NEURAL NETWORKS AND DEEP LEARNING CST 395 CS 5TH SEMESTER HONORS COURSE- Dr Binu V P, 9847390760

CS 5th Semester Honors course for the Computer Science at KTU- Dr Binu V P

Regularization

September 30, 2022

The no free lunch theorem implies that we must design our machine learning algorithms to perform well on a specific task. We do so by building a set of preferences into the learning algorithm. When these preferences are aligned with the learning problems we ask the algorithm to solve, it performs better.

So far, the only method of modifying a learning algorithm that we have discussed concretely is to increase or decrease the model's representational capacity by adding or removing functions from the hypothesis space of solutions the learning algorithm is able to choose. We gave the specific example of increasing or decreasing the degree of a polynomial for a regression problem.

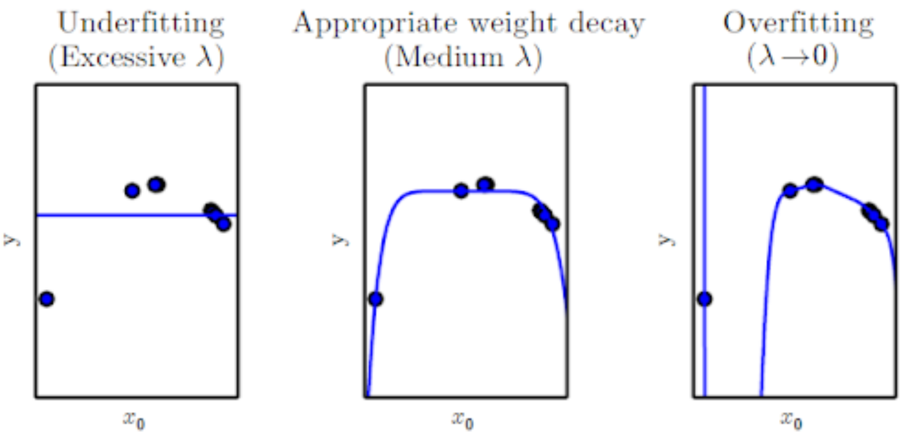
The behavior of our algorithm is strongly affected not just by how large we make the set of functions allowed in its hypothesis space, but by the specific identity of those functions. The learning algorithm we have studied so far, linear regression, has a hypothesis space consisting of the set of linear functions of its input. These linear functions can be very useful for problems where the relationship between inputs and outputs truly is close to linear. They are less useful for problems that behave in a very nonlinear fashion. For example, linear regression would not perform very well if we tried to use it to predict $sin(x)$ from x. We can thus control the performance of our algorithms by choosing what kind of functions we allow them to draw solutions from, as well as by controlling the amount of these functions.

We can also give a learning algorithm a preference for one solution in its hypothesis space to another. This means that both functions are eligible, but one is preferred. The unpreferred solution will be chosen only if it fits the training data significantly better than the preferred solution.

For example, we can modify the training criterion for linear regression to include weight decay. To perform linear regression with weight decay, we minimize a sum comprising both the mean squared error on the training and a criterion $J(w)$ that expresses a preference for the weights to have smaller squared $L2$ norm. Specifically

$$J(w) = MSE_{train} + \lambda w^T w$$

where λ is a value chosen ahead of time that controls the strength of our preference for smaller weights. When $\lambda = 0$, we impose no preference, and larger λ forces the weights to become smaller. Minimizing $J(w)$ results in a choice of weights that make a trade off between fitting the training data and being small. This gives us solutions that have a smaller slope, or put weight on fewer of the features. As an example of how we can control a model's tendency to overfit or underfit via weight decay, we can train a high-degree polynomial regression model with different values of λ. See figure below for the results.



We fit a high-degree polynomial regression model to our example training set . The true function is quadratic, but here we use only models with degree 9. We vary the amount of weight decay to prevent these high-degree models from overfitting.
(Left)With very large λ, we can force the model to learn a function with no slope at all. This underfits because it can only represent a constant function.
(Center)With a medium value of λ, the learning algorithm recovers a curve with the right general shape.even though the model is capable of representing functions with much more complicated shape, weight decay has encouraged it to use a simpler function described by smaller coefficients. (Right)With weight decay approaching zero (i.e., using the Moore-Penrose pseudoinverse to solve the underdetermined problem with minimal regularization), the degree-9 polynomial overfits significantly, as we saw early.

More generally, we can regularize a model that learns a function $f(x;\theta)$ by adding a penalty called a regularizer to the cost function. In the case of weight decay, the **regularizer** is $\Omega(w) = w^T w$.Many other regularizers are also possible.

Expressing preferences for one function over another is a more general way of controlling a model's capacity than including or excluding members from the hypothesis space. We can think of excluding a function from a hypothesis space as expressing an infinitely strong preference against that function.

In our weight decay example, we expressed our preference for linear functions defined with smaller weights explicitly, via an extra term in the criterion we minimize. There are many other ways of expressing preferences for different solutions, both implicitly and explicitly. Together, these different approaches are known as **regularization. Regularization is any modification we make to a learning algorithm that is intended to reduce its generalization error but not its training error.** Regularization is one of the central concerns of the field of machine learning, rivaled in its importance only by optimization.

The no free lunch theorem has made it clear that there is no best machine learning algorithm, and, in particular, no best form of regularization. Instead we must choose a form of regularization that is well-suited to the particular task we want to solve. The philosophy of deep learning in general is that a very wide range of tasks (such as all of the intellectual tasks that people can do) may all be solved effectively using very general-purpose forms of regularization.

we will learn this in more detail later.

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Machine Learning Algorithm

October 01, 2022

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Syllabus

October 01, 2022

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