Deep Learning with Keras : : CHEATSHEET

Keras TensorFlow

Intro

Keras is a high-level neural networks API developed with a focus on enabling fast experimentation. It supports multiple back-ends, including TensorFlow, Jax and Torch.

Backends like TensorFlow are lower level mathematical libraries for building deep neural network architectures. The `keras3` R package makes it easy to use Keras with any backend in R.

Define
- Functional Model
- Sequential model

→ **Compile**
- Optimiser
- Loss
- Metrics

→ **Fit**
- Batch size
- Epochs
- Validation split

→ **Evaluate**
- Evaluate
- Plot

→ **Predict**
- classes
- probability

https://keras.posit.co

https://www.manning.com/books/deep-learning-with-r-second-edition

The "Hello, World!" of deep learning

INSTALLATION

The keras R package uses the Python keras library. You can install all the prerequisites directly from R.

https://keras.rstudio.com/reference/install_keras.html

```
library(keras3)
reticulate::install_python()
install_keras()
```

This installs the required libraries in virtual environment named **'r-keras'**.
It will automatically detect if a GPU is available.

Working with keras models

DEFINE A MODEL

Functional API: keras_input() and keras_model()
Define a Functional Model with inputs and outputs.

```
inputs <- keras_input(<input-shape>)
outputs <- inputs |>
  layer_dense() |> layer_...
model <- keras_model(inputs, outputs)
```

Sequential API: keras_model_sequential()
Define a Sequential Model composed of a linear stack of layers

```
model <-
  keras_model_sequential(<input-shape>) |>
  layer_dense() |> layer_...
```

Subclassing API: Model()
Subclass the base Model class

COMPILE A MODEL

compile(object, optimizer, loss, metrics, ...)
Configure a Keras model for training

FIT A MODEL

fit(object, x = NULL, y = NULL, batch_size = NULL, epochs = 10, verbose = 1, callbacks = NULL, …)
Train a Keras model for a fixed number of epochs (iterations)

Ways to customize training:
- Provide callbacks to **fit()**:
- Define a custom **Callback()**.
- Subclass **Model()** and implement a custom **train_step** method.
- Define a custom loop training loop. Optionally call **train_on_batch()** to run a single gradient update on a single batch of data, or call model$optimizer$apply(gradients, weights)

EVALUATE A MODEL

evaluate(object, x = NULL, y = NULL, batch_size = NULL) Evaluate a Keras model

PREDICT

predict() Generate predictions from a Keras model

predict_on_batch() Returns predictions for a single batch of samples.

SAVE/LOAD A MODEL

save_model(); load_model() Save/Load models using the ".keras" file format.

save_model_weights(); load_model_weights()
Save/load model weights to/from ".h5" files.

save_model_config(); load_model_config()
Save/load model architecture to/from a ".json" file.

freeze_weights(); unfreeze_weights()
Freeze and unfreeze weights

Deploy

Export just the forward pass of the trained model for inference serving.

export_savedmodel(model, "my-saved-model/1")
Save a TF SavedModel for inference.

rsconnect::deployTFModel("my-saved-model")
Deploy a TF SavedModel to Connect for inference.

CORE LAYERS

layer_dense() Add a densely-connected NN layer to an output

layer_einsum_dense() Add a dense layer with arbitrary dimensionality

layer_activation() Apply an activation function to an output

layer_dropout() Applies Dropout to the input

layer_reshape() Reshapes an output to a certain shape

layer_permute() Permute the dimensions of an input according to a given pattern

layer_repeat_vector() Repeats the input n times

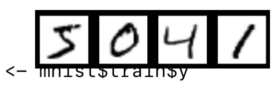
layer_lambda(object, f) Wraps arbitrary expression as a layer

layer_activity_regularization() Layer that applies an update to the cost function based input activity

layer_masking() Masks a sequence by using a mask value to skip timesteps

layer_flatten() Flattens an input

TRAINING AN IMAGE RECOGNIZER ON MNIST DATA



```
# input layer: use MNIST images
mnist <- dataset_mnist()
x_train <- mnist$train$x;  y_train <- mnist$train$y
x_test <- mnist$test$x;  y_test <- mnist$test$y

# reshape and rescale
x_train <- array_reshape(x_train, c(nrow(x_train), 784))
x_test <- array_reshape(x_test, c(nrow(x_test), 784))
x_train <- x_train / 255;  x_test <- x_test / 255

y_train <- to_categorical(y_train, 10)
y_test <- to_categorical(y_test, 10)

# defining the model and layers
model <- keras_model_sequential(input_shape = c(784))
model |>
  layer_dense(units = 256, activation = 'relu') |>
  layer_dropout(rate = 0.4) |>
  layer_dense(units = 128, activation = 'relu') |>
  layer_dense(units = 10, activation = 'softmax')

# compile (define loss and optimizer)
model |> compile(
  loss = 'categorical_crossentropy',
  optimizer = optimizer_rmsprop(),
  metrics = c('accuracy')
)

# train (fit)
model |> fit(
  x_train, y_train,
  epochs = 30, batch_size = 128,
  validation_split = 0.2
)
model |> evaluate(x_test, y_test)
model |> predict(x_test)

# save the full model
save_model(model, "mnist-classifier.keras")

# deploy for serving inference.
dir.create("serving-mnist-classifier")
export_savedmodel(modek, "serving-mnist-classifier/1")
rsconnect::deployTFModel("serving-mnist-classifier")
```

More layers

CONVOLUTIONAL LAYERS

layer_conv_1d() 1D, e.g. temporal convolution

layer_conv_2d_transpose() Transposed 2D (deconvolution)

layer_conv_2d() 2D, e.g. spatial convolution over images

layer_conv_3d_transpose() Transposed 3D (deconvolution)
layer_conv_3d() 3D, e.g. spatial convolution over volumes

layer_conv_lstm_2d() Convolutional LSTM

layer_separable_conv_2d() Depthwise separable 2D

layer_upsampling_1d()
layer_upsampling_2d()
layer_upsampling_3d()
Upsampling layer

layer_zero_padding_1d()
layer_zero_padding_2d()
layer_zero_padding_3d()
Zero-padding layer

layer_cropping_1d()
layer_cropping_2d()
layer_cropping_3d()
Cropping layer

POOLING LAYERS

layer_max_pooling_1d()
layer_max_pooling_2d()
layer_max_pooling_3d()
Maximum pooling for 1D to 3D

layer_average_pooling_1d()
layer_average_pooling_2d()
layer_average_pooling_3d()
Average pooling for 1D to 3D

layer_global_max_pooling_1d()
layer_global_max_pooling_2d()
layer_global_max_pooling_3d()
Global maximum pooling

layer_global_average_pooling_1d()
layer_global_average_pooling_2d()
layer_global_average_pooling_3d()
Global average pooling

posit™

Preprocessing

IMAGE PREPROCESSING

Load Images
image_dataset_from_directory()
Create a TF Dataset from image files in a directory.

image_load(), image_from_array(), image_to_array(), image_array_save()
Work with PIL Image instances

Transform Images
op_image_crop()
op_image_extract_patches()
op_image_pad()
op_image_resize()
op_image_affine_transform()
op_image_map_coordinates()
op_image_rgb_to_grayscale()
Operations that transform image tensors in deterministic ways.

image_smart_resize()
Resize images without aspect ratio distortion.

Image Layers
Builtin image preprocessing layers. Note, any image operation function can also be used as a layer, or used in layer_lambda().

Image Preprocessing Layers
layer_resizing()
layer_rescaling()
layer_center_crop()

Image Augmentation Layers
Preprocessing layers that randomly augment image inputs during training.
layer_random_crop()
layer_random_flip()
layer_random_translation()
layer_random_rotation()
layer_random_zoom()
layer_random_contrast()
layer_random_brightness()

SEQUENCE PREPROCESSING

timeseries_dataset_from_array()
Creates a dataset of sliding windows over a timeseries provided as array.

audio_dataset_from_directory()
Generate a TF Dataset from audio files.

pad_sequences()
Pad sequences to the same length

Preprocessing

TEXT PREPROCESSING

text_dataset_from_directory()
Generates a TF Dataset from text files in a directory.

layer_text_vectorization(), get_vocabulary(), set_vocabulary()
Map text to integer sequences.

NUMERICAL FEATURES PREPROCESSING

layer_normalization()
Normalizes continuous features.

layer_discretization()
Buckets continuous features by ranges.

Categorical Features Preprocessing

layer_category_encoding()
Encode integer features.

layer_hashing()
Hash and bin categorical features.

layer_hashed_crossing()
Cross features using the "hashing trick".

layer_string_lookup()
Map strings to (possibly encoded) indices.

layer_integer_lookup()
Map integers to (possibly encoded) indices.

TABULAR DATA

One-stop utility for preprocessing and encoding structured data. Define a feature space from a list of table columns (features).
feature_space <-
layer_feature_space(features = list(<features>))

Adapt the feature space to a dataset
adapt(feature_space, dataset)

Use the adapted **feature_space** preprocessing layer in the data input pipeline (**tfdatasets::dataset_map()** or incorporate it a layer in a Keras Model.

Available features:
feature_float()
feature_float_rescaled()
feature_float_normalized()
feature_float_discretized()

feature_integer_categorical()
feature_integer_hashed()

feature_string_categorical()
feature_string_hashed()

feature_cross()
feature_custom()

Keras TensorFlow

Pre-trained models

Keras applications are deep learning models that are made available alongside pre-trained weights. These models can be used for prediction, feature extraction, and fine-tuning.

application_xception()
xception_preprocess_input()
Xception v1 model

application_inception_v3()
inception_v3_preprocess_input()
Inception v3 model, with weights pre-trained on ImageNet

application_inception_resnet_v2()
inception_resnet_v2_preprocess_input()
Inception-ResNet v2 model, with weights trained on ImageNet

application_vgg16(); application_vgg19()
VGG16 and VGG19 models

application_resnet50() ResNet50 model

application_mobilenet()
mobilenet_preprocess_input()
mobilenet_decode_predictions()
mobilenet_load_model_hdf5()
MobileNet model architecture

IMAGENET
ImageNet is a large database of images with labels, extensively used for deep learning

imagenet_preprocess_input()
imagenet_decode_predictions()
Preprocesses a tensor encoding a batch of images for ImageNet, and decodes predictions

Callbacks

A callback is a set of functions to be applied at given stages of the training procedure. You can use callbacks to get a view on internal states and statistics of the model during training.

callback_early_stopping() Stop training when a monitored quantity has stopped improving
callback_learning_rate_scheduler() Learning rate scheduler
callback_tensorboard() TensorBoard basic visualizations