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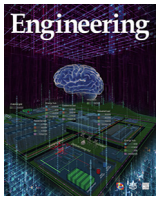

Research
AI Energizes Process Manufacturing—Perspective

Machine Learning in Chemical Engineering: Strengths, Weaknesses, Opportunities, and Threats

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ABSTRACT

Chemical engineers rely on models for design, research, and daily decision-making, often with potentially large financial and safety implications. Previous efforts a few decades ago to combine artificial intelligence and chemical engineering for modeling were unable to fulfill the expectations. In the last five years, the increasing availability of data and computational resources has led to a resurgence in machine learning-based research. Many recent efforts have facilitated the roll-out of machine learning techniques in the research field by developing large databases, benchmarks, and representations for chemical applications and new machine learning frameworks. Machine learning has significant advantages over traditional modeling techniques, including flexibility, accuracy, and execution speed. These strengths also come with weaknesses, such as the lack of interpretability of these black-box models. The greatest opportunities involve using machine learning in time-limited applications such as real-time optimization and planning that require high accuracy and that can build on models with a self-learning ability to recognize patterns, learn from data, and become more intelligent over time. The greatest threat in artificial intelligence research today is inappropriate use because most chemical engineers have had limited training in computer science and data analysis. Nevertheless, machine learning will definitely become a trustworthy element in the modeling toolbox of chemical engineers.

1. Introduction

In 130 years of chemical engineering, mathematical modeling has been invaluable to engineers for understanding and designing chemical processes. Octave Levenspiel even stated that modeling stands out as the primary development in chemical engineering [1]. Today, in a fast-moving world, there are more challenges than ever. The ability to predict the outcomes of certain events is necessary, regardless of whether such events are related to the discovery and synthesis of active pharmaceutical ingredients for new diseases or to improvements in process efficiencies to meet stricter environmental legislation. These events range from the reaction rate of a surface reaction or the selectivity of a reaction in a reactor, to the control of the heat supply to that reactor. Predictions can be made using theoretical models, which have been constructed for centuries. The Navier–Stokes equations [2,3], which describe viscous fluid behavior, are one example of such a theoretical model. However, many of these models cannot be solved analytically for realistic systems and require a considerable amount of computational power to solve numerically. This drawback has ensured that most engineers first use simple models to describe reality. An important historical—yet still relevant—example is Prandtl's boundary layer model [4]. In computational chemistry, scientists and engineers are willing to give up some accuracy in favor of time. This willingness explains the popularity of density functional theory, in comparison with higher-level-of-theory models. However, in many situations, higher accuracy is desired.

Decades of modeling, simulations, and experiments have provided the chemical engineering community with a massive amount of data, which adds the option of making predictions from experience as an extra modeling toolkit. Machine learning models are statistical and mathematical models that can "learn" from experience and discover patterns in data without the need for explicit, rule-based programming. As a field of study, machine

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learning is a subset of artificial intelligence (AI). AI is the ability of machines to perform tasks that are generally linked to the behavior of intelligent beings, such as humans. As shown in Fig. 1, this field is not particularly new. The term "artificial intelligence" was coined at Dartmouth College, USA in 1956, at a summer workshop for mathematicians who aimed at developing more cognizant machines. From that point on, it took more than a decade before the first attempts were made to apply AI in chemical engineering [5]. In the 1980s, greater efforts were made in the field with the use of rule-based expert systems, which are considered to be the simplest forms of AI. By that time, the field of machine learning had started to grow, but in the chemical engineering community, with some exceptions, a lag of about 10 years was experienced in the growth of machine learning. A sudden rise in publications on AI applications in chemical engineering in the 1990s can be observed, with the adoption of clustering algorithms, genetic algorithms, and—most successfully—artificial neural networks (ANNs). Nevertheless, the trend did not persist. Venkatasubramanian [6] names the lack of powerful computing and the difficult task of creating the algorithms as possible causes for this loss in interest.

The past decade marked a breakthrough in deep learning, a subset of machine learning that constructs ANNs to mimic the human brain. As mentioned above, ANNs gained popularity among chemical engineers in the 1990s; however, the difference of the deep learning era is that deep learning provides the computational means to train neural networks with multiple layers—the so-called deep neural networks. These new developments triggered chemical engineers, as reflected by an exponential rise in publications on the topic. In the past, AI techniques could never become a standard tool in chemical engineering; thus, it can be asked whether this is finally the moment. In this perspective article, we will first give an overview of the three major links in machine learning today, applied to chemical engineering. In what follows, the growing potential of machine learning in chemical engineering will be critically discussed; we will examine the pros and cons and list possible reasons for why machine learning in chemical engineering with remain "hot" or end up as a "not."

2. Machine learning ABCs

2.1. The "A" in machine learning ABCs: Data

A machine learning approach consists of three important links, as illustrated in Fig. 2: data, representations, and models. The first link in a machine learning approach is the data that is used to train the model. As will be discussed later, the data used also proves to be the weakest link in the machine learning process. Virtually any dataset containing results from experiments, first-principles calculations, or complex simulation models can be used to train a model. However, because it is expensive to gather large amounts of accurate data, it is customary to make use of "big data" approaches—using large databases from various existing sources. Due to the cost of real experiments, these large quantities of data are usually obtained via fast simulations or text mining from patents and published work. The increased digitalization of research provides the scientific community with a plethora of open-source and commercial databases. Examples of commonly used sources of chemical information are Reaxys [7], SciFinder [8], and ChemSpace [9] for reaction chemistry and properties; GDB-17 [10] for small drug-like molecules; and National Institute of Standards and Technology (NIST) [11] and International Union of Pure and Applied Chemistry (IUPAC) [12] for molecular properties such as solubility. In addition, several benchmarking datasets have been created to enable comparison between different machine learning models. Examples of these benchmarks are QM9 and Alchemy, for quantum chemical properties [13]; and ESOL [14] and FreeSolv [15], for solubilities. Before using any dataset for machine learning-based modeling, several steps should be undertaken to ensure that the used data is of high enough quality. The general aspect of ensuring data quality—from its generation to its storage—is known as data curation. More details about the necessity and consequences of data curation are discussed further on.

Several differences concerning data usage exist between machine learning—and, more specifically, deep learning methods—and traditional modeling. First, ANNs learn from data and

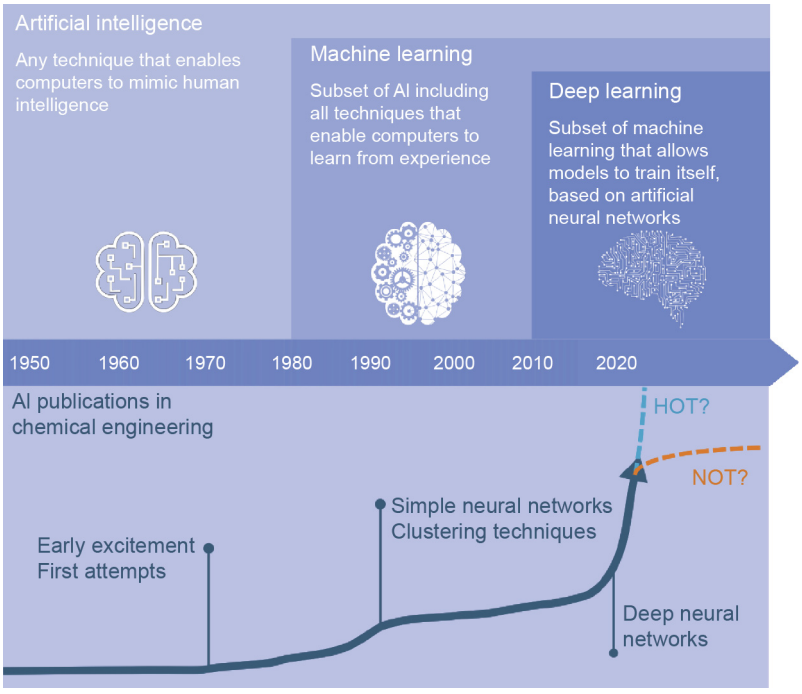

Fig. 1. Timeline of artificial intelligence, machine learning, and deep learning. The evolution of publications about AI in chemical engineering shows that a rise in publications is followed by a phase of disinterest. Currently, AI in chemical engineering is once again in a "hot" phase, and it is unclear whether or not the curve will soon flatten out.

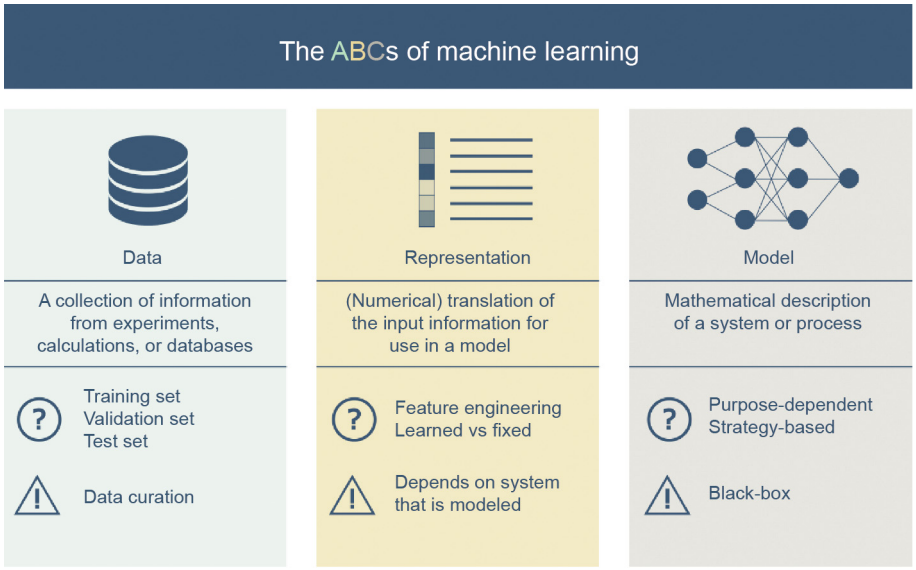

Fig. 2. The three major links in machine learning for chemical engineering; every part has an impact on the eventual prediction performance and should be handled carefully.

train themselves, although doing so requires large amounts of data. Therefore, training datasets generally contain tens to hundreds of thousands of data points. Second, the dataset is split into three instead of two sets: a training, validation, and test set. Both the training and validation sets are used in the training phase, while only the data in the training set is used for fitting. The validation set is an independent dataset that provides an unbiased evaluation of the model fit during the training phase. The test set evaluates the final model fit with unseen data and is generally the main indicator of the model quality.

2.2. The "B" in machine learning ABCs: Representation

A second important link in a machine learning method is how the data is represented in the model. Even when the data is already in numerical format, the selection of the variables or features that will make up the model input can have a significant impact on the model performance. This process is known as feature selection and has been the topic of several studies [16–19]. Limiting the number of selected features may reduce the computational cost of both training and executing the model, while improving the overall accuracy. This feature-selection process is of lesser importance in so-called deep learning methods, which are assumed to internally select those features that are considered to be important [20]. Then, an input layer that consists of basic process parameters (e.g., pressure, temperature, residence time), feed characterizations (e.g., distillation curves, feed compositions), or catalyst properties (e.g., surface area, calcination time) is often sufficient [21–27]. However, the task of representing the data becomes far more challenging in the case of non-numerical data, such as molecules and reactions.

Chemical engineering tasks often involve molecules and/or chemical reactions. Creating suitable numerical representations of these data types is a developing field in itself. In computer applications, the molecular constitution is typically represented by a line-based identifier, such as the simplified molecular-input line-entry system (SMILES) [28] or the (IUPAC) international chemical identifiers (InChIs) [29], or as three-dimensional (3D) coordinates. Recently, self-referencing embedded strings (SELFIES) [30] have been developed as a molecular string representation designed for machine learning applications. The molecular information is translated into a feature vector or tensor that is used as input for a deep neural network or another machine learning model. The first way to represent a molecule is by using a (set of) well-chosen molecular descriptor(s), such as the molecular weight, dipole moment, or dielectric constant [31–33]. Another way to generate a molecular feature vector is by starting from the 3D geometry. Coulomb matrices [34], bags of bonds [35], and histograms of distances, angles, and dihedrals [36] are a few examples of geometry-based representations. However, 3D coordinates or calculated properties are generally unavailable in many applications. In such cases, the representation can be created starting from a molecular graph, resulting in so-called topology-based representations.

In topology-based representations, only a line-based identifier is available. Encoders exist that directly translate the line-based identifier into a representation with techniques from natural language processing [37–41], but usually the line-based identifier is transformed into a feature vector in a similar fashion to geometry-based representations [42–60]. This is done by adding simple atom and bond features to the molecular graph and then transmitting the information iteratively between atoms and bonds. Circular fingerprints [42–46] based on the Morgan algorithm [61], such as the extended-connectivity fingerprint [62], were among the first molecular representations for machine learning applications. These fingerprints are so-called fixed molecular representations because they do not change during the training of the machine learning model. They remain popular in drug design for rapidly predicting the physical, chemical, and biological properties of candidate drugs [63]. Because a fixed representation vector represents a molecule by the same vector in every prediction task, this type of input layer seems to conflict with the definition of a deep neural network, which is assumed to learn the important features [64]. There is a growing tendency to focus on learning how to represent a molecule [47,52] instead of on human-engineering the feature vector, as it is assumed that better capturing of the features will lead to higher accuracy, with less data and at a lower computational cost [53,58].

Learned molecular representations are created as part of the prediction model. Starting from several initial molecular features—such as the heavy atoms, bond types, and ring features—a molecular representation is created that is updated during training. This choice also indicates that a molecule has different representations depending on the prediction task. An extensive variety of learned topology-based representations [47–58] can be

described using the message-passing neural network framework reviewed by Gilmer et al. [59]. The weighted transfer of atom and bond information throughout the molecular graph is characteristic of message-passing neural networks. Many different representations exist, ranging in complexity, but it is important to note that a single representation that works for all kind of molecular properties has not (yet) been developed [65]. For a more detailed overview of the state of the art in representing molecules, readers are referred to the review by David et al. [60].

Chemical reactions are more complex data types than molecules. Similar to line-based molecular identifiers, reactions can be identified by reaction SMILES [66] and reaction InChI (RInChI) [67], whereas SMIRKS [66] identify reaction mechanisms. As for molecules, chemical reactions should also be vectorized in order to be useful in machine learning models. The most straightforward method is to start from the molecular descriptors (e.g., fingerprints) of the reagents and sum [68], subtract [50,69], or concatenate [70–72] them. Another approach is to learn a reaction representation based on the atoms and bonds that take actively part in the reaction [73]. Reactions can also be kept as text (typically InChI) and, with a neural machine translation, the organic reaction product is then considered to be a translation of the reaction products [58,74–78].

2.3. The "C" in machine learning ABCs: Model

The final prerequisite for a machine learning method is a modeling strategy. There is a wide variety of machine learning models to choose from. Models can be categorized in different ways, either by purpose (classification or regression) or by learning methodology (unsupervised, supervised, active, or transfer learning). Generally speaking, the term "machine learning" can be applied to any method in which correlations within datasets are implicitly modeled [79,80]. Therefore, many techniques that are currently referred to as machine learning methods were in use long before they were termed machine learning. Two such examples are Gaussian mixture modeling and principal component analysis (PCA), which originated in, respectively, the late 1800s [81] and the early 1900s [82,83]. Both examples are now regarded as unsupervised machine learning algorithms. Other similar unsupervised clustering methods are t-distributed stochastic neighbor embedding (*t*-SNE) [84] and density-based spatial clustering of applications with noise (DBSCAN) [85]. Fig. 3 shows the difference between unsupervised and supervised learning techniques, with a non-exhaustive list of useful algorithms for a specific task. In unsupervised learning, the algorithm does not need any "solutions" or labels to learn; it will discover patterns by itself. Unsupervised learning techniques have been used for various purposes in chemical engineering. PalkovitsR and PalkovitsS [86] used the *k*-means algorithm [87] for clustering catalysts based on their features and *t*-SNE for the visualization of high-dimensional catalyst representations. Not only used for catalysis, *t*-SNE is the preferred method for visualizing high-dimensional data; it has also been used in the context of fault diagnosis in chemical processes [88,89] and for predicting reaction conditions [69,90]. PCA is another algorithm for reducing dimensionality and has been used multiple times by chemical engineers for determining the features that account for the most variance in the training set [91–97]. In addition, PCA is used for outlier detection [93,98]. Other algorithms used to detect anomalies include DBSCAN and long short-term memory (LSTM) [99,100]. Interested readers are referred to Géron's book [101] for a further introduction to machine learning algorithms.

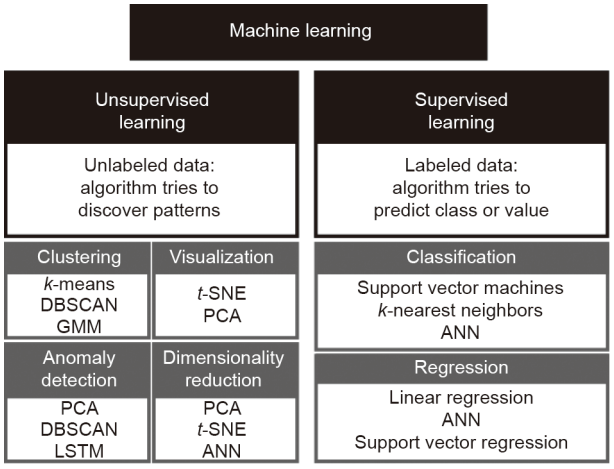

Fig. 3. Overview of unsupervised and supervised machine learning algorithms; a non-exhaustive list of useful algorithms is included. GMM: gaussian mixture modeling; LSTM: long short-term memory; *t*-SNE: *t*-distributed stochastic neighbor embedding.

When the dataset is labeled—that is, when the correct classification of each data point is known—supervised classification methods such as decision trees (and, by extension, random forests) can be used [102,103]. Support vector machines are another possible supervised classification method [104]. Although support vector machines are commonly used for classification purposes, extensions have been made to allow regression via support vector machines as well. Regression problems require supervised or active learning methods, although, in principle, any supervised learning method can be incorporated into an active learning approach. ANNs, and all their possible variations [105–113], are the method that is most commonly associated with machine learning. Depending on the application, one might choose feed-forward ANNs (for feature-based classification or regression), convolutional neural networks (for image processing), or recurrent neural networks (for anomaly detection). A chemical engineer might encounter convolutional neural networks used for representing molecules (see Section 2.2) [42–60] and ANNs [32,33,47,91,114–117], support vector machines [32], or kernel ridge regression [36,118] for predicting the properties of the representations. ANNs have been applied as a black-box modeling tool for numerous applications in catalysis [23], chemical process control [119], and chemical process optimization [120]. A popular algorithm for classifying data points when the labels are known is *k*-nearest neighbors, which has been used, for example, for chemical process monitoring [121,122] and clustering of catalysts [86,123,124].

3. Strengths

In this and the following sections, we give a detailed overview of the strengths, weaknesses, opportunities, and threats in the use of machine learning for chemical engineers. Fig. 4 summarizes what is described in the next sections.

Machine learning techniques have gained popularity in chemistry and chemical engineering for revealing patterns in data that human scientists are unable to discover. In contrast to physical models, which rely explicitly on physical equations (resulting from discovered patterns), machine learning models are not specifically programmed to solve a certain problem. For classification problems, this implies that not a single explicitly defined decision function must be programmed. For regression problems, this implies that no detailed model equations must be derived or parametrized [80]. These advantages allow efficient upscaling to large systems and datasets without the need for extensive computational resources. An example is the current boom in predicting quantum

Fig. 4. Strengths, weaknesses, opportunities, and threats in using machine learning as a modeling tool in chemical engineering.

chemical properties using machine learning [32,33,35–37,39,40,47,49,50,52,55,65,68,71,73,115]. The usual *ab initio* methods often require hours or days to calculate the properties of a single molecule. Well-trained machine learning models can make accurate predictions in a fraction of a second. Of course, other fast techniques that can predict accurately have already been developed, but they are limited in application range compared with machine learning models [125]. The inability to extrapolate is the major weakness of machine learning, but the application range can be extended quite easily by simply adding new data points. Active learning [126,127] makes it possible to expand the range with a minimal amount of new data, which is ideal for cases in which labeling is expensive (i.e., finding the true values of data points), such as quantum chemical calculations [116] or chemical experiments [72,128,129]. Furthermore, existing machine learning models, such as ChemProp [47] and SchNet [130,131], are ready to use and do not require experience. Machine learning in general has become very accessible with packages such as scikit-learn [132] and TensorFlow [133], and frameworks like Keras [134] (now part of TensorFlow [133]) or PyTorch [135], which restrict the training of a deep learning model to just a few lines of code. Such packages and frameworks give scientists the opportunity to shift their focus to the physical meaning of their research instead of spending precious time on developing high-level computer models.

4. Weaknesses

One of the main weaknesses of machine learning approaches is their black-box nature. Given a certain input, the approaches provide an output. This situation is illustrated by Fig. 5. Based on the statistical performance of the model on a test dataset, certain statements can be made about the accuracy and reliability of the generated output. Detailed analysis of the model hyperparameters (e.g., the number of nodes in an ANN) can be tedious, but can provide some insight into the correlations that have been learned by the model. However, extracting physically meaningful explanations for certain behaviors is infeasible. Hence, regardless of their speed and accuracy, machine learning models are a poor modeling choice for explanatory studies.

This lack of interpretability contributes to the difficulty of designing a proper machine learning model. As in any model, a machine learning model can overfit or underfit the data, with the proper model being situated somewhere in between. The risk of overfitting is typically much greater than the risk of underfitting for machine learning models, and depends on the quality and quantity of the training data, and on the complexity of the model. Overfitting is an intrinsic property of the model structure and does not depend on the actual values of the hyperparameters—it can be compared to fitting a (noisy) linear dataset with a polynomial of very high order. In deep learning, overfitting usually manifests itself in the form of overtraining, which arises when the model is shown the same data too many times. This results in the model memorizing noise instead of capturing general patterns. Overtraining can be identified by comparing the model performance on the training data with its performance on the validation and test datasets. If the training performance is much better than the validation performance, the model may be overtrained. Finding the number of training epochs is often a difficult exercise. In order to avoid overfitting, a machine learning model requires a stopping criterion, such as in other optimization problems. In traditional modeling, where models typically involve at least some form of simplification with respect to reality, this stopping criterion is typically based on the change in performance on the training dataset, as achieving a high accuracy of the training data is the main challenge due to the simplifications. Achieving accuracy on the training dataset is typically not the issue for machine learning models; rather, the challenge mainly lies in achieving high accuracy on data the model was not directly trained on. Therefore, the stopping criterion should be based on the performance of the model on "unseen" data—the so-called validation dataset. For rigorously testing the

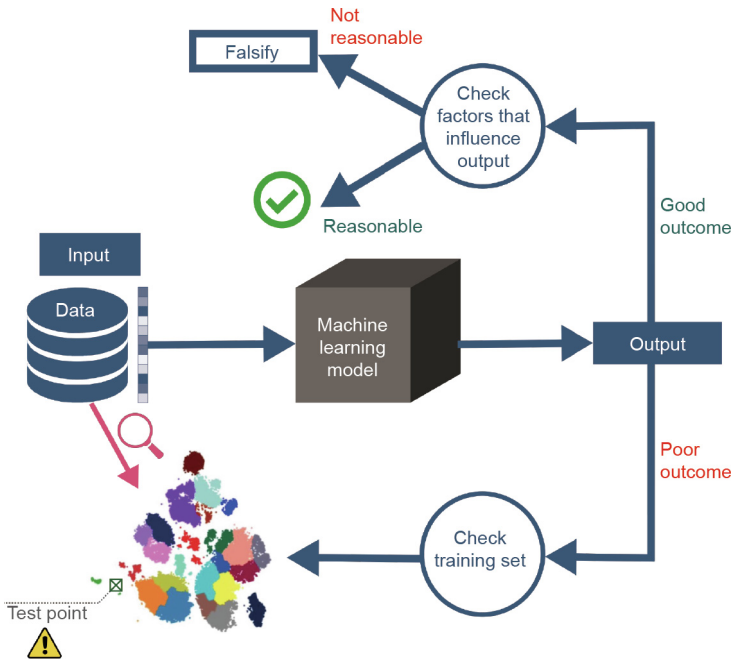

Fig. 5. Unraveling the results from black-box models. A poor result is typically related to the training set used. When testing outside of the application range, a warning signal should be raised. Good results require validation to understand what the model learns.

optimized dataset, a completely independent dataset—the test dataset—is required, as is also common practice in traditional modeling approaches.

A final—but often critical—weakness in machine learning approaches is the data itself that was used. If there are too many systematic errors in the dataset, the network will make systematic errors itself, in what is known as the "garbage in–garbage out" (GIGO) principle [136]. Some forms or sources of error can be identified relatively easily, while others—once made—are much harder to find. As in every statistical method, outliers may be present. A model trained on a small dataset is more affected by some outliers than a large dataset. This is why not only quality, but also quantity matters in machine learning. One possible solution to systematic errors is to manually remove these points from the dataset; it is also possible to use algorithms for anomaly detection, such as PCA [69,92], *t*-SNE [137,138], DBSCAN [139,140], or recurrent neural networks (LSTM networks) [111,141,142]. Recently, self-learning unsupervised neural network-based methods for anomaly detection [143] have been developed [144–146]. Next to simple outliers, there is always the possibility that the data points are actually wrong. Such data points might be one sample from an experiment in which a measurement error was made, or from a whole set of experiments that were conducted incorrectly. An example could be the results from a chemical analysis in which the apparatus was not calibrated. Training on a set of systematically false data is especially dangerous since the model will perceive the false trend as truth. Identifying such cases is possible through diligent scrutiny of the published data. This example illustrates the importance of data curation, which ensures that the data used is accurate, reliable, and reproducible.

Obviously, data can only be curated when it is available. Although decades of modeling, simulating, and experimenting have provided the chemical engineering community with a massive amount of data, this data is often stored in research laboratories or companies, and is hence not readily available. Even in a case where data is accessible, such as from an in-house database, the available data might not be completely useful for machine learning. The same applies to data extracted from research papers or patents using text-mining techniques [147]. The reason such data might not be useful is because, in general, only successful experiments are reported, while failed experiments remain unpublished [148]. Furthermore, experiments or operation conditions that seem to be nonsense to a human chemical engineer are not performed, because the engineer has insight and scientific knowledge. Machine learning algorithms, however, do not know these boundaries and not including such "trivial" data might lead to bad predictions.

5. Opportunities

The many strengths of machine learning methods present various application opportunities, and recent developments have provided ways to mitigate some of the most important criticisms. The exceptionally high execution speeds of almost any trained machine learning method makes such methods well-suited for applications in which accuracy and speed within predefined system boundaries are important. Examples of such applications include feed-forward process control and high-frequency real-time optimization [149–151]. While empirical models often lack the accuracy for these applications, detailed fundamental models are rarely fast enough to avoid computational delays. Machine learning models, trained on a fundamental model, can provide similar accuracy, yet at the computational cost of an empirical model. In this case, a model is trained on high-level data and tries to predict the difference between the empirical outcome and the true value [152,153]. Unsupervised algorithms can be used in process control applications for discovering outliers in real-time data [93]. The combination of more accurate, rapid prediction and reliable industrial data offers opportunities for the creation of digital twins and better control, leading to more efficient chemical processes.

A similar observation can be made in multiscale modeling approaches, where phenomena at a variety of different scales are modeled, resulting in a complex and strongly coupled set of equations. The potential of machine learning in such applications strongly depends on the aim of the multiscale approach. If the aim is to gain fundamental insights into the lower scale phenomena, then machine learning is not advisable, due to its black-box

nature. However, if the smaller scales are incorporated into the approach in order to obtain a more accurate model for larger scale phenomena, then machine learning could be used to replace the slow fundamental models for the smaller scales, without impacting the interpretability of the larger scale phenomena.

A final opportunity lies in providing an answer to one of the main flaws of machine learning: its non-interpretability. The issue of interpretable machine learning systems is not unique to chemical engineering problems—it is encountered in nearly any decision-making system [154–157]. An attempt has been made in the field of catalysis to rationalize what exactly machine models learn [158]. This attempt, however, still does not provide any level of direct interpretation of the model outcomes. Fig. 5 shows a workflow for explaining why a certain result is obtained. When the model outputs a good result, such as a chemical reaction predictor giving the correct product, the model should only be trusted after examining what the prediction is based on. A first step toward interpretation of the model results is to quantify the individual prediction uncertainties [159,160], as this gives an idea of the confidence the model has in its own decisions [115,161–164]. One relatively straightforward way of doing so is via ensemble modeling. This methodology has been used for decades in weather forecasting and can be used in combination with nearly any model type [165–167]. Several algorithms have also been created to determine how much certain input features influence the output [168], or to see which training points the model uses for a certain output [169,170]. When the results seem chemically or physically unreasonable, the model should be falsified instead of validated, by finding adversarial examples [159]. Furthermore, the reason is usually found in the dataset, with erroneous data or bias being present in the dataset [171,172].

Another way of making machine learning models more interpretable is to include chemically relevant and well-founded information in the models themselves. Interpretation will still require a considerable amount of postprocessing, but—if human-readable inputs are used and model architectures are not too complex—it remains a feasible task. Very complex recurrent neural networks using molecular fingerprints as input are nearly impossible to interpret, as the model input is already difficult for a human to decipher. In risk management, the "as low as reasonably practicable" (ALARP) principle is often applied [173]. Analogously, one could suggest an "as simple as reasonably possible" principle in order for machine learning models to be as interpretive as possible.

6. Threats

The accessibility of machine learning models is both a major strength and a major threat in research. While machine learning can be used by anyone with basic programming skills, it can also be misused due to a lack of algorithmic knowledge. Today, a plethora of machine learning algorithms are available, and a tremendous number of combinations of parameters and hyperparameters is possible. Even for experienced users, machine learning remains a reasoned trial-and-error method. Since researchers are often unable to explain why one algorithm works while another does not, some see machine learning as a type of modern alchemy [174]. Moreover, the majority of published articles do not provide source code, or only a pseudocode, which makes it impossible to reproduce the work [175,176]. Although chemistry and chemical engineering do not face a reproducibility crisis as much as the social sciences do [177], skepticism might grow in the community due to the increasing irreproducible use of machine learning in the field. In Gartner's hype cycle [178], machine learning and deep learning are beyond the peak of inflated expectations [179], and there is a risk of entering a period of disillusionment where interest is nearly gone. Next to irresponsible use of algorithms—and possibly more dangerous—is misinterpretation of the results. The black-box nature of the algorithms makes it difficult, and often nearly impossible, to understand why a certain result is obtained. In addition, a model might give the correct outcome for the wrong reasons [159]. Therefore, researchers should bear in mind an important rule from statistics when using machine learning: It is about the correlations, not the causations.

Another kind of unreasonable use of machine learning occurs when the model leaves the application range it is created for. The application range is determined by the training dataset and is finite. When testing unknown data points, the researcher should check whether or not these points are within the application range. When the points are outside of the range, it should be seen a warning signal for the user that the model will perform poorly [92]. The lower part of Fig. 5 depicts how the reason for obtaining a poor result is generally found by looking at the training set. Open-source applications using clustering algorithms are available for evaluating the data accuracy and its application range [180].

A last threat to applying machine learning in chemical engineering research is the growing educational gap when it comes to machine learning techniques. When applying computer and data science to chemistry and chemical engineering, it is important to understand not only the tool that is used, but also the process it is applied to. Therefore, simple training on how to use machine learning algorithms might become insufficient in the near future. Instead, a good education on AI and statistical methods will become vital in chemical engineering undergraduate programs. On the other hand, there is a need for more collaboration between computer scientists and experts on the studied topic. Whereas undertrained researchers risk a wrong use of the computational tools, computer and data scientists might obtain suboptimal results when they are not fully familiar with the topic being studied. More interdisciplinary research and a symbiosis between machine learning experts and chemical experts might be a way to avoid a phase of disillusionment.

7. Conclusions and perspectives

In the past decade, machine learning has become a new tool in the chemical engineer's toolkit. Indeed, driven by its execution speed, flexibility, and user-friendly applications, there is a strong, growing interest in machine learning among chemical engineers. On the flip side of this popularity is the risk of misusing machine learning or misinterpreting black-box results, which can potentially lead to a distrust of machine learning within the chemical engineering community. The following three recommendations can help to improve the credibility of machine learning models and turn them into an even more valuable and reliable modeling method.

First, it is important to maintain easy and open access to data and models within the community. High-quality data and open-source models encourage researchers to use machine learning as a tool and grant them the ability to focus on their topic rather than on programming and gathering data. Second, but related to the first point, is the creation of interpretable models. Since machine learning is already established in other research areas, new models for chemical applications are often inspired by existing algorithms. Therefore, the field will benefit most from studying why a certain output is generated from a given input, rather than from maintaining black boxes. The last recommendation is to invest in a profound algorithmic education. Although chemical engineers typically have very strong mathematical and modeling skills, understanding the computer science behind the graphical interface is a prerequisite for any modeler. This should also make it possible to define the

application range of the model, which is crucial for an understanding of when the model is interpolating and when it is extrapolating. This last point is definitely the most crucial: Machine learning models should be credible models, which can only be achieved by being vigilant for times when the model is being used outside of its training set.

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Compliance with ethics guidelines

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