Supervised Learning with Neural Networks

(DESCRIPTION)
Text, Introduction to Deep Learning. Supervised Learning with Neural Networks. Website, deep learning, dot, A.I.

(SPEECH)
There's been a lot of hype about neural networks.

And perhaps some of that hype is justified, given how well they're working.

But it turns out that so far, almost all the economic value created by neural networks has been through one type of machine learning, called supervised learning.

Let's see what that means, and let's go over some examples.

(DESCRIPTION)
New slide, Supervised Learning. Three columns are displayed. Input, X, Output, Y, and Application.

(SPEECH)
In supervised learning, you have some input x, and you want to learn a function mapping to some output y.

So for example, just now we saw the housing price prediction application where you input some features of a home and try to output or estimate the price y.

Here are some other examples that neural networks have been applied to very effectively.

Possibly the single most lucrative application of deep learning today is online advertising, maybe not the most inspiring, but certainly very lucrative, in which, by inputting information about an ad to the website it's thinking of showing you, and some information about the user, neural networks have gotten very good at predicting whether or not you click on an ad.

And by showing you and showing users the ads that you are most likely to click on, this has been an incredibly lucrative application of neural networks at multiple companies.

Because the ability to show you ads that you're more likely to click on has a direct impact on the bottom line of some of the very large online advertising companies.

Computer vision has also made huge strides in the last several years, mostly due to deep learning.

So you might input an image and want to output an index, say from 1 to 1,000 trying to tell you if this picture, it might be any one of, say a 1000 different images.

So, you might us that for photo tagging.

I think the recent progress in speech recognition has also been very exciting, where you can now input an audio clip to a neural network, and have it output a text transcript.

Machine translation has also made huge strides thanks to deep learning where now you can have a neural network input an English sentence and directly output say, a Chinese sentence.

And in autonomous driving, you might input an image, say a picture of what's in front of your car as well as some information from a radar, and based on that, maybe a neural network can be trained to tell you the position of the other cars on the road.

So this becomes a key component in autonomous driving systems.

So a lot of the value creation through neural networks has been through cleverly selecting what should be x and what should be y for your particular problem, and then fitting this supervised learning component into often a bigger system such as an autonomous vehicle.

It turns out that slightly different types of neural networks are useful for different applications.

For example, in the real estate application that we saw in the previous video, we use a universally standard neural network architecture, right?

Maybe for real estate and online advertising might be a relatively standard neural network, like the one that we saw.

For image applications we'll often use convolution on neural networks, often abbreviated CNN.

And for sequence data.

So for example, audio has a temporal component, right?

Audio is played out over time, so audio is most naturally represented as a one-dimensional time series or as a one-dimensional temporal sequence.

And so for sequence data, you often use an RNN, a recurrent neural network.

Language, English and Chinese, the alphabets or the words come one at a time.

So language is also most naturally represented as sequence data.

And so more complex versions of RNNs are often used for these applications.

And then, for more complex applications, like autonomous driving, where you have an image, that might suggest more of a CNN convolution neural network structure and radar info which is something quite different.

You might end up with a more custom, or some more complex, hybrid neural network architecture.

So, just to be a bit more concrete about what are the standard CNN and RNN architectures.

So in the literature you might have seen pictures like this.

So that's a standard neural net.

You might have seen pictures like this.

Well this is an example of a Convolutional Neural Network, and we'll see in a later course exactly what this picture means and how can you implement this.

But convolutional networks are often use for image data.

And you might also have seen pictures like this.

And you'll learn how to implement this in a later course.

Recurrent neural networks are very good for this type of one-dimensional sequence data that has maybe a temporal component.

You might also have heard about applications of machine learning to both Structured Data and Unstructured Data.

Here's what the terms mean.

Structured Data means basically databases of data.

So, for example, in housing price prediction, you might have a database or the column that tells you the size and the number of bedrooms.

So, this is structured data, or in predicting whether or not a user will click on an ad, you might have information about the user, such as the age, some information about the ad, and then labels why that you're trying to predict.

So that's structured data, meaning that each of the features, such as size of the house, the number of bedrooms, or the age of a user, has a very well defined meaning.

In contrast, unstructured data refers to things like audio, raw audio, or images where you might want to recognize what's in the image or text.

Here the features might be the pixel values in an image or the individual words in a piece of text.

Historically, it has been much harder for computers to make sense of unstructured data compared to structured data.

And the fact the human race has evolved to be very good at understanding audio cues as well as images.

And then text was a more recent invention, but people are just really good at interpreting unstructured data.

And so one of the most exciting things about the rise of neural networks is that, thanks to deep learning, thanks to neural networks, computers are now much better at interpreting unstructured data as well compared to just a few years ago.

And this creates opportunities for many new exciting applications that use speech recognition, image recognition, natural language processing on text, much more than was possible even just two or three years ago.

I think because people have a natural empathy to understanding unstructured data, you might hear about neural network successes on unstructured data more in the media because it's just cool when the neural network recognizes a cat.

We all like that, and we all know what that means.

But it turns out that a lot of short term economic value that neural networks are creating has also been on structured data, such as much better advertising systems, much better profit recommendations, and just a much better ability to process the giant databases that many companies have to make accurate predictions from them.

So in this course, a lot of the techniques we'll go over will apply to both structured data and to unstructured data.

For the purposes of explaining the algorithms, we will draw a little bit more on examples that use unstructured data.

But as you think through applications of neural networks within your own team I hope you find both uses for them in both structured and unstructured data.

So neural networks have transformed supervised learning and are creating tremendous economic value.

It turns out though, that the basic technical ideas behind neural networks have mostly been around, sometimes for many decades.

So why is it, then, that they're only just now taking off and working so well?

In the next video, we'll talk about why it's only quite recently that neural networks have become this incredibly powerful tool that you can use.