Deep Learning Lecture 1 - Reuters: Densily connected NN

MA8701 General Statistical Methods

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The Reuters dataset

The objective here is to classify short news stories into one of 46 topics available.

Preparing the data

Here, we use the multi-assignment operator (`%<-%`) from the `zeallot` package to unpack the list into a set of distinct variables.

```
reuters <- dataset_reuters(num_words = 10000)
c(c(train_data, train_labels), c(test_data, test_labels)) %<-% reuters
```

```
length(train_data)
```

```
## [1] 8982
```

```
length(test_data)
```

```
## [1] 2246
```

As with the IMDB reviews, each example is a list of integers (word indices):

```
train_data[[1]]
```

```
##  [1]    1    2    2    8   43   10  447    5   25  207  270    5 3095  111
## [15]   16  369  186   90   67    7   89    5   19  102    6   19  124   15
## [29]   90   67   84   22  482   26    7   48    4   49    8  864   39  209
## [43]  154    6  151    6   83   11   15   22  155   11   15    7   48    9
## [57] 4579 1005  504    6  258    6  272   11   15   22  134   44   11   15
## [71]   16    8  197 1245   90   67   52   29  209   30   32  132    6  109
## [85]   15   17   12
```

```
train_labels[[1]]
```

```
## [1] 3
```

You can vectorize the data with the exact same code as in the IMDB example

```
vectorize_sequences <- function(sequences, dimension = 10000) {
  results <- matrix(0, nrow = length(sequences), ncol = dimension)
  for (i in 1:length(sequences))
    results[i, sequences[[i]]] <- 1
  results
}

x_train <- vectorize_sequences(train_data)
x_test <- vectorize_sequences(test_data)
```

Vectorize the labels:

```
one_hot_train_labels <- to_categorical(train_labels)
one_hot_test_labels <- to_categorical(test_labels)
```

Building the model

- The dimensionality of the output space (46 classes) is much larger.

Information bottleneck

- Each layer can only access information present in the output of the previous layer.
- Each layer can potentially become an information bottleneck.
- A 16-dimensional intermediate layer may be too limited to learn to separate 46 different classes:
- Such small layers may act as information bottlenecks, permanently dropping relevant information.

For this reason we will use larger layers. Let's go with 64 units.

```
model <- keras_model_sequential() %>%
  layer_dense(units = 64, activation = "relu", input_shape = c(10000)) %>%
```

```
  layer_dense(units = 64, activation = "relu") %>%
  layer_dense(units = 46, activation = "softmax")
```

Compiling the model

The best loss function to use in this case is `categorical_crossentropy`.

```
model %>% compile(
  optimizer = "rmsprop",
  loss = "categorical_crossentropy",
  metrics = c("accuracy")
)
```

Validating your approach

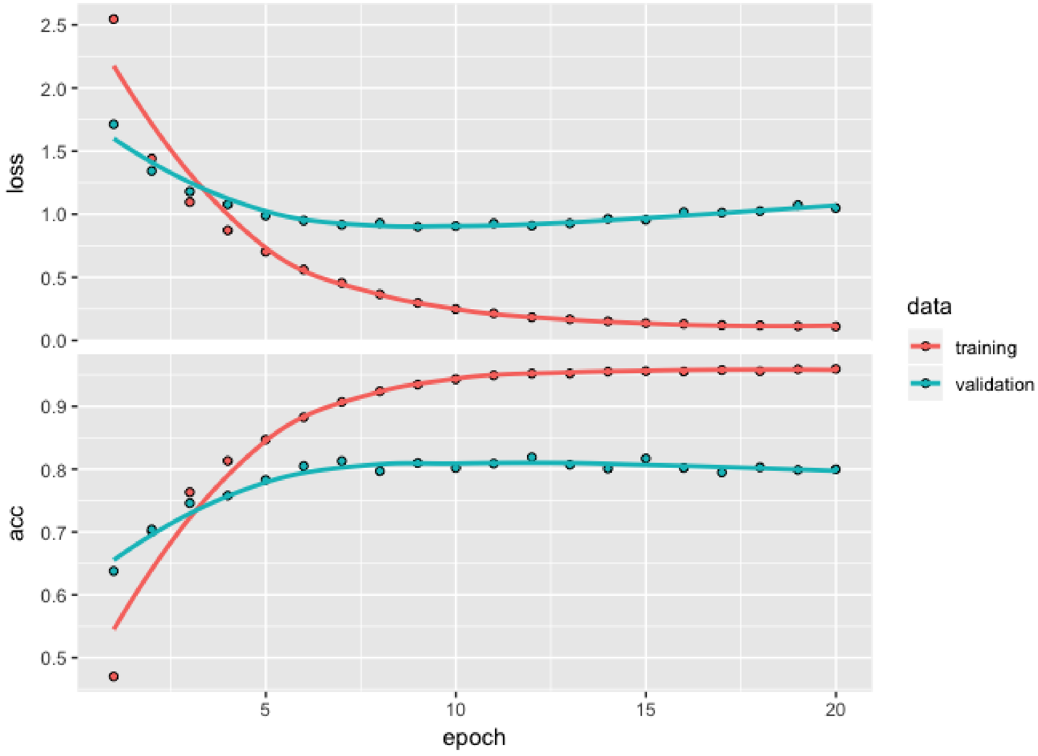
Let's set apart 1000 samples in the training data to use as a validation set.

```
val_indices <- 1:1000

x_val <- x_train[val_indices,]
partial_x_train <- x_train[-val_indices,]

y_val <- one_hot_train_labels[val_indices,]
partial_y_train = one_hot_train_labels[-val_indices,]
```

Now, let's train the network for 20 epochs.

```
history <- model %>% fit(
  partial_x_train,
  partial_y_train,
  epochs = 20,
  batch_size = 512,
  validation_data = list(x_val, y_val)
)
```

```
plot(history)
```



The network begins to overfit after nine epochs. Let's train a new network from scratch for nine epochs and then evaluate it on the test set.

```
model <- keras_model_sequential() %>%
  layer_dense(units = 64, activation = "relu", input_shape = c(10000)) %>%
  layer_dense(units = 64, activation = "relu") %>%
  layer_dense(units = 46, activation = "softmax")

model %>% compile(
  optimizer = "rmsprop",
  loss = "categorical_crossentropy",
  metrics = c("accuracy")
)

history <- model %>% fit(
  partial_x_train,
  partial_y_train,
  epochs = 9,
  batch_size = 512,
  validation_data = list(x_val, y_val)
)
```

```
results <- model %>% evaluate(x_test, one_hot_test_labels)

results
```

```
## $loss
## [1] 1.021877
##
## $acc
## [1] 0.777382
```

This approach reaches an accuracy of ~ 79%. With a balanced binary classification problem, the accuracy reached by a purely random classifier would be 50%. But in this case it's closer to 18%, so the results seem pretty good, at least when compared to a random baseline:

```
test_labels_copy <- test_labels
test_labels_copy <- sample(test_labels_copy)
length(which(test_labels == test_labels_copy)) / length(test_labels)
```

```
## [1] 0.1843277
```

Predictions on new data

```
predictions <- model %>% predict(x_test)
```

Each entry in predictions is a vector of length 46:

```
dim(predictions)
```

```
## [1] 2246   46
```

The coefficients in this vector sum to 1:

```
sum(predictions[1,])
```

```
## [1] 1
```

The largest entry is the predicted class—the class with the highest probability:

```
which.max(predictions[1,])
```

```
## [1] 4
```

Recommended exercise 2

Use a vector of integers as labels instead of the one-hot encoding used above. Remember that this choice will impact the loss function used to train the model.