Deep Learning Lecture 1 - Deep Learning Models in Keras

MA8701 General Statistical Methods

Thiago G. Martins, Department of Mathematical Sciences, NTNU

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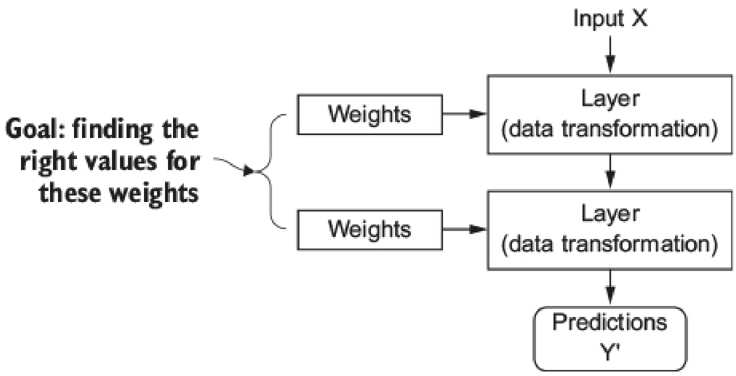
A deep-learning model is a directed, acyclic graph of layers.



Layers

Layer is a data-processing component:

- takes one or more tensors as input and outputs one or more tensors.

Stateless or stateful layers:

- Some layers are stateless, but more frequently layers have a state.
- Stateful layers contain parameters that are learned from the data

Types of layers:

- Different layers are appropriate for different tensor formats and different types of data processing.
- For example:

Tensor Type	Data Type	Data Shape	Layer Type	Layer Description
2D tensor	Vector data	`(samples, features)`	`layer_dense`	densely connected layer
3D tensor	Sequence data	`(samples, timesteps, features)`	`layer_lstm`	recurrent layers
4D tensor	Image data	`(samples, height, width, channels)`	`layer_conv_2d`	2D convolution layers

Building deep-learning models in Keras:

- It is done by clipping together compatible layers to form useful data-transformation pipelines.

Layer compatibility:

- Every layer will only accept input tensors of a certain shape and will return output tensors of a certain shape.
- When using Keras, you don't have to worry about compatibility, because the layers you add to your models are dynamically built to match the shape of the incoming layer.

Examples

Fully connected model for MNIST

```
model <- keras_model_sequential() %>%
  layer_dense(units = 512, activation = "relu", input_shape = c(28*28)) %>%
  layer_dense(units = 10, activation = "softmax")
```

Fully connected model for IMDB

```
model <- keras_model_sequential() %>%
  layer_dense(units = 16, activation = "relu", input_shape = c(10000)) %>%
  layer_dense(units = 16, activation = "relu") %>%
  layer_dense(units = 1, activation = "sigmoid")
```

Fully connected model for Boston House dataset

```
model <- keras_model_sequential() %>%
    layer_dense(units = 64, activation = "relu", input_shape = c(13)) %>%
    layer_dense(units = 64, activation = "relu") %>%
    layer_dense(units = 1)
```

Explaining the code

The pipe operator

- `%>%`

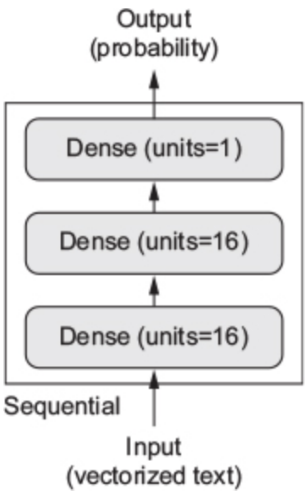
- The pipe operator comes from the `magrittr` package.
- Shorthand for passing the value on its left as the first argument to the function on its right.

```
model <- keras_model_sequential()
layer_dense(model, units = 512, activation = "relu", input_shape = c(28*28))
layer_dense(model, units = 10, activation = "softmax")
```

- Besides compactness, the `%>%` reminds that Keras models are modified in-place.
  - You don't operate on `model` and then return a new `model` object.
  - Rather, you do something to the `model` object.

Linear Stack of Layers

- `keras_model_sequential`
- Defines a Keral model composed of a linear stack of layers.



- Not to be confused with it being a model for sequential data

Dense layer

`layer_dense`

- Dense or fully connected layer

Implements the operation: `output = activation(dot(input, weight) + bias)`

- `input` : 2D input tensor. Gets flattened if `rank > 2` .
- `weight` : 2D weight tensor created by the layer.
- `bias` : 1D bias tensor created by the layer (`use_bias=TRUE`).
- `dot(input, weight)` : Dot product between two tensors.
- `activation(.)` : Element-wise activation function.

Most important inputs:

- `input_shape` : Dimensionality of the input, not including the samples axis.
  - Required only for the first layer in a model.
- `units` : Dimensionality of the output space.
- `activation` : The name of the activation function. Default to `linear` .
  - `relu(x) = max(x,0)` is the most commonly used non-linear activation function.

Some observations

- With Neural Networks, we are able to build models able to capture complex patterns in the data from simple, differentiable operations.
- The importance of the non-linear activation function

Without them each layer would only be able to learn linear transformations of the input data and a deep stack of linear layers would still implement a linear operation. The activation function relu add non-linearity to the model.

Reference material

This lecture note is based on (Chollet and Allaire 2018).

References

Chollet, F., and J. Allaire. 2018. *Deep Learning with R*. Manning Publications. https://books.google.no/books?id=xnIRtAEACAAJ.