societal scenes, we perform the two analysis issues in a complementarity base. Thus, so far, in the spheres requiring ordinarily for modeling, this is usually not autonomous and needs a confirming observation, just to be trustworthy. The philosopher Maurice Merleau-Ponty (1908-1961) expressed, regarding lonely modeling, that science considers the world as an item of knowledge "detached" from the present subject, too that the model and the mind are accorded and that scientists perceive the world with an essence linked solitary to the model (see for example, Merleau-Ponty 1960). Furthermore, in the fields requiring commonly the observation, this is also commonly not self-sufficient and necessities modeling for profounder research. Claude Lévi-Strauss (1908-2009) stated, about lonely observation, in the sphere of Structural Anthropology (Lévi-Strauss 1958), that Structural social sciences studies are indirect corollaries of advanced mathematics: logic, sets, groups…

From the above discussion, we can realize that the evaluation concepts of observation and modeling are intimately linked. Furthermore, in theoretical investigation it is universally acknowledged that theories are matter to crucial elementary rulings concerning the Theory Observation couple. Thus, generally, a theory is deliberated only founded once validated by observation. In addition, such a theory remains actual until discrepancy with observation.

Therefore, the theory observation pair is unavoidably constantly allied. The occasioning join of this couple, could be operated in the concept of numerous theoretical studies, industrial settings or clinical healthcare protocols.

The present work relates to the investigations concerning the link theory observation and the concepts utilizing the particularities of such link. When the observed behavior and its model are contrasting, it is necessary to amend the model to move toward reality, the resulting revised model will be the first study in such plan. After introducing the modeling by prediction matched to observation and its relation to the uncertainty problem, we will assess, through literature review, predictive models in the two categories of biological and artificial phenomena. We will survey the most widespread theory corresponding to brain functioning in neuroscience, the Bayesian Brain, where sensory expectations are accorded to observation data to identify observables. Then we will reflect the concept of digital twins (DT), that is built of an accorded real (process, product or facility) with a real time arithmetic element (model) that is a doubling of the real observable, and their links. A last illustration relates the clinical case of infections by an unknown mutant virus. In such an instance and due to the unknown comportment of the object, the pair observation model will apply in an adapted mode.

Knowledge Uncertainty and Amended Theories

Regarding the link prediction-observation, the observed behavior and its model are usually matched. When the observed behavior and its model are contrasting, we are facing a problem of knowledge uncertainty. We comprehend that observation is exact and that it is necessary to amend the model to move toward reality. It is worthy to note that, most of scientific models originate of coherent and pleasant theories on the topic of one field of science. Such elegant theories involve simplifying assumptions concerning the environmental conditions as temperature, pressure, etc., and the specifications of materials such as viscosity, linearity, homogeneity…In the real societal situations, the environments and the stuff barely meet such perfect contexts. In general, the inadequacy of the scientific related field is caused by neglecting other scientific grounds. Additionally, in numerous societal panoramas, various spheres of science may govern the affected behavior. Concerning the elegance of theories, we can mention the example of Francis Crick. Few years after Francis Crick co-discovered the DNA double helix and few years before he co-won a Nobel Prize, he taught that (Crick et al. 1957) the same is not necessarily true for all science activities "In biology, it is possible to be elegant and to be wrong,". Therefore, in the real societal situations, the adjusted final model will be a combined model consequent to the association of diverse scientific topics (Razek 2020a, Razek 2020b). These amended modeling situations concern many systems and processes where the functioning involves different scientific occurrences and phenomena. The involved variables might be interdependent and the parameters could vary caused by the behavior of these variables. For instance, the scenery of the phenomena ruling electromagnetic systems is a composite and a comprehensive model supposed to consider in general the magnetic, electrical, mechanical and thermal occurrences (see for example, Issa et al. 2019, Ouchetto et al. 2007, Carpes et al. 2000, Sun et al. 2019, Bottauscio and Manzin 2013, Ren and Razek 2000). The revised model will be, more or fewer coupled in function of the significance of the related phenomena interdependence.

The resulting amended coupled model for a given system, process, or phenomenon will be the ultimate actual model. Such model, as in the case of classical models, is deliberated only founded once validated by analytical solutions for adequate simplified cases, and predominantly by observation (Ren and Razek 1990). This ultimate actual model will be the one to be used in the link prediction-observation.

Prediction Matched Observation

We examine here first the practice of modeling for the prediction of future behaviors of a phenomenon that is well known, and owning identified behavior. That is the case in many reliable situations where prediction is allied to observation to return accurate suitable result. The theory of the Bayesian brain in neuroscience and the concept of Digital Twins are representative specimens of such a circumstance, as we will see in the next section. Moreover, the prediction is often operated in the control of industrial devices and permits accompanying observation, to achieve precise and quick execution (see for example, El Moucary et al. 2002, Ren and Chen 2006). In these cases, the problem of knowledge uncertainty is presumed solved. Such uncertainty question is inside counted in the case of Bayesian brain theory, while in the other industrial applications it could be considered via amended models concept.

In all these situations, the prediction and observation are interconnected and operate in an iterative real time matching two way process involving adjustment of observation through minimization of prediction error association.

In dissimilarity, the alliance prediction-observation has to be exercised with restriction in some special situations. This is the case of circumstances where the theoretical behavior is not well known, or phenomenon comportment changing random. In this case, we are in presence of a problem of aleatory uncertainty and it is obvious that the practice of lonely mathematical modeling for such a case would be hopeless. The case of infections by an unknown mutant virus is a typical example of such situation, as we will see later.

Bayesian Brain Theory and Digital Twins Concept

This section intends to illustrate the circumstance of prediction matched to observation operated in, the most popular Brain functioning theory in neuroscience and the Digital Twins industrial concept. This will be illuminated through a review of works published in these two cases.

Bayesian approaches for brain actions assess the aptitude of the neural system to work under conditions of uncertainty to converge with the optimum suggested by Bayesian statistics (Knill and Pouget 2004). Bayesian brain theory in neuroscience regularly tries to illuminate the reasoning capabilities of the brain established on statistical rules where it is supposed that the neural assembly keeps interior probabilistic models updated by sensory data via neural managing by means of Bayesian probability (Penny 2012). It is supposed that Bayesian inference works at the cortical macrocircuits level. These circuits are structured along with a hierarchy that reflects the classified arrangement of the observable entities around us. The brain instructs a model of these things and creates predictions regarding their sensory input; that is the so-called predictive coding. The overall features of the scene, including things, will be denoted by action in zones of the brain nearby to the higher hierarchy. The links from the upper zones to the lower ones then put into code a model illustrating how the scenes contain objects and the appearances of the objects. The lowermost level predictions are matched to sensory input and the prediction error is circulated up in the hierarchy. These zones are hierarchically structured such that the lower level supplied prediction error creates the input of a higher-level area. At once, the return from the higher-level part conveys the former convictions for the lower level one. In this situation, the prediction error indicates that the existing model has not completely taken into account the input. Readapting the next level can enhance accuracy and diminish the prediction error (Beck et al. 2013, Hohwy 2017). Yet, if not, higher-level adjustments are required. Generally, higher levels supply information to lower ones and ensure inside consistency of presumed supplies of sensory input at different levels. This occurs at once at all hierarchical levels. The predictions are sent down and their errors are sent back up in a dynamic process. Therefore, the running of neural system in situations of uncertainty corresponds to a real time matching two way process. This comprises a top down tuning of observation via minimization of prediction error operation. All the levels of the neural organization contain probabilistic models (predictions) revised by sensory observed information across neural processing iterative matching.

Considering now the case of Digital Twins DT, that is characterized by a gainful two way communications between the digital and physical spheres. DT is unlike both of Computer aided design (CAD), which exclusively focuses on the digital territory, and Internet of things (IoT) that intensely deliberates on the physical one via direct data collecting in real time. The three components of a DT are a matched physical observable, a real time replicated numerical item and their sensorial and matching connections. The physical item behaves more "smart" that dynamically adjust its real time conduct matching to the "advocacies" made by the digital one. While, the digital item performs more "factual" to properly replicate the real territory state of the physical product. This could be accompanied by a knowledge uncertainty accomplishment via an amended model. Consequently, the DT offers a smart alliance of the physical and the digital spheres (Tao et al. 2019). Therefore, in the DT technology, the physical observation and the prediction modeling are interconnected in a real time two-way communications acting as an amalgam of (matching, imitating and validating) link. The DT concept is principally used for fault diagnosis, predictive maintenance, performance analysis and product design (He and Bai 2020). This concerns various societal domains such as health care, mobility, energy and generally innovative industrial devices.

From the last discussion, we see that in both cases of Bayesian Brain and Digital Twins, we are in presence of a real time two way interconnected matched process. Such matching involves an observed item and a predictive one. The observed item corrects the prediction error and the predictive item rectifies the sensory observed inputs. This iterative process leads to more objective and smarter association. We can remark that this common process of the two examined cases is independent of their nature. One concerns an artificial phenomenon while the other regards a natural biological one.

Infections by an Unknown Mutant Virus

This part relates the practice of modeling for the prediction of forthcoming behaviors of a phenomenon that is not well known, or owning conduct varying random. We may meet such situation mainly in natural phenomena. In this case, the problem of aleatory uncertainty corresponds to a strong obstacle and it is obvious that the practice of lonely mathematical modeling for such a case would be useless. In such a case, the association prediction-observation has to be applied with constraint.

Mathematical modeling can be only achieved with proven and validated theories. In occurrence of problems where the theoretical behavior is not well established, or phenomenon comportment fluctuating random, it is obvious that the practice of solitary mathematical modeling or Bayesian assessment would be critical and uncertain. In such occasion, the practice of inductive prediction: this is when one might develop a judgment concerning the future by means of preceding knowledge, would handle to mistaken result (Popper 1934). A typical example of such an incorrect use of prediction could be approached in the modeling of complex infection behaviors in nature such as contagion by an unknown mutant virus.

One could admit in some less complex situations that mathematical and computational models seem to be powerful tools for studying the dynamics of infections. Recent years have seen an increased interest in such modeling studies, and it is likely that studies through modeling, generally in medical applications, will likely increase in the future (Razek 2019). To achieve this in dynamics of infections, it will be crucial that the models are linked as closely as possible to the data and that the type and complexity of the model are appropriate to the question nearby. As long as these simple rules are followed, there is no doubt that modeling will continue to provide important information on the dynamics of infection (Beauchemin and Handel 2011). Additionally, much of the progress will not only benefit understanding of the virus, but will also help study other acute infections.

However, in the context of contagions by an unknown mutant virus, an approximate mathematical performance of the endemic contagion (Enserink and Kupferschmidt 2020) must be assumed from the condition of a number of infected subjects to maneuver it for future other contaminations. Likewise, several diagnostic and prognostic models for viral infections are currently proposed. However, these models all have a high risk of bias and their performance estimates are likely optimistic and misleading (Wynants et al. 2020). There are also prognostic models limited to predict the risk of mortality (Torres-Macho et al. 2020) and the progression to severe disease. The proposed models carry a high risk of prejudice, which raising concerns that their predictions are unreliable when applied in daily practice. In such situation, only sharing of data and expertise for validating and updating prediction models related to infections could offer outcome (Wynants et al. 2020).

The different practices of predictive modeling described in the upper lines can help the positioning of research processes but not the acquisition of reliable and functional results. Consequently, as observation is reputed truthful, the link predictive modeling-observation in such situation will not present a matched subject. Therefore, observation will be the central element in elucidating this category of problems and can only be assisted by prediction. This could be done by adjusting the clinical observation protocol.

In this clinical instance, the prediction acts a tendency role while the observation participates the main concern of treatment across protocol amendment. This is a characteristic case of complementarity aided by corroboration throughout iterative matching of the couple observation with prediction. The fact that the source of such phenomenon is subject to random uncertainty will be discussed in the next section.

Discussion

From the precedent analysis based on literature review, we note the importance of the role played by the uncertainty in the practice of prediction. Uncertainty is present in many circumstances in the nature and prediction is often practiced to reduce it through more intelligent analysis when possible. This reduction approach depends on the type of uncertainty. The reduction is possible in the case of the knowledge uncertainty that is due the lack of information in respect to quantities and processes within the concerned phenomenon. In the opposite, in the case of the aleatory or random one, the reduction becomes complicated almost unviable; one can only identify and quantify such random variability. Apart from natural processes, uncertainty is unavoidable in most of artificial systems. It exists in material, geometry and environmental conditions. When we analyze the uncertainties in complex models, we have to consider different uncertainties namely, parameter uncertainty, simulator uncertainty (including initial condition and forcing function uncertainty), structural uncertainty (simplifications in the physics), observational error uncertainty (arises when we match our model to system observations). Many works have been published in this subject (see for example, Vono et al. 2019, Razek et al. 2019, Conejo et al. 2010, Dantzig 2011, Vernon et al. 2010, Vernon et al. 2014, Haylock and O'Hagan 1996, Kennedy et al. 2006, Kabir et al. 2018). These uncertainties can be reducible or not as explained for natural activities. The cases presenting a problem interest the aleatory uncertainty. Such uncertainty is an intrinsic system property and refers to characteristic variation in the physical system to be modeled by prediction. Such random changes may be associated with variability in time or space.

The cases considered in the present work concern a theory governing the functioning of a natural system (Brain functioning), the operation of industrial artificial smart systems, and a health care protocol. The theory of the first case involves a self or internal uncertainty treatment. The industrial systems are subject to knowledge uncertainty that could be treated by amended models. The last case is more complicated that is a medical protocol for the infection by means of a natural process. This last is characterized by an unknown aleatory uncertainty phenomenon. The prediction has to account for the contamination infection of human by an unknown mutant virus. The fact that the source of such phenomenon is natural, unknown and subject to random uncertainty makes the task difficult.

Only additional investigations to dominate the knowledge of the virus allow a correct prediction for a single facet of the virus before the mutation. Such a survey would be based on observation practices. We can take the example of several recent viruses in this category, which are frequently accompanied by clinical acute respiratory distress syndrome. The result is respiratory failure, the manifestation responsible for the majority of deaths. For instance, X-ray imaging of the chest and clinical computed tomography can easily detect lung damage associated with this syndrome. In such a case, the opacities of the ground glass of the peripheral lung observed are the main radiological mark of the syndrome and may be related to the histological observation of a diffuse alveolar lesion. For the moment, credible investigations could be carried out by observation e.g. phase contrast X-ray tomography (Eckermann et al. 2020) where virtual 3D pathohistology of lung tissue from infected patients could be performed. In addition, similar technical methods using synchrotrons (Morgan et al. 2020) allow also promising results.

Conclusion

From the review of works, relating to the prediction of phenomena in artificial and natural instances we can conclude that the link prediction-observation that reputed matched is fully implicated and useful in many natural and artificial situations. Such implication is strongly related to the treatment of the uncertainty problematics. Most of artificial situations involve knowledge uncertainty that could be reduced by amending the mathematical model, which has been illustrated from the accomplished review. In the situations involving random or aleatory uncertainty, the prediction side of the link suffers of inconsistency due to the approximated treatment of the uncertainty. In such case, the observation side will be the main evaluation means that may be assisted by prediction depending on the circumstance. This has been also reinforced by achieved review.

We can recall that we evaluated in this work the relevance of predictive models in the two categories of biological and artificial phenomena considered in the assessed literature review. In the case of artificial phenomena, the prediction manifests a successful delivery. In the field of natural biological phenomena, we have discussed two applications, which are the theory of brain function of the Bayesian brain and the contamination of humans with an unknown mutant virus. In the brain functioning situation, prediction again shows an effective approach. This makes sense because prediction is the basis of Bayesian brain theory throughout a two way real time paired process interconnected with observation. In contrast, in the situation of contamination of human infection with an unknown mutant virus, the prediction shows an unsuccessful attempt to use it in a medical modeling protocol. This is due to the characterization of this situation by a phenomenon of unknown random uncertainty. As long as knowledge of the phenomenon is not ruled, the prediction in this situation can only allow a possible adjustment of the clinical observation protocol.

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