"I know it when I see it". Visualization and Intuitive Interpretability

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Abstract

Most research on the interpretability of machine learning systems focuses on the development of a more rigorous notion of interpretability. I suggest that a better understanding of the deficiencies of the intuitive notion of interpretability is needed as well. I show that visualization enables but also impedes intuitive interpretability, as it presupposes two levels of technical pre-interpretation: dimensionality reduction and regularization. Furthermore, I argue that the use of positive concepts to emulate the distributed semantic structure of machine learning models introduces a significant human bias into the model. As a consequence, I suggest that, if intuitive interpretability is needed, singular representations of internal model states should be avoided.

1 Re-investigating Intuitive Interpretability

Philip Agre has argued that “technology at present is covert philosophy” (Agre, 1997). While the scope of this claim is certainly debatable, in the quest for interpretable machine learning models, certain philosophical issues are evident, above all the fact that interpretability itself is an intuitive notion. As Wolfgang Iser remarks: “For a long time, interpretation was taken for an activity that did not seem to require analysis of its own procedures. There was a tacit assumption that it came naturally, not least because human beings live by constantly interpreting.” (Iser, 2000)

Nevertheless, Kim and Doshi-Velez (2017) and many others have shown that interpretability can be transformed into a more rigorous notion. While most investigations into the interpretability of machine learning models thus focus on the further development of this rigorous notion of interpretability, I suggest that a re-investigation of the intuitive notion of interpretability can help to better understand the limits of interpretability in general.

When we talk about intuitive interpretability in the context of machine learning, we assume a Cartesian concept of intuition that posits intuitive concepts as rational concepts, and thus intuition as an adequate measure of reality. The statement “I know it when I see it”, which is often employed to illustrate this concept, indicates the dependency of such intuition on visualization. To intuitively understand a machine learning model, we need to visualize it, make it accessible to the senses. This process, however, is not as straightforward as it seems. I argue that specifically for machine learning models, visualization – and thus intuitive interpretation – necessarily implies two levels of pre-interpretation.
2 Intuitive Interpretability Depends on Dimensionality Reduction

Machine learning models operate in high-dimensional vector spaces. High-dimensional vector spaces are geometrically counter-intuitive. While low-dimensional vector spaces can always be intuitively correlated with our physical reality, with the existence of objects in space and time, high-dimensional vector spaces have no intuitive equivalent in the real world. Beyond this general inaccessibility, however, high-dimensional vector spaces also specifically impede interpretation, as distances between data points have a tendency to lose their meaning (Beyer et al., 1999) – this is commonly known as the “curse of dimensionality”. Making a high-dimensional vector space intuitively interpretable thus requires its mathematical pre-interpretation, its representation in human terms, i.e. usually in no more than three dimensions.

While there is certainly a quantifiable limit to the damage dimensionality reduction can inflict (Johnson and Lindenstrauss, 1984) it is nevertheless important to acknowledge the reason for the inevitability of this mathematical pre-interpretation. Internal states of machine learning models are non-concepts, concepts that have no intuitive equivalent in the real world and that can only be represented in terms of what they are not. This notion of the non-concept will guide our further investigation of intuitive interpretability.

3 Intuitive Interpretability Depends on Regularization

Artificial neural networks trained on image data are notoriously opaque. Particularly for deep convolutional neural networks (Krizhevsky et al., 2012), it is very hard to infer from the training dataset and the final weights of the fully trained neural network how exactly the network makes its decisions. Many different approaches to this problem have been suggested, most prominently two types of feature visualization: activation maximization (Zeiler and Fergus, 2014, Simonyan et al. (2014), Mahendran and Vedaldi (2015), Mahendran and Vedaldi (2016), Nguyen, Dosovitskiy, et al. (2016), Nguyen, Yosinski, et al. (2016)) and saliency maps, a technique also called attribution (Olah et al., 2017, Simonyan et al. (2014), Zeiler and Fergus (2014)). We will focus here on activation maximization.

Naive optimizations of an image to maximally activate a specific “neuron”, i.e. the part of an artificial neural network that encodes a specific feature, often result in noise and “nonsensical high-frequency patterns” (Olah et al., 2017) – patterns that are without meaning and are thus, again, inaccessible to an intuitive interpretation. The regularization of this optimization is thus another pre-interpretation that is necessary to establish intuitive interpretability. The goal of activation maximizations is thus to generate “natural” pre-images (Mahendran and Vedaldi, 2015, Mahendran and Vedaldi (2016)) – images that are visual representations of intermediate stages in the neural network, expressed in terms of a set of natural images. This regularization is achieved by introducing natural image priors into the objective function.

4 Non-Concepts and the Place of Semantic Information

The natural pre-images of activation maximization usually consist of an arbitrary “mix” of different representations. This mix of representations can either be a set of images that each show a different aspect of the activation maximization, or a “blend” of different images, i.e. a single image that maximizes different aspects of the neuron. Most recently, such “multifaceted” representations have been improved significantly (Nguyen, Dosovitskiy, et al., 2016, Nguyen, Yosinski, et al. (2016)) through the automatic generation of natural image priors with the help of an additional, generative adversarial neural network. Other approaches have used techniques from style transfer to likewise increase the “diversity” (Olah et al., 2017) of the visualization.

However, as Olah et al. (2017) observe, many of the resulting images are “strange mixtures of ideas” suggesting that single neurons are not necessarily the right semantic units for understanding neural nets.” In fact, as Szegedy et al. (2013) showed, looking for meaningful features does not necessarily lead to more meaningful visualizations than looking for any features, i.e. for arbitrary activation maximizations. This is also the reason for the effectiveness of many adversarial strategies (Su et al., 2017, Papernot et al. (2017), Kurakin et al. (2016), Goodfellow et al. (2014)).
In other words, not only is the representation of non-concepts mediated twice, by means of dimensionality reduction and regularization, it is also questionable if non-concepts can be approximated at all in human terms. Szegedy et al. (2013) suggest that the entire space of activations, rather than the individual units contain most of the the semantic information. As also pointed out in Szegedy et al. (2013), a “similar but even stronger conclusion” was reached for word embedding models, and in fact the concept of a distributed semantic structure becomes even more obvious when we look at the text and not the image domain.

Word embedding models (Mikolov et al., 2013) employ shallow artificial neural networks to construct high-dimensional vector spaces that not only reflect syntactic but also semantic properties of the source corpus. Most prominently, word embedding models are able to solve analogy queries, like “what is to woman what king is to man”. This is achieved by not extending, but reducing the dimensionality of the vector space in relation to the number of n-grams in the source corpus. Accordingly, no vector represents just a single n-gram. Instead, the totality of vectors represents the totality of the semantic structure of the source corpus. This distributed semantic structure, however, has peculiar consequences. The solution to an analogy query is given by the model not as a definite answer, but as a hierarchy of answers. Why? Simply because there are no “intermediate” words. If the best possible analogy is a (new) data point right in between two (existing) data points representing n-grams in the source corpus vocabulary, the best possible solution to the analogy query is neither of them, but it still can only be described in terms of them. Even if the input vocabulary consisted of all words in the English language, the solution to the analogy query could still be a data point that is “in between everything” but has no equivalent in the real world – a non-concept. Every computational solution to an analogy task is thus, ironically, itself an analogy.

5 Non-Concepts as a Critical Technical Practice: Revealing Human Bias

A demonstration of this dilemma of non-concepts, and an example for a critical technical practice based on it, is “Image Synthesis from Yahoo’s open_nsfw” (Goh, 2016), a project by Gabriel Goh. Using the technique developed in (Nguyen, Dosovitskiy, et al., 2016) Goh produces images that maximally activate certain neurons of a classifier network called “open_nsfw”, which was created by Yahoo to distinguish workplace-safe (“SFW”) from “not-safe-for-work” (“NSFW”) imagery: a literal mathematical model of “I know it when I see it”. By generating sets of images ranging from most to least pornographic, Goh produces some interesting insights into Yahoo’s specific interpretation of “nsfw”, and the essence of the concept of pornography. Most interesting, however, are the “least pornographic” images. What really is the “opposite” of pornography? Fully clothed people? Non-pornography, again, is a non-concept which has never been defined but through its negation. Except in this particular case it hasn’t. Goh notes that the least pornographic images “all have a distinct pastoral quality – depictions of hills, streams and generally pleasant scenery” and concludes that, most likely, this is the result of providing negative examples during training. Apparently, the non-concept of non-pornography was made into a positive concept – pastoral landscapes – to improve the training of the model. This, of course, becomes particularly problematic if, as it is the case with open_nsfw, a fully trained model is provided without access to the training data. While the Github page for open_nsfw acknowledges that the “definition of NSFW is subjective and contextual”, what is at stake here is exactly the opposite: the fact that “SFW” is subjective and contextual, and that regardless a very specific notion of “SFW” was built into the model. More generally speaking, the approximation of non-concepts with positive concepts necessarily introduces a significant human – aesthetic – bias into the equation.

6 Conclusion

Goh’s project serves to show the non-conceptual structure of machine learning models and the problems this structure creates for intuitive interpretability. While one possible way to address these problems (if intuitive interpretability is needed) is to avoid strategies that present singular images as
representations of internal model states altogether, and instead switch to multitudes of images, there is no general solution to the problem of finding human-readable representations of non-concepts. Research in interpretability thus has to take the non-conceptual structure of machine learning models into account. To make the notion of interpretability more rigorous we have to first identify where it might still be impaired by intuitive considerations: we have to consider it precisely in terms of what it is not.

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