Deep Mediations

THINKING SPACE IN CINEMA AND DIGITAL CULTURES

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CHAPTER FIFTEEN

Depth in Deep Learning

Knowledgeable, Layered, Impenetrable

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Over the past decade, research in machine learning has made remarkable progress in the processing of text and image data. Computational models are now able to outperform human experts in certain classes of well-defined tasks. These improvements have come in part through advances in computer hardware, as well as access to larger public datasets for training models. Perhaps the largest contributing factor, however, has been the refinement and application of so-called deep learning models. The incredible accuracy achieved through these models has led directly to real-world applications, including automated medical imaging diagnoses and machine translation software. Deep learning models have also been employed in troubling ways as tools for the security state, as justification for heavily policing minorities, and in the resurgence of a computational study of eugenics.[1] The prevalence of deep learning demands that we take seriously the study of their structure and impact in society. The unmatched predictive power of these models in certain critical domains guarantees that deep learning will continue to inject algorithmic logic into critical decisions affecting everyday lives.

Deep learning models are a class of algorithms that find latent hierarchical structures within large datasets. They are constructed by chaining together layers of smaller transformations. Taken together, these layers transform input data—raw text, images, sound files, and other unstructured formats—into predictive outputs that capture semantic features detected in the original data. While the internal structures of deep learning models make them ideal for certain tasks, these benefits come at a significant cost. State-of-the-art models contain dozens of layered models and billions of numerical parameters. This complexity makes their inner workings impossible to fully understand, even for experts in the field.

In order to understand what exactly is meant by "deep learning," we argue that the "depth" explicit in the term has a triple meaning: *knowledgeable,* the accuracy displayed in the model's ability to excel in certain image process tasks; *layered,* a visualization of the learned hierarchical structures; and *impenetrable,* the inherent lack of interpretability and understanding (such as in the "deep sea" or "deep space") of their algorithmic operations. In this chapter, we interrogate these three meanings and then argue that all three are intricately linked to each other. There is no way to achieve the observed levels of accuracy without constructing layered models and introducing black-box methods. Further, there is an intrinsic depth to the tasks in domains where deep learning models are applied. That is, depth is not just an instrumental feature of working with text and image data. The deepness is inherent in the tasks themselves. Meaningful computational results in these domains require a deep learning approach. Finally, we relate the essential deep nature of certain computational tasks to implications for future study in the humanities and social sciences and to the proliferation of deep learning models throughout society. We will limit our analysis to the task of processing image and text data, as they are particularly well suited for deep learning and also are a primary object of study for humanists and social scientists.

Knowledgeable

Deep learning techniques are now used in nearly all subfields of machine learning but are most well known for their application within predictive modeling. Predictive models make use of tagged datasets to algorithmically discover patterns that can be used to predict tags for new objects outside of the original collection. A classic example consists of starting with a collection of e-mails tagged as being "spam" or "not spam" and finding patterns that can be used for automatic spam detection on new messages. Several classes of powerful, general-purpose predictive models that are frequently used in machine learning have been shown to produce reliable predictions within a wide range of applications.[2] The majority of models struggle, however, on some important classes of problems, most notably when applied to tasks involving the processing of text and image data. Processing unstructured inputs such as raw text and images is precisely the type of problem where deep learning models excel.

The inherent difficulty of building predictive models with text and image data can be understood from two related perspectives. First, the way that text and image data are stored digitally does not directly capture semantic meaning. Consider, as a point of contrast, the task of predicting the sale price of a work of art. Features that may be available to determine the price include who created the work of art, the medium of the object, the original date of creation, and its overall size. Each of these values measures real-world quantities that directly impact the value of the work. Compare this with the task of building a model that detects sarcasm in a corpus of text or determines the identities of people depicted in a collection of photographs. What features will be available for these tasks? Machine-readable text is stored as a stream of characters. Digital images are represented as three rectangular grids of pixel intensities (red, green, and blue). Unlike the semantic variables describing the sale price of works of art, individual characters and pixels are essentially meaningless in isolation. It is only in context that we comprehend the significance of the textual or visual message. Further, there is no obvious alternative representation that would map directly onto a semantic meaning.[3]

A second, closely related, challenge of working with text and image data concerns the machine learning concept known as "dimensionality." Textual data are represented as a stream of characters; however, the converse does not hold: many streams of characters are not (understandable) textual documents. In fact, only a very small proportion of randomly constructed streams of characters will result in readable text. Similarly, almost no random constructed rectangular grids of pixels will resemble a recognizable image. Most will look like static noise. This creates a challenge for predictive models because the majority of possible inputs, random streams of characters or grids of pixels, fail to be sensible objects for consideration in the first place. Therefore, a predictive model must simultaneously detect the hidden structures within text and image data while also predicting the specific tag of interest. This task turns out to be very difficult but well-suited to deep learning approaches, the specifics of which we discuss in the next section.

Text and image processing, in addition to being difficult objects of study in machine learning, share another common feature: the human brain seems particularly well-designed for both tasks.[4] The power of billions of interconnected neurons firing signals to one another inspired the neurophysiologist Warren McCulloch and logician Walter Pitts to design a computational model in which signals are passed between independent nodes using a threshold potential similar to the biochemical functioning of neurons.[5] The approach of McCulloch and Pitts, applied to predictive modeling tasks, is considered the genesis of the class of models known as "neural networks," the earliest example of a deep learning algorithm.[6] Early work on neural networks was heavily integrated with neurophysiology. Modern developments have diverged sharply from biological motivations to the point where "state-of-the-art deep learning algorithms rely on mechanisms that seem biologically implausible."[7] Despite this disconnect, the language of neurology—*neurons, neural* networks, *potential,* long-term *memory, activation* functions, *developmental* networks—remains dominant within the machine learning community. Partially this is a result of momentum from the earliest research, but today it also serves as a strong cultural signal that deep learning represents, more than alternatives, "real" humanlike intelligence.[8]

Interest in neural networks has varied over time. Early excitement was dampened by the negative results of Marvin Minsky and Seymour Papert, and the inability to train large networks with the computational resources available at the time.[9] Advances in the 1980s and 1990s addressed some of these concerns and led to several well-known examples, including Yann LeCun's classification of handwritten digits.[10] However, continued computational challenges and lack of strong empirical motivations for neural network models held off general interest until very recently.

The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is an image classification contest held annually since 2010 in which teams compete to build algorithms that classify images into one of one thousand categories.[11] In 2012, building off of nearly a decade of work refining neural network architectures, Alex Krizhevsky, Ilya Sutskever, and Geoffry Hinton produced a winning neural network model—commonly known as AlexNet—that had a top-5 error rate of only 16 percent, compared with the 25 percent top-5 error rate achieved by the second-place team's model.[12] In 2017, for example, a neural network model achieved an error rate of only 2 percent on the ILSVRC dataset.[13] Early and continued success on ILSVRC is largely seen to have launched the deep learning "revolution in computer vision," which continues with no sign of slowing down anytime soon.[14] Today, the vast majority of research in predictive models for computer vision is built on neural networks. Text analysis had at first been slower to adopt deep learning, but neural networks have recently become popular in the processing of text too. Neural networks have produced state-of-the-art results in machine translation, sentiment analysis, and topic classification.[15]

The popularity of deep learning models is a direct result of their unmatched power to produce predictive models for difficult tasks such as text and image processing. In other words, they stand out for their ability to build off of existing knowledge to predict new knowledge. For this same reason, deep learning is an important object for humanistic study. Neural network applications are not confined to relatively obscure academic competitions; rather, they are already being employed today behind the scenes in a wide variety of applications. Some of these applications directly serve the public good, such as advances in the automated detection and classification of brain tumors from MRI scans.[16] Others play directly into the needs of mass surveillance.[17] The power of deep learning allows for the automation of wide-scale privacy invasions for national and capitalistic motivations, without the limiting cost of having humans manually analyze each element of data. It is likely that many of the technological advances of the near future, such as self-driving cars, will be built on top of deep learning models.[18] In order to understand how these extant and future applications affect society, it is necessary to also understand the deep learning models themselves. The next section proceeds to explain the internal architecture of deep learning models and the relationship of this structure to their observed predictive strengths.

Layered

The focus of the discussion so far has been on the impressive predictive power of deep learning models in the difficult domains of text and image processing. Other than the original connection of neural networks to neurophysiology, which has largely been lost in modern developments, we have not explained why deep learning is particularly well adapted to these applications. It is this task that we now address. As a starting point, a suitable definition of deep learning is required.

Deep learning models apply a sequence of successive transformations to an input object of study and ultimately produce a modified output value. In the predictive modeling context, the final outputs are the predicted tags, and the transformations are adaptively learned by a training algorithm applied to a large collection of pretagged objects. Each transformation should, at least in theory, assist in moving from “raw” input formats, such as pixel intensities or character streams, toward meaningful features that capture semantic meaning within an image or textual document. Typically, the first few transformations consider interactions only between small groups of nearby pixels or characters. Successive transformations

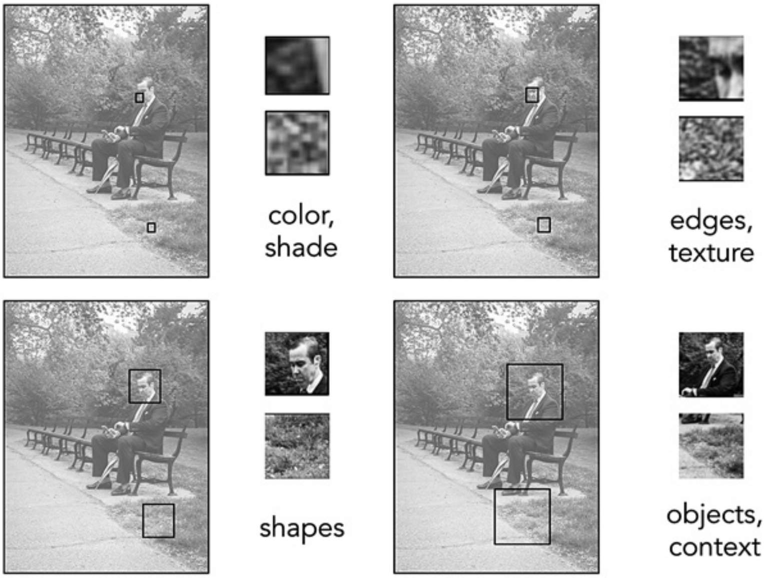

FIGURE 15.1. Conceptual depiction of features detected by subsequent layers in a neural network when applied to a photograph image. Photo by Greg Parish, "NYC Central Park," 2015. Licensed under CC-BY 4.0.

are applied to larger "windows" of the object, with the final layers applied to the entire image.[19] An example of a particular, highly idealized deep learning model is useful to further explain the concept.

Consider the example image in Figure 15.1 and the selected boxes of interest. The first few layers of a neural network may look only at nearby swatches of the image and convert the raw pixels into numbers that at first describe their overall color and shading. A slightly larger view provides information about the texture of the grass and edges that make up the nose of the man. Subsequent layers reveal small objects (noses), larger objects (faces), and finally objects within their context. A final layer, not shown within the boxes, could be applied to the entire image to aggregate information about the individual objects. This layer would capture features about the scene as a whole. Figure 15.2 shows a similar linguistic example. Subsequent layers of the neural network look at larger windows of the text by grouping characters into words, words into phrases, phrases into sentences, and sentences into entire documents.[20] The layered nature of deep learning models, likely the original motivation behind the term

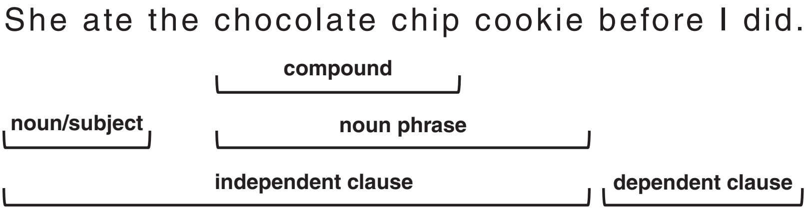

FIGURE 15.2. Depiction of hierarchical features detected applying a neural network algorithm to a sentence of textual data.

"deep," is the fundamental feature differentiating them from other approaches and directly addresses the representational issues presented as the primary challenges to working with text and image data.

It is not an easy task to build deep learning models from scratch. Dozens of complex transformations operating seamlessly together must be created and iteratively modified in an attempt to address the most challenging problems in predictive modeling. Very large datasets are required in order to estimate the hundreds of millions of parameters that describe state-of-the-art neural networks. Public datasets for training image models, such as the ILSVRC and VGGFace2 dataset, typically provide millions of tagged images to produce accurate face-detection models.[21] These datasets are typically constructed by making use of digitized corpora such as MediaWiki and Google Image Search. Once a large dataset is assembled, special hardware in the form of expensive and powerful graphics processing units (GPUs) is required to process such large datasets through the complex architectures of modern neural networks.[22] Even with good training data and the required hardware, the actual construction of neural networks is still a significant challenge. Adjusting the millions of training parameters is known to be an incredibly fraught task; subtle changes to the structure of the network can drastically alter the output of the model.[23] It would appear that the power of neural networks may be restricted to well-funded companies or research groups and available only for a small set of high-impact tasks for which the payoff in time and money is worthwhile. In practice, this is far from the case due to the special layered structure of deep learning models.

When trained on sufficiently large image datasets, the initial transformations described by large neural networks tend to be generalizable to new problems unrelated to the original prediction task. Recall that the first layers in a neural network only work locally over small regions of an image. These initial layers detect general features such as shading, color, and texture. Even layers in the middle of the network correspond to rough shapes and the formation of larger objects. It is only the last few layers that are directly related to the specific predictive modeling tasks of interest. As a result, predictive neural networks can be adapted through the process of transfer learning to predict new outputs by reusing the trained values in the interior layers and only learning the form of the final one to three transformations. This drastically reduces the amount of data, hardware, and expertise required to construct a new model. For example, recently a research group built a highly predictive image-processing neural network using a set of only 443 frontal chest X-ray images through transfer learning applied to the AlexNet model.[24] The researchers copied all but the final layer of the network and trained the relatively small set of final weights with their own data. The ability to perform transfer learning, which drastically increases the number of feasible applications of deep learning, is another direct feature of the layered nature of the models.

The underlying idea of transfer learning—that interior layers in neural networks code generic features that can be adapted to new problems—can also be used to motivate the related concept of "embeddings." An embedding applies a selection of lower-level transformations from a neural network to an object of interest, the output of which can be viewed as a sequence of numeric values. In transfer learning a predictive model is built on top of these embedded values, but there is also intrinsic value in the embedding itself. Embeddings have, for example, recently received attention in applications as diverse as cognitive psychology and the digital humanities.[25] The numbers described by the embedding capture, according to our description of how neural networks function, important semantic features present within the input image or textual document. Each number in the embedding does not directly correspond to a meaningful quantity. Rather, the spatial relationships of the objects within the embedding capture various semantic meanings. Inputs with similar features, in particular, will have similar sequences of numbers. Connecting objects that have similar embeddings to one another has been shown to provide accurate image and document similarity metrics that require no manual tagging or retraining.[26] As an example, Figure 15.3 illustrates a two-dimensional word embedding for a small collection of words. The full embedding these are taken from was trained on the English-language text from Wikipedia containing three hundred thousand words arranged in 300-dimensional space.[27] Food items and verbs/professions are visibly separated in the embedding space. Pairs of closely related terms, such as "journalist-writer," "believe-understand," and "read-write," are embedding next to one

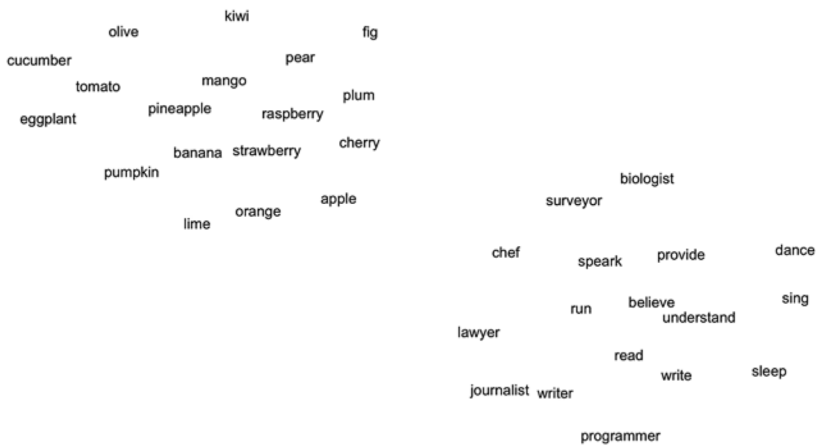

FIGURE 15.3. Two-dimensional word embedding of various fruits, vegetables, occupations, and verbs.

another. Also, the profession "chef" is situated closer to the food items than any other profession. As with transfer learning, the feasibility of embeddings is directly tied to the layered nature of deep learning models.

The layered structure of deep learning models is a direct consequence of the challenges posed by the processing of image and textual data. Without the sequential application of transformations, deep learning would offer no immediate benefit to predictive modeling for these difficult classes of important machine learning problems. The layers also immediately make way for the significant application of transfer learning and embeddings, without which deep learning models would be inaccessible to all but a small number of applications. Unfortunately, the layered nature also comes at the cost of interpretability. It is notoriously difficult, if not outright impossible, to comprehend how neural networks achieve their amazing predictive results. As we witness a proliferation of neural network applications in society, our inability to understand exactly what they are doing poses a number of concerns.

Impenetrable

Modern neural networks for text and image processing typically consist of dozens of layered transformations and hundreds of millions of learned parameters. Our description here of how neural networks transform images, by successively detecting larger and larger regions of interest and stitching them together, is a highly idealized version of how networks actually function. The general concepts have been validated through the efficacy of transfer learning and visualizations of embedding spaces, but the specific meaning of any given internal representation is generally impossible to discern. Because of the complex dependencies present within the layers of a neural network, classic approaches to interrogating a particular model, such as applying small perturbations to a single parameter and watching the result, are rarely very enlightening. The general lack of interpretability in deep learning is a well-known problem; several recent workshops were specifically dedicated to papers on the interpretability of neural network models.[28] A collection of approaches have been proposed in an attempt to build an understanding of how neural networks function.

One approach for understanding the inner workings of neural networks is to focus on the objects in a predictive modeling task that are incorrectly tagged. One simple approach is to investigate those categories that have particularly high error rates. Does the model have trouble with a specific category, or does it struggle to differentiate between a certain set of objects? Analysis of the results can be insightful in understanding the internal mechanisms of the neural network. For example, the ILSVRC revealed that animals with distinctive furs (e.g., foxes, porcupines, and tigers) are particularly easy to classify. On the other hand, long, slender objects (e.g., letter openers, flagpoles, and water bottles) are typically the hardest to detect. Abstract concepts such as “restaurant” and “grocery store” are also among the most difficult categories for algorithms to distinguish.

Taken together, this evidence shows that neural networks are best at understanding localized features and struggle the most on categories that require putting together contextual knowledge across the entire image. Looking at specific objects that are misclassified by a model, the *negative examples,* is another method of understanding the behavior of neural networks. For example, an investigation of the negative examples from the GoogLeNet model—the 2014 winner of ILSVRC—showed particular difficulty with “images that contain multiple objects, images of extreme close-ups and uncharacteristic views, images with filters, images that significantly benefit from the ability to read text [a salt shaker], images that contain very small and thin objects [fishing reel], images with abstract representations.”[29] These highlight challenges in the existing model and suggest significant gaps between the way the model understands images and humanlike processing of visual data. Ongoing research in computer vision is often motivated by understanding where, and ideally why, current models fail on certain tasks.

Alternatively, another approach to understanding neural networks is to focus on objects where the model performs well. The motivation behind the use of neural networks is their incredible predictive power. It seems reasonable that if we want to understand how neural networks function, some attention should be paid to the many objects that are correctly tagged. A clever approach to studying these *positive examples* is to occlude part of the object and observe the extent to which these occlusions affect the predicted categories. For an image, this involves replacing a region of the image with a monochromatic box, effectively hiding a region of the image from the neural network.[30] In text analysis, a similar approach removes one or more words or phrases.[31] Visualizing the regions that most directly impact the predicted values, and quantifying how much of the text or image can be removed without significantly impacting the results, provides an additional understanding of how the neural network represents knowledge. Similarly, the embeddings of correctly classified categories can be investigated for each layer of a neural network. Identifying which layers separate specific categories provides a window into the specific role of each layer in the overall prediction task.

Despite the existence of techniques for understanding neural network architectures, there remains a fundamental inability to understand how the network performs the task of transforming inputs into reliable predictions. Negative examples elucidate those abstract features that are generally missed by the network. Positive examples, along with occlusion, hint at those regions and features that are captured by the model. How these features are captured, however, remains a mystery. The fundamental trouble is the depth of the model. Each layer is codependent on all of the others, and understanding the network therefore requires understanding the entire network all at once, which is impossible given the size and depth of modern neural networks. And the problem is only getting worse.

Over time, neural networks have grown deeper and more complex. The winning ILSVRC model "ResNet" from 2015 had a total of 152 layers (for comparison, AlexNet has only 8 layers).[32] By 2016, the ResNet model had expanded to a total of 1,000 layers.[33] Popular models for text analysis now commonly employ recurrent neural networks, which contain complex architectures for storing "memories" as the network cycles through characters and words within a document. As further evidence of our inability to understand neural network models, recent research has revealed strange and unintuitive results from seemingly powerful predictive models. Carefully constructed perturbations can be applied to an image that are imperceptible to the human eye but that cause arbitrarily large changes in the

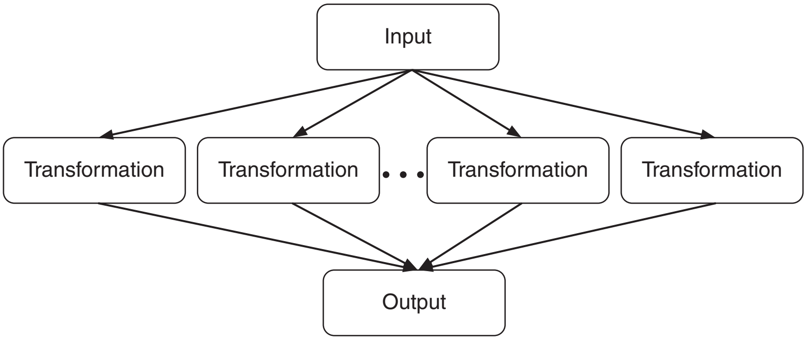

FIGURE 15.4. Schematic visualization of a "shallow learning" predictive model.

predicted tags associated with the image.[34] Conversely, images can be found that appear to be pure noise but are confidently categorized with an extremely high probability on one particular tag. These examples point to a significant gap in the way that neural networks process data compared with the human processing of images and text.

As neural networks become integrated into systems that directly affect people, it becomes increasingly important to understand how deep learning models function. Most of the work on interpretability has so far focused on understanding neural networks in order to modify their architecture and improve the predictive power of future models. However, it is arguably even more important to understand the models from a social perspective. How can we be convinced that an algorithm for tracking passengers at airport security is not motivated by racial profiling? What checks exist to detect when models employed by the medical industry are being optimized for insurance money rather than patient health? Or, what confidence do we have that autonomous vehicles trained in sunny California will accurately deal with snowy New England winters? All of these questions can be addressed on a macroscopic scale through external validation and regulatory transparency, but it becomes difficult for an individual to trust or challenge the results of a specific model that eludes any direct ability to understand its internal mechanisms.

While many machine learning algorithms have been characterized as being uninterpretable black boxes, our characterization of neural networks as impenetrably difficult to understand draws on features unique to deep learning methods. Figure 15.4 displays a schematic representation of a "shallow"—a model that is not deep—predictive model. A collection

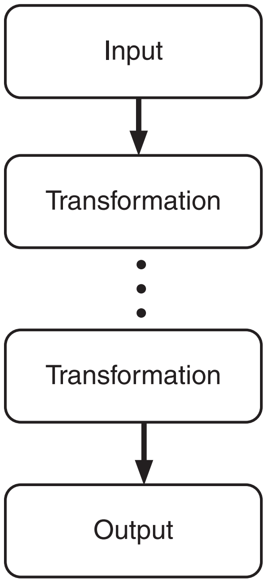

FIGURE 15.5. Schematic visualization of a "deep learning" predictive model.

of transformations is applied to the raw input data and then combined again to produce the output classifications. For comparison, Figure 15.5 provides a diagram of a deep learning model in which transformations are sequentially applied to the input data in order to yield the output categories. Shallow models may become quite complex if there are a large number of transformations. For example, models such as boosted trees also often involve millions of parameters, and it can be difficult to understand how these parameters come together to produce a final set of predicted tags.[35] However, shallow models can be decomposed into individual elements that each act independently on the input variables and produce distinct contributions to the output classification values. On a local level, at least, there is a possibility for understanding how regression and tree-based models construct predictions from their inputs. In contrast, the layered structure of deep learning models makes even this level of understanding impossible. The lack of a local understanding makes it difficult to assess the structure of a neural network and determine whether a specific application is (algorithmically) reasonable or advisable. The layered structure, then, is a fundamental cause of the impenetrable nature of deep learning models.

Unavoidable Trichotomy

We have shown that deep learning models exhibit their depth along three alternative meanings of the term "deep." They exhibit a deep knowledge in understanding image and textual data by producing accurate labels for a range of predictive modeling tasks. This predictive power is achieved through structures that consist of a deep succession of transformations that gradually push the input objects toward the predicted output tags. Finally, these chains of interrelated transformations hide the parameters of the model with an impenetrable depth that obscures exactly how they arrive at their results. Crucially, we have seen that these three elements are related by far more than the polysemous nature of the English word "deep." The layered nature of deep learning models is a necessary feature for their ability to make predictions for hard tasks such as text and image processing, and these layers in turn are fundamentally difficult to interpret. From the unavoidable interdependence between these elements of deep learning, we conclude here with implications for continued study of deep learning as an object of humanistic inquiry.

First, it is important to start describing the concept of a *deep problem* in addition to deep learning. The way in which text and image data are stored, as streams of characters and pixel intensities, necessitates the use of layered models that modify the original data and represent objects within a new space. In other words, the nature of working with text and image data requires deep learning models in order to achieve high levels of accuracy. Analysis of these objects is an intrinsically deep problem, irrespective of the specific models used to study them.

The classification of tasks, rather than the algorithms for performing them, as "deep" is important. It signals that many of the challenges underlying modern machine learning are actually problems of how knowledge is transmitted and represented. In turn, this directly draws connections from machine learning into well-trodden areas of humanistic inquiry such as epistemology, semiotics, and communication theory. A word-embedding model maps directly onto Ferdinand de Saussure's assertion that words draw meaning through their "simultaneous coexistence" with all other words.[36] Autoencoders, a particular class of neural networks, provide a mathematical formulation directly related to Stuart Hall's encoding/decoding model of social communication.[37] Erwin Panofsky's tripartite series of levels to understanding works of art, which starts with the literal subject matter and proceeds up through iconography and iconology, mirrors the layered hierarchy of levels in modern convolutional neural networks and hints at the application of transfer learning.[38] The first level of interpretation is, in theory, universal; cultural considerations become more explicit higher up the chain of understanding. In short, by focusing on the tasks and not their explicit solutions, we find numerous points of contact between predictive modeling tasks and ongoing questions in a wide range of other fields. Providing points of connection across fields allows for more productive critiques and fruitful interdisciplinary interactions.

As a second implication, embeddings—the output of a particular sequence of transformations within a deep learning model—should be considered as an object of study in its own right. We have argued that the intermediate representations offered by the internal layers of a neural network do encode generalizable semantic information that can be utilized in new tasks through transfer learning. The internal representations, unlike the raw inputs, more directly encode useful semantic information. They have the potential to allow for the utilization of shallow models, even for many complex tasks.[39] If we are able to find good general-purpose embeddings that work with shallow models, this would help alleviate some concerns about the lack of interpretability in deep learning models. While the process of converting raw inputs into the embedding space may remain opaque, with time and analysis, a direct characterization of the embedding space could be achieved. Several results suggest that a general-purpose embedding that can be used across all tasks, or a close approximation to one, can be attainable. In image processing, it has been shown that significant sequences of layers in neural networks can be *inverted* to re-create "photographically accurate information" about the image, establishing that relatively little information is being lost in (at least the lower-level) transformations.[40] For text analysis, where transferable embeddings initially proved more difficult to detect, recent work has produced several candidates that appear to have generalized very well to a variety of tasks.[41] The culture in deep learning research of making research, code, and datasets openly available is a great start for making it possible to offer meaningful studies of embedding spaces. We now need more scholars actively engaged in treating these embeddings as an important object of study.

Finally, it is also important to train scholars from a wide range of fields in the technology of deep learning, specifically neural networks. Layered models that successively reparametrize raw inputs are, as we have seen, necessary for sufficiently predictive models. Deep learning techniques will likely remain popular for a considerable amount of time and are poised to become even more integrated into important real-world systems. We need domain experts from fields such as medicine, biology, public policy, law, economics, and across the humanities to understand this technology. To do so opens up avenues for both important innovations and meaningful critiques of current practices. As we have shown, deep learning models are difficult enough to comprehend even for those in the field of machine learning who have been working with them for decades. Due to this complexity, meaningful collaborations between domain experts and researchers in deep learning require a working understanding of the power and challenges of neural networks across disciplinary boundaries.

Deep learning approaches are here to stay. They offer amazing predictive accuracy and a plethora of exciting technological advances, but they also make way for a wide range of troubling applications. As deep learning becomes increasingly ubiquitous in real-world systems, the unavoidable trichotomy between knowledge, layers, and a lack of interpretability has important implications for anyone concerned with the use and proliferation of algorithmic logic in society.[42] Direct humanistic inquiry into the algorithms behind deep learning is needed as we grapple with their cultural and social implications.

Notes

1. Xiaolin Wu and Xi Zhang, "Responses to Critiques on Machine Learning of Criminality Perceptions," *arXiv preprint arXiv:1611.04135* (2016): 1–14, https://arxiv.org/pdf/1611.04135; Yilun Wang and Michal Kosinski, "Deep Neural Networks Are More Accurate Than Humans at Detecting Sexual Orientation from Facial Images," *Journal of Personality and Social Psychology* 114, no. 2 (2018): 246.

2. Trevor Hastie, Robert Tibshirani, and Jerome Friedman, *The Elements of Statistical Learning,* 2nd ed. (New York: Springer, 2009).

3. This is not entirely true for textual data. The characters could be grouped together into words in a process known as "tokenization," and words do have some intrinsic meaning. Many text-processing tasks, such as spam detection and authorship attribute, can be accurately modeled with general-purpose algorithms using only word counts. However, more advanced tasks such as document summarization and automatic language translation require taking word order and high-level grammatical features into account. There is no such analogue for image data, and the problem remains for even relatively simple tasks.

4. While interesting in their own right, the contentious evolutionary details behind these two strengths, and the specific pathways for language acquisition such as Chomsky's language acquisition device (LAD), are not important for the

discussion here. For more details on both, see Simon Thorpe, Denis Fize, and Catherine Marlot, "Speed of Processing in the Human Visual System," *Nature* 381, no. 6582 (1996): 520; and Noam Chomsky, *Aspects of the Theory of Syntax* (Cambridge, Mass.: MIT Press, 1965).

5. Warren S. McCulloch and Walter Pitts, "A Logical Calculus of the Ideas Immanent in Nervous Activity," *Bulletin of Mathematical Biophysics* 5, no. 4 (1943): 115–33.

6. In fact, neural networks are arguably the *only* practical example of a deep-learning algorithm. Often the terms are used interchangeably. In this article, "deep learning" is used to describe the general modeling approach, and the term "neural networks" is used only to refer to specific applications of deep learning.

7. Yoshua Bengio, Dong-Hyun Lee, Jorg Bornschein, Thomas Mesnard, and Zhouhan Lin, "Towards Biologically Plausible Deep Learning," *arXiv preprint arXiv:1502.04156* (2015), 1, https://arxiv.org/pdf/1502.04156.

8. In an effort to reclaim the physiological legitimacy of neural networks, some have called for a renewed partnership with neuroscience, with minimal recent success. See Adam H. Marblestone, Greg Wayne, and Konrad P. Kording, "Toward an Integration of Deep Learning and Neuroscience," *Frontiers in Computational Neuroscience* 10 (2016): 94.

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