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A Review Paper on Operational Learning

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ABSTRACT: Operational learning is about gaining deeper operational intelligence about how work actually is completed. Goal-oriented approaches are becoming increasingly popular as a means of gathering, developing, analysing, and defining software requirements. The development of a proper and comprehensive set of operational criteria, in the form of pre- and trigger-conditions that ensure the system goals is a fundamental task in these methods. Few existing techniques assist this critical activity and rely mostly on the engineer's considerable effort and skill. An operational definition offered in this paper posits learning as a multi-dimensional and multi-phase phenomenon occurring when individuals attempt to solve what they view as a problem. To model someone is learning accordingly to the definition, it suffices to characterize a particular sequence of that person's disequilibrium–equilibrium phases in terms of products of a particular mental act, the characteristics of the mental act inferred from the products, and intellectual and psychological needs that instigate or result from these phases.

KEYWORDS: Learning, Machine Learning, Model, Operational, Variability.

1. INTRODUCTION

Learning conceptual concepts successfully transmit signals about many theoretical viewpoints on learning, but they lack operability. Many commonly used in mathematics education discourse conceptualizations of learning, such as learning as acquisition, learning as participation, learning as problem solving, or learning as assimilation and accommodation, refer to the key processes involved but fall short of operationally capturing the essence of the intended change[1].

The machine-learning algorithm in the simultaneous process includes a regularisation term that encodes the policy and its associated cost and has an adjustable regularisation parameter. If the cost of solving the problem is uncertain, the regularisation parameter can be swept through an interval to find a range of possible costs, from optimistic to pessimistic[2].

After that, the method generates the most likely scenario for each cost value. We can sweep out costs for all reasonable probabilistic models by looking at the full range of the regularisation parameter. This range can be used to determine how much money should be set aside to solve the problem. With the full range of costs for reasonable models, the first paragraph's question about allocation, "What is a reasonable amount to allocate for this task so we can react best to whatever nature brings?" can be directly answered[3]. For example, one could allocate the maximum cost to the set of reasonable predictive models. “Can we produce a reasonable probabilistic model, supported by data, where we might expect to pay a specific amount?” is the second question. This is an important question because business managers frequently want to know if the data supports a particular scenario/decision pair[4].

RE (Required Engineering) is an important component of the software development life cycle, and it deals with the elicitation, elaboration, specification, analysis, and documenting of a system's goals. Each of these processes leads to the creation of a full and accurate software requirements specification that meets the system's objectives. Many goal-based approaches have been developed to aid in the collection of requirements, but few have focused on the derivation of operational needs from high-level objectives[5]. Operationalization patterns that enable the derivation of operational requirements in the form of pre- and trigger-conditions from Linear Temporal Logic goals (LTL). This method generates requirements that are guaranteed to be correct. Patterns, on the other hand, are limited to a set of goal and requirement templates, and their use necessitates a fully developed goal model. As a result, elaborating operational needs from goals is limited to a collection of templates, which can be time-consuming and error-prone. As a result, the availability of a more systematic and automated approach would benefit the goal-setting process[6].

The data usually disclose the result, the effective solution to the new challenge, in a strategy that focuses on fostering disruption. There may be little or no data on the learning (changing) process since the student was previously unable to generate a solution of this type and is now able to. In our method, the researchers utilise a series of activities to elicit specific action from the students that promotes the desired learning. The researchers will be able to watch the students' activities throughout the task sequence if the task sequence is effective[7].

We present what we term the simultaneous process, in which we examine a range of predictive models and associated policy decisions at the same time in order to transmit the uncertainty in modelling to the uncertainty in costs. The simultaneous process was named to contrast with a more traditional sequential process, in which data is first input into a statistical algorithm to produce a predictive model that makes future recommendations, and then the user develops a plan of action and estimated costs for implementing the policy. Even though there may be a complete class of models that might be applicable for the policy decision problem, the sequential approach is usually employed in reality. The sequential process is based on the assumption that the probability is "accurate enough" to make a "near enough" conclusion[8].

This approach may be used to a variety of situations. Predictions based on a statistical model of the number of patients, for example, may be used to determine the possible policies and costs for staffing in a medical clinic. Predictions based on a model of the expected traffic may be beneficial in defining load-balancing rules on the network and their related costs in traffic flow difficulties. Predictions based on payback and ad-click rate models may be utilised in online advertising to determine regulations for when the ad should be displayed and the related income[9].

1.1 Operational and environmental variability:

Non-stationary sources of variability in the observed dynamic response of structures can be linked to operational and environmental factors. Live loads (for example, traffic loads on bridges), speed of operation, and changing excitation sources are all examples of varying operating circumstances. Thermal impacts, wind loading, and moisture content are all examples of varying environmental circumstances[10].

Many researchers have looked at the impact of traffic loads on bridge modal characteristics. Heavy traffic reduced the observed natural frequencies of a 46-m long simply supported plate girder by 5.4 percent, discovered 10 percent fluctuations in the first natural frequency in a box-girder concrete bridge. The scientists ascribed the large fluctuations to changes in the bridge's mass because of traffic and environmental factors. Following further study, it was discovered that the cars changed the overall mass of the bridge by 10% and the modal frequency of the bridge by 5%.

These changes were associated with surface temperature differentials across the deck at the moment and one year later, but not with absolute air temperature. In a 2008 research, the

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authors discovered an asymmetrical variation in the first mode shape that changed during the day in one simply supported span at the end of the same bridge.

The time of day and accompanying solar heating were linked to the asymmetry along the longitudinal axis. Because of the bridge's north–south direction, these thermal impacts were more prominent. Such variations in the dynamical response characteristics, if not adequately accounted for, might lead to misleading signals of damage. A classification system would identify the mode in Figure 1(a) was regarded the baseline condition and in Figure 1(b) as an outlier if the mode. If the environmental variability associated with this characteristic was not taken into consideration in the outlier detection procedure, this outlier might be incorrectly classified as damaged.

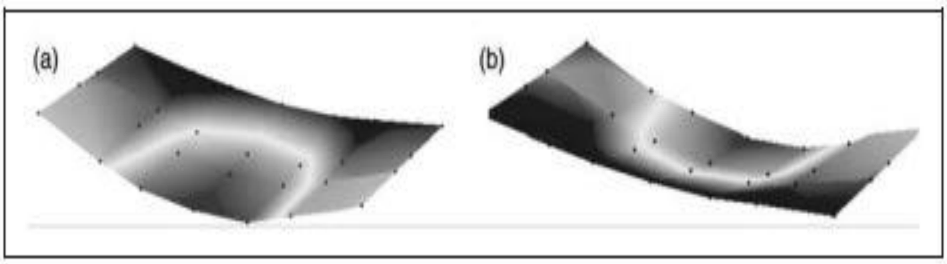

Figure 1: The above figure shows the shape of supported span (a) in the morning, (b) in the afternoon.

1.2 Machine learning algorithms:

Several techniques for data normalisation have been published in the literature. Because they are created and developed in such a way that their performance is enhanced based on the analysis of normal operating data (i.e., they "learn" from the normal condition data), these methods are also known as machine learning algorithms.

Briefly, these algorithms provide a functional connection that predicts how changing operational and environmental variables affect the underlying distribution of damage-sensitive characteristics. Because the varying operational and environmental conditions have been incorporated into the classifier, when subsequent features are analysed with these algorithms and the new set of features is shown not to fit into an appropriate distribution, they may be more confidently classified as outliers or, potentially, features from a damaged structure.

Even though the underlying mathematical formulations of these algorithms differ, they are all implemented in the same way: first, each algorithm is trained and its parameters are adjusted using feature vectors extracted from time-series data collected under various operational and environmental conditions. Second, all machine learning algorithms will transform each input feature vector during the test phase; it should be nearly invariant for feature vectors extracted from the normal condition, assuming the test data was obtained from operational and environmental conditions represented in the training data.

After that, a one criterion for a particular degree of significance is used to classify the data. When feature vectors come from the damaged state, even if they include operational and environmental variability, should be labelled as outliers if robust data normalisation has been performed. It is worth noting that a feature vector reflects a property of the system at a certain point in time. The modal parameters have traditionally been utilised in civil engineering as characteristics that define the structure's overall state.

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The AR model is employed to extract damage-sensitive features in this work because the underlying linear stationary assumption allows for the detection of nonlinearities in the time-series. The notion is that the estimated parameters should fluctuate between intervals in a system where distinct dynamics are present at various times.

The AR models have been used in SHM to extract damage-sensitive features from time-series data, using either the model parameters or residual errors. For a measured time-series $s_1, s_2, \ldots, s_N$ the AR (p) model of order p is given by:

$$s_i = \sum_{j=1}^{p} \phi_j S_{i-j} + e_i$$

Where s_i is the measured signal and e_i an unobservable random error at discrete time index i. The unknown AR parameters, ϕ_j, can be estimated using the least squares. The order of the model is always an unknown integer that needs to be estimated from the data. The Akaike information criterion (AIC) has been reported as one of the most efficient techniques for order optimization. The AIC is a measure of the goodness-of-fit of an estimated statistical model that is based on the trade-off between fitting accuracy and number of estimated parameters. In the context of AR models:

$$AIC = N_t \, ln(\varepsilon) + 2N_p$$

Where N_p is the number of estimated parameters, N_t the number of predicted data points, and $\varepsilon = SSR/N_t$ the average sum-of-square residual (SSR) errors. The AR model with the lowest AIC value gives the optimal order p.

1.3 Auto-associative neural network:

AANN is trained to describe the underlying dependency of the detected characteristics on unobserved operational and environmental parameters (e.g., traffic loads and temperature). The mapping layer, the bottleneck layer, and the de-mapping layer are all hidden layers in the AANN architecture. The references provide more information about the network, including the number of nodes to utilise.

1.4 Simultaneous Process in the Context of Structural Risk Minimization:

When dealing with finite data sets, there is often, no one right statistical model; in fact, there may be a whole class of good models. Furthermore, a small change in the predictive model chosen could result in a large change in the cost of implementing the policy recommended by the model. This happens, for example, when costs are based on items that come in discrete quantities. Figure 2 illustrates this possibility by demonstrating that the class of good models can have a wide range of costs. The simultaneous process can determine the cost range for a set of good models that can be used for cost allocation.

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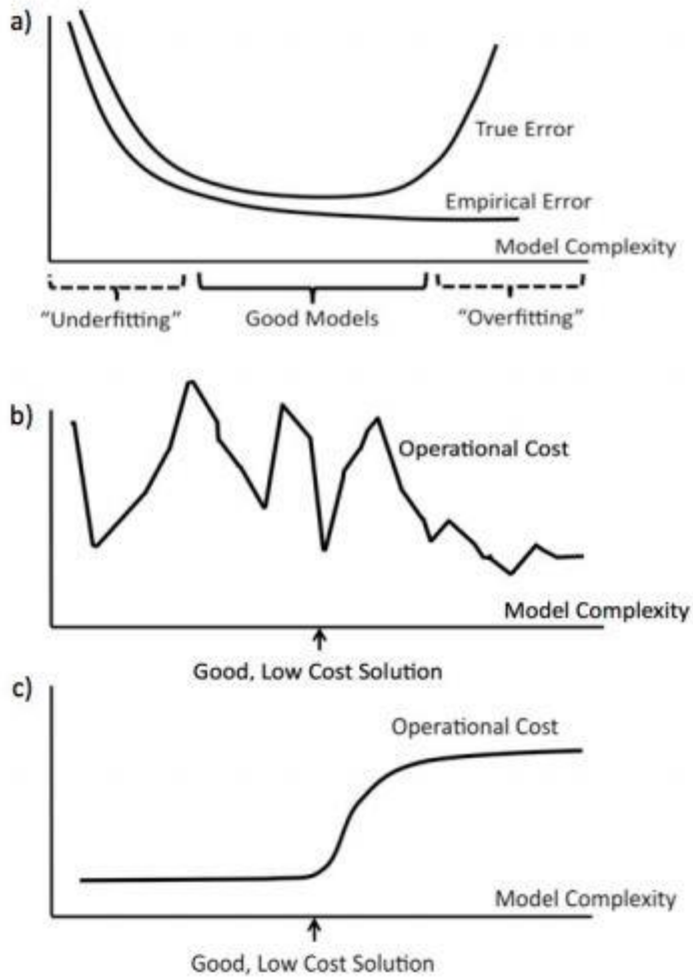

Figure 2: In all three plots, the x-axis represents model classes with increasing complexity. a) Relationship between training error and test error as a function of model complexity. b) A possible operational cost as a function of model complexity. c) Another possible operational cost.

2. DISCUSSION

The author has discussed about the operational defined learning, the learning conceptual concepts successfully transmit signals about many theoretical viewpoints on learning, but they lack operability. The definition also addresses the question of why the changes occurred by focusing on the reciprocity between ways of understanding and ways of thinking, as well as the intellectual and psychological needs that drive the initial involvement in a problematic situation and the pursuit of it in a specific manner. For example, the following explanation shows how and why Burt was finally capable of performing the interview problem independently by repeated reasoning about it. In general, the identified combination of psychological and intellectual needs plausibly explained how the interview task required Burt to examine his experience as a mathematics teacher and gradually shift from naively adapting the available word problem contexts to making subtle observations about the essence of fraction division over a long period. Many commonly used in mathematics education discourse conceptualizations of learning, such as learning as acquisition, learning as participation, learning as problem solving, or learning as assimilation and accommodation, refer to the key processes involved but fall short of operationally capturing the essence of the intended change. The machine-learning algorithm in the simultaneous process includes a regularisation term that encodes the policy and its associated cost and has an adjustable regularisation parameter. If the cost of solving the problem is uncertain, the regularisation parameter can be swept through an interval to find a range of possible costs, from optimistic to pessimistic. Because the varying operational and environmental conditions have been incorporated into the classifier, when subsequent features are analysed with these algorithms.

Operational learning is about gaining deeper operational intelligence about how work actually is completed. Goal-oriented approaches are becoming increasingly popular as a means of gathering, developing, analysing, and defining software requirements. The development of a proper and comprehensive set of operational criteria, in the form of pre- and trigger-conditions that ensure the system goals is a fundamental task in these methods. Few existing techniques assist this critical activity and rely mostly on the engineer's considerable effort and skill. An operational definition offered in this paper posits learning as a multi-dimensional and multi-phase phenomenon occurring when individuals attempt to solve what they view as a problem. Several techniques for data normalisation have been published in the literature. Because they are created and developed in such a way that their performance is enhanced based on the analysis of normal operating data. Second, all machine learning algorithms will transform each input feature vector during the test phase; it should be nearly invariant for feature vectors extracted from the normal condition, assuming the test data was obtained from operational and environmental conditions represented in the training data. When there are several potentially excellent probabilistic models, the simultaneous process yields a huge number of (optimal-response) policies. This occurs when training data is limited, the problem's dimensionality is high in comparison to the sample size, and the operating cost is uneven. These requirements are simple to meet and occur often.

3. CONCLUSION

The author has concluded about the operational defined learning, the simultaneous process is useful in cases where there are many potentially good probabilistic models, yielding a large number of (optimal-response) policies. This happens when the training data are scarce, or the dimensionality of the problem is large compared to the sample size, and the operational cost is not smooth. These conditions are not difficult to satisfy, and do occur commonly. For instance, data can be scarce (relative to the number of features) when they are expensive to collect, or when each instance represents a real-world entity where few exist; for instance, each example might be a product, customer, purchase record, or historic event. The shortcomings, which are beyond the scope of this already extensive article, may be explained, once again, in terms of the instructors' psychological and intellectual requirements, as well as the absence of some especially beneficial methods of knowing and thinking throughout the interviews.

When there are several potentially excellent probabilistic models, the simultaneous process yields a huge number of (optimal-response) policies. This occurs when training data is limited, the problem's dimensionality is high in comparison to the sample size, and the operating cost is uneven. These requirements are simple to meet and occur often. Operational cost calculations commonly involve discrete optimization; there can be many scheduling, knapsack, routing, constraint-satisfaction, facility location, and matching problems, well beyond what we considered in our simple examples. The simultaneous process can be used in cases where the optimization problem is difficult enough that sampling the posterior of Bayesian models, with computing the policy at each round, is not feasible. The author had end the paper by discussing the applicability of our policy-oriented estimation strategy in the real world. Prediction is the

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end goal for machine learning problems in vision, image processing and biology, and in other scientific domains, but there are many domains where the learning algorithm is used to make recommendations for a subsequent task.

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