Introduction to Keras

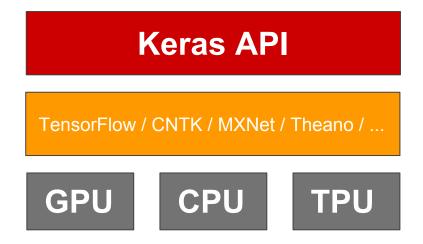
Francois Chollet March 9th, 2018

Outline (45 min + questions)

- What's Keras?
 - What's special about it?
 - TensorFlow integration
- How to use Keras
 - 3 API styles
 - An image captioning example
- Distributed, multi-GPU, and TPU training
- Eager execution (a.k.a define-by-run, a.k.a. dynamic graphs)

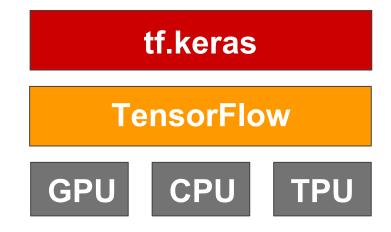
What's Keras?

Keras: an API for specifying & training differentiable programs



Keras is the official high-level API of TensorFlow

- tensorflow.keras (tf.keras) module
- Part of core TensorFlow since v1.4
- Full Keras API
- Better optimized for TF
- Better integration with TF-specific features
 - Estimator API
 - Eager execution
 - o etc.



Who makes Keras? Contributors and backers

44 633 contributors









What's special about Keras?

- A focus on user experience.
- Large adoption in the industry and research community.
- Multi-backend, multi-platform.
- Easy productization of models.

250,000

Keras developers

> 2x

Year-on-year growth













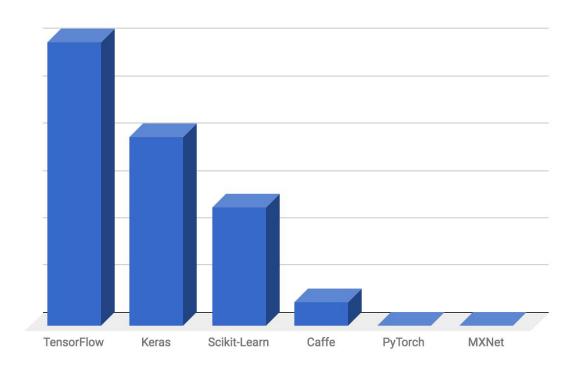




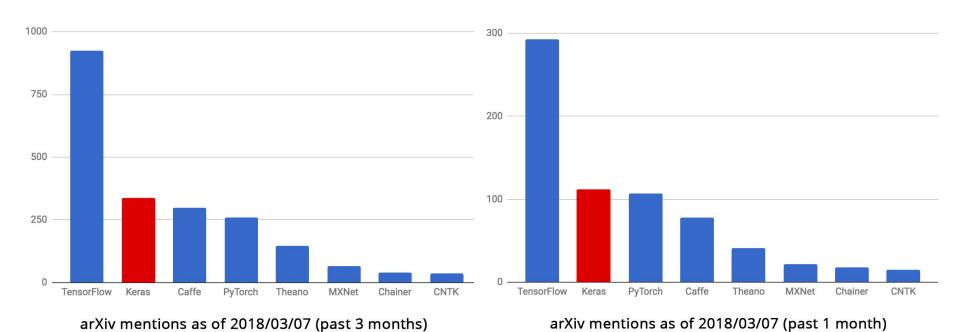
etc...

Startup-land traction

Hacker News jobs board mentions - out of 964 job postings



Research traction



The Keras user experience

Keras is an API designed for human beings, not machines. Keras follows best practices for reducing cognitive load: it offers consistent & simple APIs, it minimizes the number of user actions required for common use cases, and it provides clear and actionable feedback upon user error.

This makes Keras easy to learn and easy to use. As a Keras user, you are more productive, allowing you to try more ideas than your competition, faster -- which in turn helps you win machine learning competitions.

This ease of use does not come at the cost of reduced flexibility: because Keras integrates with lower-level deep learning languages (in particular TensorFlow), it enables you to implement anything you could have built in the base language. In particular, as tf.keras, the Keras API integrates seamlessly with your TensorFlow workflows.

Keras is multi-backend, multi-platform

- Develop in Python, R
 - On Unix, Windows, OSX
- Run the same code with...
 - TensorFlow
 - CNTK
 - Theano
 - MXNet
 - PlaidML
 - ??
- CPU, NVIDIA GPU, AMD GPU, TPU...

Largest array of options for productizing models

- TF-Serving
- In-browser, with GPU acceleration (WebKeras, Keras.js, WebDNN...)
- Android (TF, TF Lite), iPhone (native CoreML support)
- Raspberry Pi
- JVM

Go build cool AR apps with Keras + TF + CoreML + ARKit

How to use Keras: An introduction

Three API styles

- The Sequential Model
 - Dead simple
 - Only for single-input, single-output, sequential layer stacks
 - Good for 70+% of use cases
- The functional API
 - Like playing with Lego bricks
 - Multi-input, multi-output, arbitrary static graph topologies
 - Good for 95% of use cases
- Model subclassing
 - Maximum flexibility
 - Larger potential error surface

The Sequential API

```
import keras
from keras import layers
model = keras.Sequential()
model.add(layers.Dense(20, activation='relu', input_shape=(10,)))
model.add(layers.Dense(20, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))
model.fit(x, y, epochs=10, batch_size=32)
```

The functional API

```
import keras
from keras import layers
inputs = keras.Input(shape=(10,))
x = layers.Dense(20, activation='relu')(x)
x = layers.Dense(20, activation='relu')(x)
outputs = layers.Dense(10, activation='softmax')(x)
model = keras.Model(inputs, outputs)
model.fit(x, y, epochs=10, batch_size=32)
```

Model subclassing

```
import keras
from keras import layers
class MyModel(keras.Model):
    def __init__(self):
        super(MyModel, self).__init__()
        self.dense1 = layers.Dense(20, activation='relu')
        self.dense2 = layers.Dense(20, activation='relu')
        self.dense3 = layers.Dense(10, activation='softmax')
    def call(self, inputs):
       x = self.densel(x)
        x = self.dense2(x)
        return self.dense3(x)
model = MyModel()
model.fit(x, y, epochs=10, batch_size=32)
```

Remember: use the right tool (API) for the job!

Example: building a video captioning model

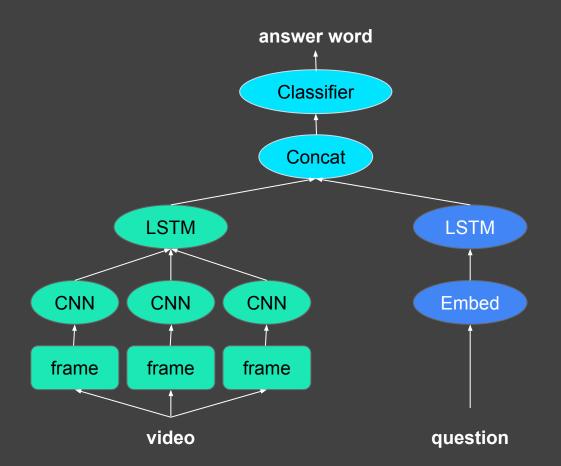
Toy video-QA problem





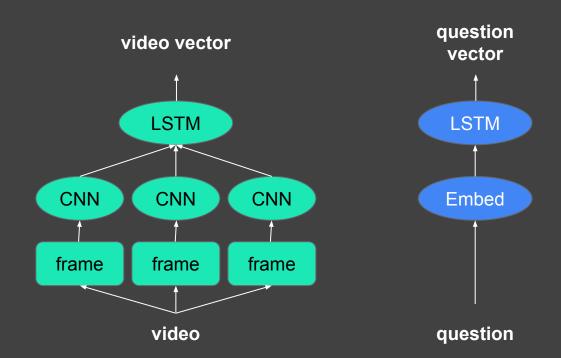


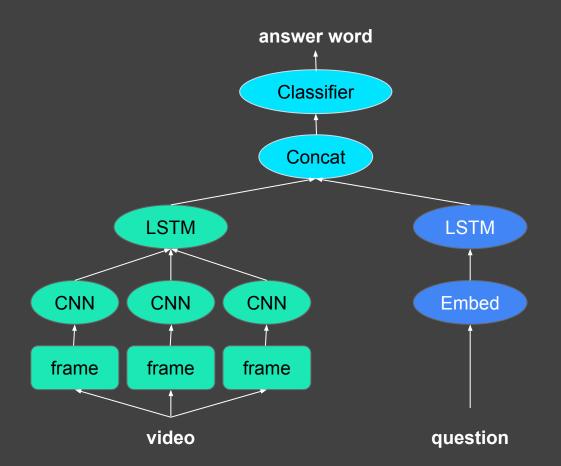
- > "What is the man doing?"
- > packing
- > "What color is his shirt?"
- > blue

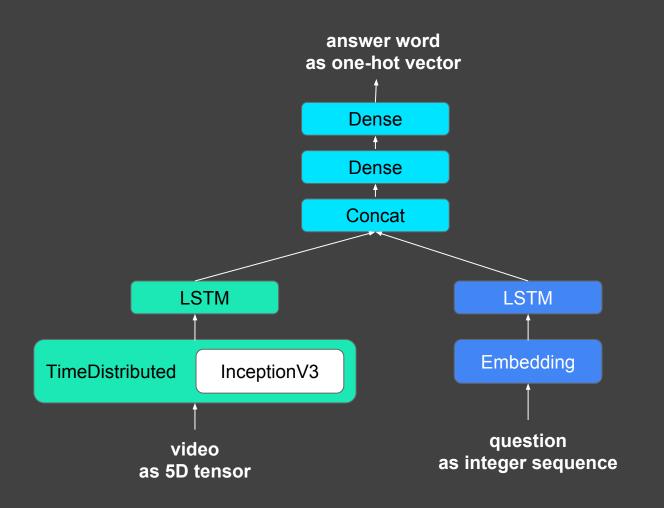


from frames to a vector

video vector **LSTM CNN CNN CNN** frame frame frame video







Turning a sequence of words into a vector

```
question = keras.Input(shape=(None,), dtype='int32', name='question')
embedded_words = layers.Embedding(input_voc_size, 256)(question)
question_vector = layers.LSTM(128)(embedded_words)
```

Predicting an answer word

Setting up the training configuration

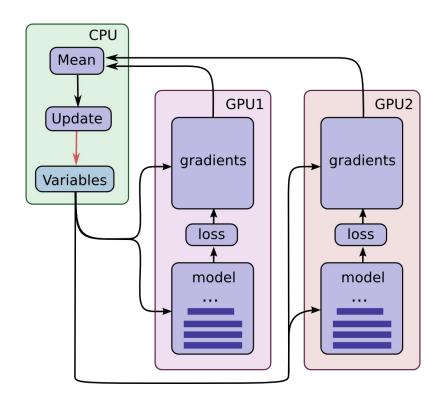
Distributed, multi-GPU, & TPU training

Distributed

- Uber's Horovod
- Estimator API (TF built-in option)
- Dist-Keras (Spark)
 - Also Elephas (Spark)

Built-in multi-GPU support

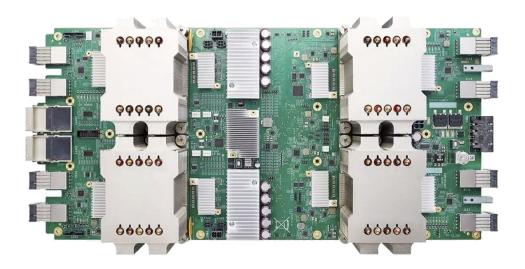
```
import tensorflow as tf
from keras.applications import Xception
from keras.utils import multi_gpu_model
# Instantiate the base model
# (here, we do it on CPU, which is optional).
with tf.device('/cpu:0'):
    model = Xception(weights=None,
                     input shape=(height, width, 3),
                     classes=num classes)
# Replicates the model on 8 GPUs.
# This assumes that your machine has 8 available GPUs.
parallel model = multi gpu model(model, gpus=8)
parallel model.compile(loss='categorical crossentropy',
                       optimizer='rmsprop')
# This `fit` call will be distributed on 8 GPUs.
# Since the batch size is 256, each GPU will process 32 samples.
parallel model.fit(x, y, epochs=20, batch size=256)
```



TPU support

Training + inference

Via Estimator API



Eager execution

Understanding deferred (symbolic) vs. eager (imperative)

Deferred: you use Python to build a computation graph that gets executed later

Eager: the Python runtime is the execution runtime (like Numpy)

In short:

- Symbolic tensors don't have a value in your Python code (yet)
- Eager tensors have a value in your Python code
- With eager execution, you can use value-dependent dynamic topologies (tree-RNNs)

The Keras functional API and Sequential API work with eager execution

```
import keras
from keras import layers
import tensorflow.contrib.eager as tfe
tfe.enable_eager_execution()
inputs = keras.Input(shape=(10,))
x = layers.Dense(20, activation='relu')(x)
x = layers.Dense(20, activation='relu')(x)
outputs = layers.Dense(10, activation='softmax')(x)
model = keras.Model(inputs, outputs)
preds = model(x) # Works on *value arrays*!
model.fit(x, y, epochs=10, batch size=32) # The Model API works too.
```

Eager execution allows you to write imperative custom layers

```
class DynamicLayer(tf.keras.Layer):
  . . .
  def call(self, x):
    print(x) # debug!
    if tf.reduce_sum(x) == 0:
      # dynamic if!
      return x
    for t in x.shape[1]:
      # dynamically iterate over time axis!
      . . .
    return outputs
```

Maximum flexibility: imperative Model subclassing

```
class MyRNN(keras.Model):
   def __init__(self, units=10):
        super(MyRNN, self).__init__(name='my_rnn')
        self.units = units
        self.dense_1 = keras.layers.Dense(units, activation='relu')
        self.dense_2 = keras.layers.Dense(units, activation='relu')
   def call(self, inputs):
        outputs = []
        state = tf.zeros(shape=(inputs.shape[0], self.units))
        for t in range(inputs.shape[1]):
            x = inputs[:, t, :]
            h = self.dense_1(x)
            y = h + self.dense_2(state)
            state = y
            outputs.append(y)
        return tf.concatenate(outputs, axis=1)
```

That's it. Thank you!