DEEP LEARNING FOR EDUCATIONAL DATA SCIENCE

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ABSTRACT

With the ever-growing presence of deep artificial neural networks in every facet of modern life, a growing body of researchers in educational data science—a field consisting of various interrelated research communities—have turned their attention to leveraging these powerful algorithms within the domain of education. Use cases range from advanced knowledge tracing models that can leverage open-ended student essays or snippets of code to automatic affect and behavior detectors that can identify when a student is frustrated or aimlessly trying to solve problems unproductively—and much more. This chapter provides a brief introduction to deep learning, describes some of its advantages and limitations, presents a survey of its many uses in education, and discusses how it may further come to shape the field of educational data science.

1 Introduction

As artificial intelligence (AI) continues to penetrate ever deeper into modern life, one particular family of machine learning algorithms—namely, deep neural networks—have come to be seen as the solution to many of the challenges that have stumped more classical algorithms in the past. Modeled loosely on the structure of *biological* neural networks, *artificial* neural networks consist of chains of simple mathematical transformations that can model complex non-linear decision boundaries in large problem spaces. In particular, *deep* neural networks—artificial neural networks that consist of multiple layers of transformations—allow for sufficient complexity to tackle tasks in a wide variety of fields. These models are collectively and more colloquially referred to as deep learning.

A growing body of education researchers are now also turning their attention to leveraging the power of deep learning algorithms for the tasks of improving and understanding human learning. Researchers in educational data science, a field consisting of various interrelated research communities such as Educational Data Mining (EDM), Learning Analytics (LA), and AI in Education (AIED), have been involved in this endeavor. Given the histories of these communities and their goals, the contexts and rationales behind the use of deep learning in education are highly varied. It has been used in K–12 (Som et al., 2021; Southwell et al., 2022), higher education (Rashid & Ahmad, 2016; Y. Zhang et al., 2021), and non-traditional online education (Chen & Pardos, 2020; Feng et al., 2019). Within these contexts, it has been used to tackle different tasks, including predicting students' future actions (Feng et al., 2019; Qiu et al., 2022), knowledge tracing (Piech et al., 2015; Pu & Becker, 2022), automated assessment (H. Tan et al., 2020; Tay et al., 2018), affect detection (Botelho et al., 2018; Lan et al., 2020), and recommendation systems (W. Jiang et al., 2019; Shen et al., 2016), to name a few use cases. Yet, despite the recent upsurge in educational publications using deep learning, many challenges remain that make it difficult for existing learning platforms to adopt these models outside of research laboratories.

In this chapter, we first provide a brief introduction to machine learning and place deep learning in its greater context. We then highlight the advantages and limitations of using deep learning in education. We follow this with a survey of how this novel technology has been applied, with the section organized around specific use cases. Finally, we discuss what the future of deep learning in education may hold, including the principal challenges that must be overcome to advance how these algorithms impact learners at scale.

2 Deep learning in context

To understand how deep learning is being used for educational data science, as well as its future potential, it is helpful to have a cursory familiarity with machine learning more broadly. Machine learning models are algorithms that can predict or estimate the value of a target variable of interest (predicted variable, or output) given data related to the problem (predictor variables, or inputs). Through the process of 'training' on this data (the *training dataset*), a model begins to identify the patterns of inputs that lead to specific outputs. Once trained, the model has 'learned' these patterns and can be used to make predictions on inputs it has never seen before. The model's accuracy is then measured through a series of metrics that compare its predictions on this *testing dataset* to the true values of the target variable being predicted.

Deep learning is only one subset of the larger family of machine learning models, which include many other algorithms, such as *random forest*, *K-nearest neighbors*, *support vector machines*, and *linear regression*. Deep learning is itself a group composed of different model architectures which have been developed and refined over the years to suit different purposes. A deep learning model's architecture refers to the structures that define how artificial neurons are connected to each other and the different parameters that are used to model such connections.

Many different neural architectures have been used in education. Fully connected (or dense) neural networks connect each input node to each output node for each layer. These are simpler architectures that are most often used as part of a larger model but are rarely used as stand-alone models. Convolutional neural networks (CNNs) include at least one convolutional layer, in which a sliding window shifts across the input vector or matrix and a dot product is calculated. These are most commonly used for image inputs, but they can also be used with sequential data. Recurrent neural networks (RNNs) have at least a single recurrent layer, in which a looping function processes a sequence of inputs—one item at a time—while carrying information from previous items to future items in the sequence. Two common variations of the RNN architecture are the long short-term memory network (LSTM) and the gated recurrent unit (GRU), which include slight memory modifications to improve performance. Transformers, another common neural network architecture, convert inputs into vectors called encodings and then decode them into different types of outputs depending on the task. These are used with sequential data (most commonly natural language text) and rely on a neural attention mechanism to identify the relevance of neighboring data when encoding a particular input (Vaswani et al., 2017). Popular generative models such as GPT-4 and DALL-E are based on this transformer architecture. Graph neural networks (GNNs) take graphs as inputs (data organized into nodes connected by edges) and create a separate network for each node (and, optionally, each edge) in the graph. Each sub-network makes its own calculations based on the neighbors of its pertaining node. Information can be shared between parts of the graph and pooled together for final prediction. For a more in-depth survey of the most common deep learning architectures, see Alom et al. (2019) and Alzubaidi et al. (2021).

3 Why deep learning in education

3.1 Advantages

The widespread adoption of deep learning suggests that these models hold certain advantages over more traditional data-driven approaches to prediction, clustering, and analysis tasks. Overall, deep learning provides greater flexibility compared to other machine learning approaches. This flexibility manifests itself in the increased predictive power that is made possible by having such a large solution space to work with. It also allows for models that require less direct human intervention during training, that can use more varied types of input data, and for which training can easily be paused and resumed at a later time when more data is available.

3.1.1 Increased predictive accuracy

Among the many studies in education that have compared deep learning models to more traditional algorithms, most of them have reported an overall increase in accuracy. The accuracy of deep neural networks can be largely attributed to the large number of learnable parameters that these models have—from tens of thousands to millions or even billions. Improvements in hardware, along with the large amounts of data that are now regularly collected through digital platforms, have made it possible to train models that can fit very complex functions. These models can also project data to high-dimensional spaces, which can help with identifying patterns.

Data-driven approaches in education (including both deep learning and more traditional algorithms) are only as good as their ability to accurately model the real world. For example, in knowledge tracing—the task of predicting how students will perform in future problems based on an estimation of what they have learned in previous problems—traditional algorithms usually treat individual parameters and skills as independent from each other (Corbett & Anderson, 1995). This naive approach is easier to implement, interpret, and optimize, but it is a simplified assumption of reality that deep

learning approaches don't necessarily make. From this perspective, predictive accuracy serves as a proxy for how well the learning process has been simulated. This makes increased accuracy an important goal to pursue, and something with which deep learning can help. Of course, beyond the architecture and details of the model itself, other aspects can have a big impact on accuracy, including the amount and quality of available data and the way features are engineered.

3.1.2 Automatic feature engineering

Feature engineering refers to the act of extracting predictor variables from raw data that are useful for a prediction task. Despite tools that can automatically create large sets of features through simple transformations (Kanter & Veeramachaneni, 2015), feature engineering continues to be a largely human-driven and inexact 'art' more than a science. It often requires extensive experience and domain expertise, and it can also be a very time-consuming part of the process of developing data-driven models.

As opposed to traditional machine learning techniques that make predictions directly from a set of pre-engineered features, deep learning techniques conduct their own representation learning through multi-step transformations that can create very complex features. These models learn which transformations to their inputs lead to accurate predictions. Much of the increased predictive accuracy of deep neural networks comes from this ability to learn complex high-level features from raw, low-level data. This ability bypasses the need for resource-intensive feature engineering.

3.1.3 Flexible inputs

Related to the idea of automatic feature engineering is deep learning's ability to use a wider variation of inputs than traditional algorithms. This helps explain why deep learning has gained such a strong reputation for computer vision and speech recognition tasks (Alam et al., 2020)—video and sound data are difficult to convert to useful tabular features, but they can be used directly as raw inputs in a neural network.

In educational data science, input flexibility has implications for multimodal learning analytics, which by definition involves data of different modalities. It also makes it possible to directly analyze students' responses to open-ended questions, such as for automated essay and short answer scoring (Dascalu et al., 2013; H. Tan et al., 2020; Tay et al., 2018), the scoring of open responses in math education (Baral et al., 2021; Erickson et al., 2020), and the direct analysis of student code in computer science education (Shi, Mao, et al., 2021; Shi, Shah, et al., 2021). This same flexibility can also apply to outputs, making it possible to predict sequential outputs of different kinds—useful for providing writing suggestions, code hints, and automated targeted feedback.

3.1.4 Continuous model training

Traditional machine learning models are trained on an entire dataset and then deployed for use. If new data is made available, the model must typically be retrained from scratch to get the best results. Some traditional machine learning algorithms, such as tree-based models, do make it possible to introduce new data—but only in a limited fashion that does not alter the pre-existing learned parameters. Deep neural networks, on the other hand, do not have this limitation. Because they are trained over multiple epochs (rounds of training), introducing new data simply means picking up where training left off with additional epochs, using either the new data exclusively or a combined dataset of old and new data.

The ability to update models is especially important when deployed in real-world scenarios that may require periodic adjustment to combat concept drift (the changes that input-output patterns undergo as time progresses) or simply to improve accuracy. For example, the effectiveness of an intelligent tutoring system (ITS) may be improved if its underlying algorithm can be updated after it has been in use for some time. New data on student interactions can provide an accuracy boost, or they can be used to capture changes in how students interact with the learning platform following changes in the platform's design.

3.1.5 Transfer learning

Taking continuous model training a step further, transfer learning is a machine learning approach in which a model that has been trained in one domain and for a specific task is then reused in either a different domain or for a different task (Zhuang et al., 2021). The goal is to leverage the knowledge learned from one domain to improve the performance of the model on the other. Often, there is abundant labeled data for the source domain and only limited labeled data for the target domain.

While transfer learning is possible with traditional algorithms, the ability to continue training a deep neural network makes more powerful transfer learning possible. A trained model can be partly frozen (only a subset of its parameters is retrained), it can be expanded with additional layers that can completely reshape its architecture, or it can be used

largely as is with only minor modifications, based on the needs of the target domain and task. The recurring theme of flexibility applies here as well. In education, transfer learning may one day lead to more generalizable models that can be used across different platforms, with different populations, or for different courses. Transfer learning can also be helpful in situations where labeled data is limited—not a rare occurrence in education.

3.2 Limitations

As we will see in the next section, deep learning is being used more and more for educational data science, but it has yet to significantly shape our understanding of the learning process or to affect large numbers of students and instructors in real-world settings. Instead, it has been the subject of rigorous study in university laboratories. While this may partly be attributed to its novelty, it is also likely that the limitations inherent in the technology have played a role. Here we discuss some of the biggest limitations of deep learning and how these may apply in the domain of education.

3.2.1 Diminished interpretability

When compared with simpler, more traditional models, the principal limitation of deep neural networks is their inherent lack of transparency. Due to their complexity, it is often impossible to determine why a model is making specific decisions. This ability to peel back the curtain on a model's inner workings is often referred to as interpretability (Cohausz, 2022). In fields such as education, where implications can be serious and many stakeholders are involved (students, parents, teachers, administrators, politicians), interpretability can be of utmost importance, carrying implications for trustworthiness, accountability, and trust. This means that where performance is similar between models, or where interpretability is more important than an increase in accuracy, it is often preferable to go with more traditional, interpretable approaches.

At a more general level, there remain fundamental questions about how exactly some deep learning algorithms are able to do what they do. It has been noted that *untrained* neural networks can surprisingly perform almost as well as trained ones for specific use cases (Botelho et al., 2022; Ding & Larson, 2019). This serves as a startling reminder of the black-box nature of these models, and it is easy to see why caution must be exerted when making claims about their understanding of the world. On the other hand, the fact that some can identify patterns so effectively, even when untrained, hints at some possible untapped potential. Moreover, these models can still be useful in cases where predictive accuracy trumps interpretability (Botelho et al., 2022) and in the classic EDM task of 'discovery with models' (Baker & Yacef, 2009).

3.2.2 Heightened model complexity

As stated, the reason for diminished interpretability in deep neural networks lies in their complexity. This complexity can come both in terms of model architecture and number of parameters. Even 'simple' neural networks with only one or two hidden layers can consist of thousands of learnable parameters, with more complex ones having orders of magnitude more. Aside from the issue of interpretability that this creates, it can also make designing, training, and using these models more resource intensive. As Y. Jiang et al. (2018) have pointed out, deep learning models are often used for the time- and effort-savings promised by their automatic feature engineering. However, the act of refining complex architectures and effectively selecting proper hyperparameters (unlearnable, human-set parameters that determine how a model functions) may negate this advantage, especially when adapting models to new domains or tasks. It may be that further research reveals consistent best practices and ideal models for varying situations, but for now this remains a largely open-ended task in itself.

3.2.3 Need for large datasets

The heightened model complexity of deep neural networks also leads to an increased requirement for large datasets. It is generally accepted that the more parameters a model has, the more data is needed to adequately train it. This is a major reason why deep learning has only taken off after the internet made big data more easily available, despite the principal theories behind the technology having been known about for many decades (Tappert, 2019).

In educational data science, this makes deep learning impractical for tasks and domains where not enough data exists. Data scarcity is particularly common in use cases that require labeled data (i.e. data that has been tagged with meaningful information) due to the resources required to label large amounts of data. Studies have found that deep learning models are more likely to overfit when datasets are smaller (Gervet et al., 2020). Besides the obvious (but not always possible) solution of simply collecting more data, there exist ways to make deep learning useful when data is limited—such as transfer learning, semi-supervised learning (Livieris et al., 2019; Shi, Mao, et al., 2021), or data augmentation (Cader, 2020). Still, researchers rely on large datasets when available, while keeping in mind that high-quality data can be more effective than big, noisy data (Yudelson et al., 2014).

3.2.4 Expanded risk from expanded scale

Lastly, many of the same issues faced by traditional machine learning algorithms also apply to deep learning, simply at a bigger scale. Because of the bigger data requirements, privacy and security breaches have the potential to affect more people, more quickly, and more deeply. This can be especially damaging when sensitive data is involved, such as video or speech recordings, which are more likely to be used with deep learning models due to their ability to process this raw data. The increase in predictive ability for tasks such as tracking, identification, or behavior modeling also increases the potential that such tools will be maliciously used for surveillance. There are documented cases of algorithmic bias and unfairness in education, in which biased data disproportionally and negatively affects students from historically disadvantaged populations (Baker & Hawn, 2022; Kizilcec & Lee, 2022). It is clear that there is still much we don't know about the real-life implications of these biases, and the black-box nature of deep neural networks further obscures our understanding.

While none of these risks are exclusive to deep learning, their increased potential for damage requires that ongoing work be done to find ways to mitigate their reach. Until researchers find ways to appropriately do so, the expanded risks and diminished interpretability of deep learning suggest that it may be unwise—and in some cases even unethical—to use them for high-stakes educational tasks. Luckily, this is an area of research that is receiving increasing levels of attention and interest, both inside and outside of education.

4 A survey of deep learning in education

To better understand the various ways that deep learning has been used in education, this section organizes the literature into two separate categories: *direct* and *indirect* uses. By direct uses, we mean contexts in which a specific problem or task is tackled for which deep learning plays a central role. For example, in knowledge tracing, the problem is measuring what a student knows or what they may struggle with based on their past actions. In affect detection, the problem is measuring the various emotions (and consequently the level of engagement and motivation) that a student may be experiencing. In both of these cases, deep learning can be the mechanism itself by which the problem is tackled.

Indirect uses, on the other hand, make use of deep learning only as a steppingstone towards a separate main goal. For example, useful features can be extracted by leveraging the automatic feature engineering that deep learning models conduct, which can then be used as the inputs for a separate algorithm to conduct the prediction or analysis desired (Erickson et al., 2020). Similarly, deep learning can be used to transcribe student speech, which can then be analyzed using a variety of different methods (Pugh et al., 2021). Indirect uses are typically tasks that have been very successfully performed by deep learning in other domains, and which are now being leveraged for educational purposes. In many of these cases, "off-the-shelf" models already exist.

The difference between these two categories may not be immediately clear, but it can be helpful for understanding the efforts required for implementation. Note that the distinction is mainly about the immediate purpose for which the deep learning model was designed. In one case, a deep learning model specifically and directly tackles an educational task (e.g. assess student writing), whereas in the other, the model predicts something other than the project's ultimate educational goal (e.g. transcribe student speech). The outputs of the indirect models serve as inputs to a separate analysis in order to arrive at the phenomenon of interest. In both direct and indirect uses of deep learning, a deep neural network is used somewhere along the pipeline, but the specific architecture or design of the network can vary drastically depending on the inputs and desired outputs.

4.1 Direct uses of deep learning in education

4.1.1 Predicting future actions

Models for future prediction are those that use data gathered up to a certain point in time as input and make a prediction about some event that will take place after said time. The most common use cases for these models have been to predict student grades and student dropout. Multiple studies have used past grades as the primary or exclusive predictor of future grades, including some using the LSTM architecture with a neural attention mechanism (Q. Hu & Rangwala, 2019; Qiu et al., 2022), as well as more traditional fully connected networks (Livieris et al., 2012; Livieris et al., 2019). Y. Zhang et al. (2021) interestingly used a CNN with a neural attention mechanism, with course descriptions and demographic features as input data.

Student dropout prediction has been thoroughly studied in massive open online courses (MOOCs) using clickstream data (often called log data) gathered from these digital platforms. Deep learning architectures for this purpose have included fully connected networks (Whitehill et al., 2017), CNNs with neural attention (Feng et al., 2019), and LSTMs (Fei & Yeung, 2015). As an example of deep learning's ability to make use of highly varied data, Cohausz (2022) used

student behavioral features, classes taken, past grades, and demographic information to predict student dropout in a mandatory computer science course. Similarly, Swamy et al. (2022) used measures of engagement, student participation, and study habits to predict students' probability of passing a MOOC.

Aside from these predictions of course success, deep learning has also been used to predict future course enrollment (Doleck et al., 2020), college success for admissions purposes (Oladokun, 2008), students' next action on an online course (Chen & Pardos, 2020; Tang et al., 2016), program graduation (Kim et al., 2018), and learning gains (Lin & Chi, 2017). Yeung & Yeung (2019) interestingly used the last hidden state of an LSTM along with student profile features to predict whether students would choose a STEM or non-STEM job after college. Jarbou et al. (2022) were able to predict short- and long-term school absenteeism among students with autism spectrum disorder—a population that is disproportionally affected by school absenteeism and for whom missing class can be especially detrimental (Gottfried, 2014; Munkhaugen et al., 2019).

4.1.2 Knowledge tracing

Knowledge tracing (KT), or knowledge inference, refers to the process of estimating what a learner knows at any given time and how that knowledge changes over time. Because knowledge is not a directly observable trait, the process is also known as latent knowledge estimation. KT ultimately serves a different purpose than predicting future actions. However, because of the latent nature of student knowledge, predictive accuracy on the performance of subsequent tasks is typically the defining characteristic by which the success of a KT model is measured.

Historically, KT has been dominated by approaches such as Bayesian Knowledge Tracing (BKT; Corbett & Anderson, 1995) and its many variants (Baker et al., 2008; Gonzalez-Brenes et al., 2014; M. M. Khajah et al., 2014; Pardos & Heffernan, 2009, 2010, 2011; Yudelson et al., 2013). BKT estimates learners' knowledge using a hidden Markov model, dynamically updating latent variables based on ongoing student performance. Other popular techniques include performance factors analysis (PFA; Pavlik Jr et al., 2009) and item response theory (IRT; Rasch, 1993). While these approaches are still commonly used, much of the research focus on KT has shifted in recent years to ever-more-complex deep learning models.

In the first paper that utilized deep learning for knowledge tracing research, Piech et al. (2015) described two models, which they named deep knowledge tracing (DKT)—one was a standard RNN while the other used an LSTM. Both models relied exclusively on prior student performance as inputs—an approach that follows the example of the classical BKT approach. Their positive results showed the potential of deep learning knowledge tracing (DLKT) models, even after accounting for issues in their methods and reporting (M. Khajah et al., 2016; Xiong et al., 2016), sparking a race toward ever-more-elaborate uses of deep learning for KT.

Since then, the many DLKT models that have been developed thus far can be categorized into five general groups based on their model architectures and intended inputs (Q. Liu et al., 2023; Sarsa et al., 2022). First, RNN-based models are those most similar to the original DKT by Piech et al. (2015) in that they consist of at least one recurrent layer (eg. Delianidi et al., 2021; Xiong et al., 2016) and variations such as LSTM (eg. Mao et al., 2018; Penmetsa et al., 2021; Shi et al., 2022; Tato & Nkambou, 2022; L. Wang et al., 2017). Second, memory-based models attempt to address the lack of explicit knowledge component (KC) tracking by introducing a memory module to the architecture (eg. Abdelrahman & Wang, 2019; Ai et al., 2019; Karumbaiah et al., 2022; Zhang et al., 2017). This allows them to align more closely with the intended goal of KT rather than simply relying on predictive ability. Third, exercise-based models include additional information about each problem as input, which is gathered from the text of the problem using natural language processing (NLP) techniques (eg. Q. Liu et al., 2021; Y. Liu et al., 2020; Su et al., 2018). Fourth, attention-based models make use of neural attention to weight the relevance of surrounding actions (eg. Choi et al., 2020; Ghosh et al., 2020; Pandey & Karypis, 2019; Pandey & Srivastava, 2020; Pu & Becker, 2022; Shin et al., 2021). Exercise-based models also make use of neural attention, as does the memory-based model described by Abdelrahman & Wang (2019). Fifth, graph-based models use graph-based data as inputs (eg. Long et al., 2022; Nakagawa et al., 2019; Song et al., 2021; Tong et al., 2020). Graphs can leverage the interconnected nature of learning from various angles, such as similarities between KCs or hierarchical course structures.

4.1.3 Automated assessment

Automated assessment has been conducted in many forms, most recently with deep learning models. Automated essay scoring and short answer scoring have been attempted with LSTMs, fully connected networks, bidirectional transformers, CNNs, memory networks, and GNNs [Taghipour & Ng (2016); Dascalu et al. (2017); Zhao et al. (2017); Riordan et al. (2017); Tay et al. (2018); H. Tan et al. (2020)). ReaderBench—an open-source multilingual text analysis tool (Dascalu et al., 2013)—uses deep learning to automatically evaluate student summaries of texts based on how well they covered the main idea of a reading (Botarleanu et al., 2021).

Another use case involves peer evaluations, which often play an important role in many large-scale courses such as MOOCs. However, it can be difficult to evaluate the rigor of peer reviews at scale. To help address this, Xiao et al. (2020) trained various deep and traditional models to identify whether reviewers' responses to rubric items explicitly suggest ways for the author to improve their work—an important aspect of high quality peer reviews. Taking a different approach, Namanloo et al. (2022) used a GNN to predict the proper score that a student's project should receive based on peer evaluations, essentially acting as a peer assessment aggregation mechanism that emulates expert scorers.

Within the realm of collaborative learning, T. Hu et al. (2020) used a CNN to automatically score student edits on a collaborative Wiki assignment. Meanwhile, Som et al. (2021) used a temporal residual network (Z. Wang et al., 2017)—a specific CNN architecture that leverages residual connections—to assess overall group collaboration quality using individual students' changing roles within the group as input.

Automated assessment has also been tackled in the domain of computer science education. Shi, Shah, et al. (2021) trained a code2vec model—a specific architecture using neural attention and designed to create meaningful embeddings of programming code (Alon et al., 2019)—to predict the accuracy of student code submissions to programming problems. Shi, Mao, et al. (2021) compared the efficacy of code2vec with its competitor Abstract Syntax Tree based Neural Network (ASTNN; Zhang et al., 2019) at automatically detecting and classifying bugs in students' code.

4.1.4 Affect detection

Student affect refers to the various emotions that students experience as they undergo the learning process, such as delight, engagement, surprise, confusion, frustration, and boredom (D'Mello & Graesser, 2012). Affect has been correlated with academic performance and achievement (Craig et al., 2004; Pardos et al., 2014; Rodrigo et al., 2009) and has even been found to be predictive of later college attendance (San Pedro et al., 2013). Affect has often been detected using a variety of physical and physiological sensors. Deep learning has been successfully used to detect student affect using only log data—a practice known as sensor-free affect detection (Botelho et al., 2017; Botelho et al., 2018; Lan et al., 2020). However, this is also possible using simple models such as logistic regression, and it has been demonstrated that each approach brings its own advantages (Y. Jiang et al., 2018).

4.1.5 Recommendation systems

Recommendation systems are one of the most pervasive use-cases for AI in modern daily life, and research has been devoted to bringing them to education. In the deep learning space, Shen et al. (2016) trained a CNN model that can recommend learning resources to students in online courses. The model can automatically identify the latent factors of learning resources by analyzing the textual information they contain.

In another study, W. Jiang et al. (2019) devised an algorithm that recommends to students certain prerequisite courses to take in order to succeed in a future course they wish to take, based on their past grades and the other courses in which they will enroll. Reinforcement learning has also been used, such as by Ai et al. (2019) who trained a model that can recommend the next exercises for students to attempt based on their estimated latent knowledge. To do this, they trained the model on a student simulation that used a KT model to imitate the actions of a real student.

4.1.6 Behavior detection

Deep learning models have been used to automatically detect different student behaviors, such as wheel spinning (Botelho et al., 2019; Matsuda et al., 2016)—a form of unproductive persistence (Beck & Gong, 2013). Pinto et al. (2023) created an interpretable CNN-based detector of gaming the system behavior, which has been defined as 'attempting to succeed in an interactive learning environment by exploiting properties of the system rather than by learning the material' (Baker & de Carvalho, 2008). Deep learning has also been used to detect self-regulated learning (SRL) behaviors in a collaborative context (A. Nguyen et al., 2022). For detecting off-task behavior, Y. Jiang et al. (2018) created various detection models using different deep learning architectures, as well as traditional algorithms with expert-engineered features. As with their evaluation of affect detectors, they found with off-task behavior detection that the deep models only outperformed the more traditional algorithms some of the time.

4.1.7 Other uses

Other direct uses of deep learning for educational data science include automatic teacher evaluation (Hongmei, 2013; Rashid & Ahmad, 2016), optimized spaced repetition algorithms for memory retention (Reddy et al., 2017), and automatic translation in online chat for collaborative learning (Sato et al., 2018). Fernández Alemán et al. (2010) also used deep learning to cluster students into one of various 'states of knowledge,' depending on their level of understanding of the subject matter (computer science, in this case). They then provided targeted feedback to students based on the results of the clustering, which were continuously updated as students answered more questions.

4.2 Indirect uses of deep learning in education

4.2.1 Feature extraction

Deep learning can be used to generate useful features from raw data that can then be extracted and used as inputs in a different machine learning model for a separate task. This process, also known as representation learning, takes advantage of neural networks' ability to pick out patterns in raw data that correspond to latent features that are helpful for a prediction task.

For example, L. Jiang & Bosch (2022) trained a neural network to detect anomalous student activities, the results of which were then used as features in a random forest regressor that predicted course grade. Similarly, Karimi et al. (2020) used a GNN to extract separate student and course embeddings (vectors that map concepts to a meaningful space) from a knowledge graph of student-course relations, while using an LSTM to encode students' sequential behavioral data. They then concatenated these outputs and used them as features in a classifier that predicted student-course performance. Shi, Shah, et al. (2021) used code2vec embeddings (Alon et al., 2019) to identify student misconceptions by clustering the embeddings. Azcona et al. (2019) further used these embeddings to represent students based on their code. To automatically grade students' responses to open-ended math problems, sentence-BERT—a sentence-level embedding method that keeps semantic information (Reimers & Gurevych, 2019)—has been used alongside traditional machine learning models (Baral et al., 2021).

4.2.2 Computer vision

Another common indirect use of deep learning in education is in computer vision. Deep learning models have found extraordinary success in this area over the last few years, far surpassing the accuracy of other models. In the domain of education, deep-learning-based computer vision algorithms have been used to detect students' affective states by leveraging the front camera of a tablet to capture facial cues (Wampfler et al., 2020). Likewise, some research has used OpenPose, a deep learning pose tracker (Cao et al., 2017), to capture motion tracking information of students and teachers (Hur & Bosch, 2022). This information has in turn been used to create meaningful features for measuring student collaboration (Hur et al., 2023). Computer vision has even been used to automatically detect what young students are looking at in classroom video data, making it easier to measure levels of attentiveness (Aung et al., 2018).

4.2.3 Automatic speech recognition

Automatic speech recognition (ASR) has also been used in educational research. As with computer vision, this is another area where deep learning is unquestionably the leading technique. This technology has been used to transcribe noisy classroom speech in collaborative learning settings, the results of which have been used to analyze group formation and collaborative problem solving (CPS) skills (Pugh et al., 2021; Southwell et al., 2022; Tao et al., 2019). It has also been used in the domain of language learning to allow learners to interact with their environments more easily in their target language (T.-H. Nguyen et al., 2018). Panaite et al. (2018) incorporated ASR into the self-explanation module of ReaderBench (Dascalu et al., 2013) so that students can record oral self-explanations of their understanding of a text and have instant feedback on their comprehension. Besides transcription, some of these tools have the ability to capture prosodic features and identify individual speakers (Southwell et al., 2022).

4.2.4 Automated qualitative coding

Using NLP techniques that leverage the power of neural networks to analyze language, deep learning has also been used to automatically code student chat logs in a computer-supported collaborative learning (CSCL) setting (Shibata et al., 2017). This is typically a time-consuming task that makes it possible to conduct analyses for a variety of educational research purposes.

5 Looking to the future of deep learning in education

Extrapolating from the many ways deep learning has been used for educational data science, and taking into account its advantages and limitations, we suggest important directions that may allow the field to make the most of this technology. We describe three primary areas of focus: further research on model transparency, making contributions to our understanding of the learning process, and expanding the use of deep neural networks outside of the research laboratory to impact learners.

5.1 Increasing trust through greater transparency

The issue of trust is central to ensuring that models are adopted and used by stakeholders such as parents and teachers. Without trusting that an algorithm is not only accurate but fair, deep learning models for education will have a very difficult time breaking out of the lab and into classrooms and homes. The limitation of diminished interpretability discussed earlier is a roadblock to increasing trust. This is why there is increasing interest in creating more transparent models that can be more easily understood, audited, and learned from.

In the machine learning world, this situation has given rise to explainable AI (XAI) methods, which are beginning to be explored in educational data science (Cohausz, 2022; see Liu et al. in this volume; also Som et al., 2021; Swamy et al., 2022). While post-hoc explainability methods may not be as transparent as intrinsically interpretable models (Rudin, 2019), they provide some transparency to the process by allowing a better understanding of the inputs, features, and instances that lead to a model's predictions. This is a helpful step in understanding *why* a model predicts that a student is likely to behave or learn a certain way (Hur et al., 2022). In many cases, these post-hoc approaches are the only currently existing way to make deep learning models more transparent due to their intrinsic complexity. However, the field has yet to converge on a set of explainability best practices, with fundamental problems of existing approaches still unaddressed (Swamy et al., 2023).

Along with advancing the work of explaining a model's inner workings, there is the need to develop novel and robust ways to quantify and evaluate both the interpretability of a model itself and the use of specific interpretations/explanations in real-world settings. This requires first understanding the scenarios in which transparency is important in education, as well as the needs of end users in these cases. The taxonomy proposed by Doshi-Velez & Kim (2017) can be a good starting point, providing a common lexicon for researchers. From most specific and costly to least robust and resource-intensive, they organized interpretability evaluation methods into application-grounded, human-grounded, and functionally grounded evaluations.

As with other concepts borrowed from disciplines such as machine learning, educational data science will encounter its own challenges specific to the use cases, concerns, and stakeholders in this field. One might imagine a near future in which researchers frequently report not only a deep learning model's accuracy measures but also its interpretability evaluations or specific explanations of its decision-making process. This may lead the field to confidently create models and explanations that are not merely accurate but also trustworthy and useful, overcoming the black box problem currently holding back deep learning for educational data science.

5.2 Making contributions to learning theory

As evidenced in the survey section of this chapter, deep learning has thus far been used in education primarily for practical applications designed to help with teaching and learning. However, there has been very little focus on contributing to learning theory. While uses of deep learning are being informed by our latest understanding of the learning process, this research has not yet contributed much in return.

It is true that the literature has already identified some interesting phenomena. From a practical perspective, outcomes related to student success can often be predicted with surprising accuracy based on just a few early results (Iqbal et al., 2019; Murata et al., 2021). What can this teach us about the learning process or about our educational systems? The same has been found for predictors of some learning behaviors, such as wheel spinning (C. Zhang et al., 2019). What this says about the nature of persistence and its relation to learning has yet to be explored. While these findings have come as a result of optimizing predictions, there are plenty of reasons to also consider how they might inform our theories.

Many predictive models have been designed with the hopes of eventually being used to either directly intervene and guide students or to provide helpful information to instructors. Some, however, also have the potential to aid the research process itself. Detection of behaviors and characteristics such as affect can theoretically make it easier for researchers to study these areas and their impact on learning. The same can be said of various aspects of collaborative learning, such as the dynamics of group formation (Tao et al., 2019), the development of CPS skills (Pugh et al., 2021; Southwell et al., 2022), or the existence of socially shared regulation of learning behaviors (A. Nguyen et al., 2022). Likewise, traditional machine learning models have been used to predict mind wandering among students based on the speech patterns and behaviors of instructors (Bosch et al., 2018; Gliser et al., 2020). Chounta et al. (2017) also attempted to model students' zone of proximal developments (ZPD) using KT, though not with deep learning. If the deep learning trend continues and its use expands to replace other algorithms in educational data science, one can expect that it will begin to make more contributions to our overall understanding of theories of learning and engagement.

5.3 Exploring real-world uses beyond the lab

As with the previous question, actual uses 'in the wild' of deep learning for education are not nearly as ubiquitous as the amount of research on the topic would have one think. Knowledge tracing is a perfect example of this. It is possibly the singular use of deep learning that has attracted the most attention in educational data science, judging by the number of publications and the need for recent surveys on the topic (see Abdelrahman et al., 2023; Q. Liu et al., 2023; Sarsa et al., 2022). Yet the KT algorithms currently being used by intelligent tutoring systems to track students' knowledge, suggest next problems, and provide feedback continue to be traditional approaches such as BKT. This may be partly due to the challenge of interpretability and partly due to the fast-changing pace of the technology. The widespread availability of large datasets has made it so that educational data science researchers can easily try new advanced methods without the need to collect data or interact even indirectly with students. While this allows for rapid prototyping without danger of negatively affecting students, it also means that there has been little opportunity to actually support learning or teaching.

The most common educational uses of deep learning out in the real world are the indirect uses of the technology described previously, such as speech recognition or automatic translation services. The recent excitement surrounding advanced chatbots such as ChatGPT—a transformer-based model—has brought a lot of attention to both the positive and negative potential of such tools to affect how we learn or to alter the way students are assessed (Baidoo-Anu & Owusu Ansah, 2023; García-Peñalvo, 2023). Similarly, the recent explosion of interest surrounding generative text-to-image tools, such as DALL-E (Ramesh et al., 2021) or Stable Diffusion (Rombach et al., 2022) may prove to have implications for art educators or aspiring art students. These are tools that are already widely available to learners. At present, however, it is impossible to predict how these and forthcoming deep learning tools may shape the way people obtain and process new knowledge.

In terms of existing research in education, very little has been experimental in nature. In a rare, early attempt, Fernández Alemán et al. (2010) found that their approach to automatic feedback—which used a simple neural network architecture—successfully helped the students in the experimental group pass their exam when compared with those in the control group. T.-H. T.-H. Nguyen et al. (2018) also demonstrated how a mobile app for authentic target-language practice using automatic speech recognition and feedback can improve students' motivation and confidence. On the topic of experimental design, Sales et al. (2018) creatively used a deep neural network to improve data usability in randomized control trials in an effort to bring more causal modeling to this type of educational research. However, these real-world experiments are still quite rare. On the other hand, the *proposed, hypothetical* scenarios for supporting learners and instructors with deep learning models are many.

Knowledge tracing algorithms are typically pursued with the intention of presenting students with the most appropriate problems for their current levels of understanding and of allowing students and/or instructors to track learning progress through open learner models and learning analytics dashboards (Bull, 2020; Valle et al., 2021). Many ITSs already perform these tasks to a certain degree. Research into deep learning knowledge tracing often highlights implications for implementing the proposed state-of-the-art models for the same purposes (Ai et al., 2019; W. Tan et al., 2022).

Likewise, automated assessment is already used in real life learning scenarios, including high-stakes exams such as the Graduate Record Examination (GRE; Attali et al., 2008), but deep learning is not typically the standard method in practice. We have described research that shows evidence in favor of implementing deep learning more widely for this purpose (Taghipour & Ng, 2016; Tay et al., 2018; Zhao et al., 2017), though it remains to be seen if it is eventually adopted. Automated assessment can help instructors save time grading to have more time for targeted support, it can help students receive timely feedback, and it can help tackle problems of scale in large online courses. Botarleanu et al. (2021) have even suggested that automatic essay scoring could benefit students get an early idea of the score they would receive on an essay, giving them the chance to iterate before submission.

Milani et al. (2020) designed an intelligent tutoring system that specifically tailors its tutoring policies to students of different abilities using reinforcement learning, which can have a direct impact on these populations. They do this by predicting questions that fall within a student's ZPD, in a similar vein as the ZPD modeling done by Chounta et al. (2017). Some have also suggested providing feedback to students and instructors about different CPS skills being used in collaborative work in order to make possible more targeted intervention (Pugh et al., 2021; Southwell et al., 2022). Interventions that encourage academically productive talk (APT) have been shown to enhance learning in CSCL settings (Tegos et al., 2015). Other proposed uses of deep learning include informing instructors of the weak points in their teaching style (Rashid & Ahmad, 2016), giving students useful ideas about courses to take based on their goals (W. Jiang et al., 2019), optimizing students' learning gains through personalized spaced repetition algorithms (Reddy et al., 2017), providing feedback on students' code even when it contains syntax errors (a difficult task since most code feedback methods rely on abstract syntax trees; Bhatia et al., 2018), and providing targeted feedback early based on students' misconceptions (Shi, Shah, et al., 2021).

As with contributions to theory, it remains to be seen if deep learning methods begin to be more widely implemented in real-world applications that directly support learners and instructors in coming years.

6 Conclusion

In this chapter, we discussed a technology that has been at the forefront of some of the most exciting and powerful uses of artificial intelligence in recent years—deep artificial neural networks, or deep learning—and its uses and potential for the field of educational data science. We provided a brief introduction to deep learning, described some of its advantages and limitations, presented a survey of its many uses in education, and discussed how it may further come to shape the field in the near future. Like any technology, deep learning faces challenges with implications for its use and adoption, including the justified mistrust it can create due to its often inscrutable nature. However, as researchers continue to make headway on creating highly accurate and interpretable deep neural networks, the potential of deep learning for educational data science makes the rapid advancements in this area worth keeping an eye on.

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