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PERSPECTIVE

Rehearsal: learning from prediction to decision

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Machine learning [1] studies focus mostly on **prediction**, where a model is built from a set of observational data for making correct predictions on unseen instances. It has been addressed very well by modern techniques such as deep learning [2], though some issues, e.g., open environment machine learning [3], remain to be developed.

What's next?

May we consider the following scenario. Suppose a very powerful machine learning model has given a prediction result, suggesting that some things we do not want are going to happen. Can we get help for **decision** making about taking some action to avoid these undesired things to occur?

For example, imagine that a gentleman has trained a machine learning model based on data such as last month's oil prices, local traffic information, international news information, etc. Today he received prediction notice from the model, suggesting that next month his commuting expenses will dramatically increase; this is very unpleasant for him. After careful thinking, the gentleman decided to take bus and give up driving by himself from next week.

In this story, the prediction itself does not constitute a decision. It only offers a warning message that some undesired thing, i.e., commuting expenses will dramatically increase, is going to happen. This is easy to understand, as it is well known that prediction relies on *correlation*, whereas correlation does not offer deep "understanding". Then, how about resorting to *causality* [4]? Though causality is crucial for scientific discovery and other tasks pursuing truths, it is generally not necessary for decision making.

First, making decision does not need to have a thorough characterization of causal relation about variables, or even responsible variable corresponding to the "undesired future event". This is easy to understand: We human beings make decisions everyday, but we do not have a full understanding about the world around us. Second, causality usually represents a *static* generating process, while the real environment is often *open* and *dynamic*, where the causality may change. Hence, even when causality can be discovered with historical data, it is not always sensible to guide decisions in real tasks. For example, the oil price in Europe depends on the transaction price in Russia before the Russia-Ukraine conflict, whereas it is not the case afterwards. Third, even when a closed and static environment were assumed, with true causality discovered, it will be helpless for decision making if the identified causal factors are unactionable. For example, in the above story, suppose the discovered causal relation indicates that the gentleman's commuting expenses will increase dramatically because of the dramatically increased oil price due to the Russia-Ukraine conflict. This discovered relation does not offer any helpful advice to decision making, since the gentleman does not have the power to control the oil price or stop the conflict; actually, his decision of taking bus influences neither oil price nor the conflict. Furthermore, even when the aforementioned three points were ignored, it should be noted that making decisions does not really need a faithful understanding of the causal relations, just like that we human beings often make good decisions even based on misperception or incorrect understanding of the situation.

Generally, *prediction* relies on correlation, *discovery* relies on causation, whereas *decision* relies on something between: We call it **rehearsation**. We believe that a decision is the consequence of a series of hypothesized "rehearsal" of possible actions. In the above story, the gentleman rehearses the action of switching from car to bus hypothetically in his mind and then make the decision. Note that this is very different from *intervention* [4], as the rehearsal is just a hypothetical surmise about the undesired event under action, without ambitiously pursuing the identification of the causal effect on the event under intervention in the decision process. The relation between correlation, rehearsation, and causation are summarized in Fig. 1. Briefly, if X and Y have causal/rehearsal relation, they must have correlation; if X and Y have causal relation and X is actionable, they have rehearsal relation, but not vice versa.

From the aspect of Bayesian decision theory, to simplify the

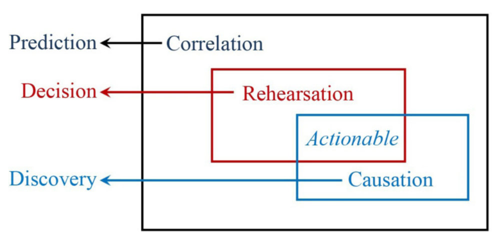

Fig. 1 Relationship between correlation, rehearsation, and causation

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discussion, let $P(Y = undesired)$ denote the probability that an undesired event will happen, and suppose all the variables are binary, where $\tilde{\mathbf{X}}$ and $\mathbf{Z}$ denote the set of actionable and unactionable variables, respectively. When $P(Y = undesired|\tilde{\mathbf{X}},\mathbf{Z}) > 1 - P(Y = undesired|\tilde{\mathbf{X}},\mathbf{Z})$, we receive a warning message that the undesired event will happen. Then, we want to do something on some actionable variables to make the inequality reversed. The variables can be solved according to

$$\underset{|\tilde{\mathbf{X}}^* \subseteq \tilde{\mathbf{X}}|}{\arg\min} \frac{1 - P(Y = undesired|Rh(\tilde{\mathbf{X}}^*), \tilde{\mathbf{X}} \backslash \tilde{\mathbf{X}}^*, \mathbf{Z})}{P(Y = undesired|Rh(\tilde{\mathbf{X}}^*), \tilde{\mathbf{X}} \backslash \tilde{\mathbf{X}}^*, \mathbf{Z})} > 1 , \qquad (1)$$

where $|\cdot|$ denotes set cardinality, $\cdot\backslash\cdot$ denotes set subtraction, $Rh(\cdot)$ denotes rehearsal operation. Eq. (1) implies that the decision action should involve as few variables as possible. It can be easily extended to consider different action costs, as well as multiple or continuous action values. The identification of $\tilde{\mathbf{X}}^*$ relies on $Rh(\cdot)$ because nothing happened yet. Note that the accurate identification of the effect of $Rh(\cdot)$ is not pursued, because we only want to enable the inequality shown in Eq. (1) to hold, without the need to have the exact values of the probability terms. The hypothesized rehearsal requires more discussion.

First, once we get a warning message that some undesired event is going to happen, we can try to construct a relation graph among the variables. Note that generally we do not need a graph covering all variables, and in most cases a graph covering the responsible variables concerning the undesired event is enough. We need to know which variables are actionable, possibly by domain knowledge. For example, in Fig. 2, the white nodes denote actionable ones whereas the gray ones are unactionable.

Note that the edges in Fig. 2 are undirected. We do not need a perfect characterization of causal relation, though it can be helpful if available. Returning to the gentleman story, some causality fans might claim that the decision can be made if a variable `vehicle type` had been identified as a causal factor of commuting expenses. As we have emphasized, however, we should never take it as a prerequisite for decision making that we can have thorough understanding of causality. Indeed, in most situations we human beings can make excellent decisions even when we have only partial or wrong understanding of the world around us. Figure 2 implies that variables that are not identified as causal factors can also be considered by rehearsal for decision.

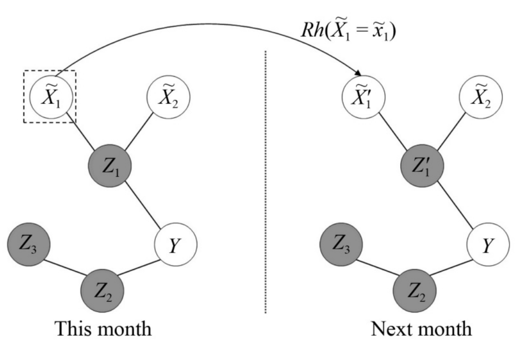

Fig. 2 Rehearsal involves current observations and estimated influences on future

Based on the relation graph shown in the left part of Fig. 2, we can try rehearsal operation on actionable variables. Suppose we are considering $Rh(\tilde{X}_1 = \tilde{x}_1)$. Note that nothing happened yet, and there is no real data about how the situation becomes after executing the hypothesized decision action. Now, the rehearsal operation can be realized by artificially generating pseudo-data mimicking the decision action, e.g., replacing the value of fuel consumption of the original data to zero to mimic that the gentleman in story taking bus instead of car.

Second, in contrast to prediction, decision concerns about the influence of actions on future. As shown in Fig. 2, the rehearsal effect should be evaluated in future environment (right part) rather than the current environment (left part). Unfortunately, when we make the decision, we only have observational data exhibiting current environment. A simple approach is to evaluate the rehearsal effect by assuming that all other variables, except those directly influenced by the rehearsed variable (e.g., Z_1'), never change significantly. Such a simple approach can be particularly useful when the decision is very short-term, where the environment does not change much during the short period. A demanding remedy is to consider the possible changes of the variables in the environment; this is somewhat related to environment modeling techniques and open environment machine learning [3].

Furthermore, the estimation of the effect of $Rh(\cdot)$ is based on hypothesized rehearsal rather than taking real action, without elaborate assumptions such as preknown causal relations [4] or ignorability [5]. Therefore, the effect of $Rh(\cdot)$ could not be estimated exactly. It has to be accompanied with adequate hypothesis tests. Note that, as aforementioned, rehearsal is very different from pursuing the identification of causal effect under intervention. As shown in Eq. (1), rehearsal only needs to enable the *odds* of undesired things reversed, with neither the need of pursuing identification of exact effect of $Rh(\cdot)$ nor the need of attaining exact estimate of the probability terms.

Overall, we believe that rehearsal can be a practical and sound way from prediction to decision. Developing effective algorithms and establishing theories for rehearsal are challenging but fascinating.

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