

Large-scale deep learning with Keras

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Outline

- Introduction: what's Keras?
- Overview of distributed training, multi-GPU training, & TPU training options
- Example: building a video captioning model with distributed training on Google Cloud

Keras: an API for specifying & training differentiable programs

Keras API

TensorFlow / CNTK / MXNet / Theano / ...

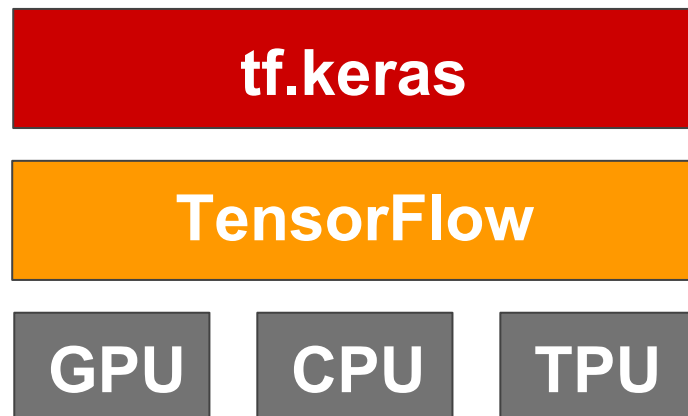
GPU

CPU

TPU

Keras is the high-level model-building 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
 - etc.



What's special about Keras?

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

250,000

Keras developers

Industry traction

NETFLIX

UBER

Google

 instacart

 HUAWEI

 NVIDIA®

 Square

 Expedia®

 Zocdoc

yelp.

etc...

Distributed,
multi-GPU,
& TPU training

Distributed Keras

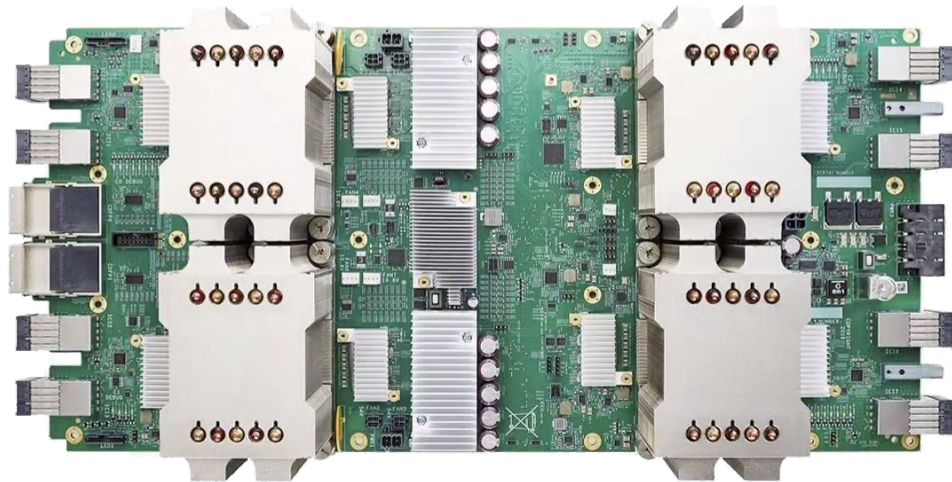
- Uber's Horovod
- TF Estimator API (TF built-in option - only tf.keras)
- Keras on Spark
 - Dist-Keras (from CERN)
 - Elephas

There's also built-in support for single-node, multi-GPU training

TPU support

Only tf.keras

Via Estimator API



Example: building a video captioning model

with distributed training via the TF Estimator API

Toy video-QA problem



> ***"What is the man doing?"***

> **packing**

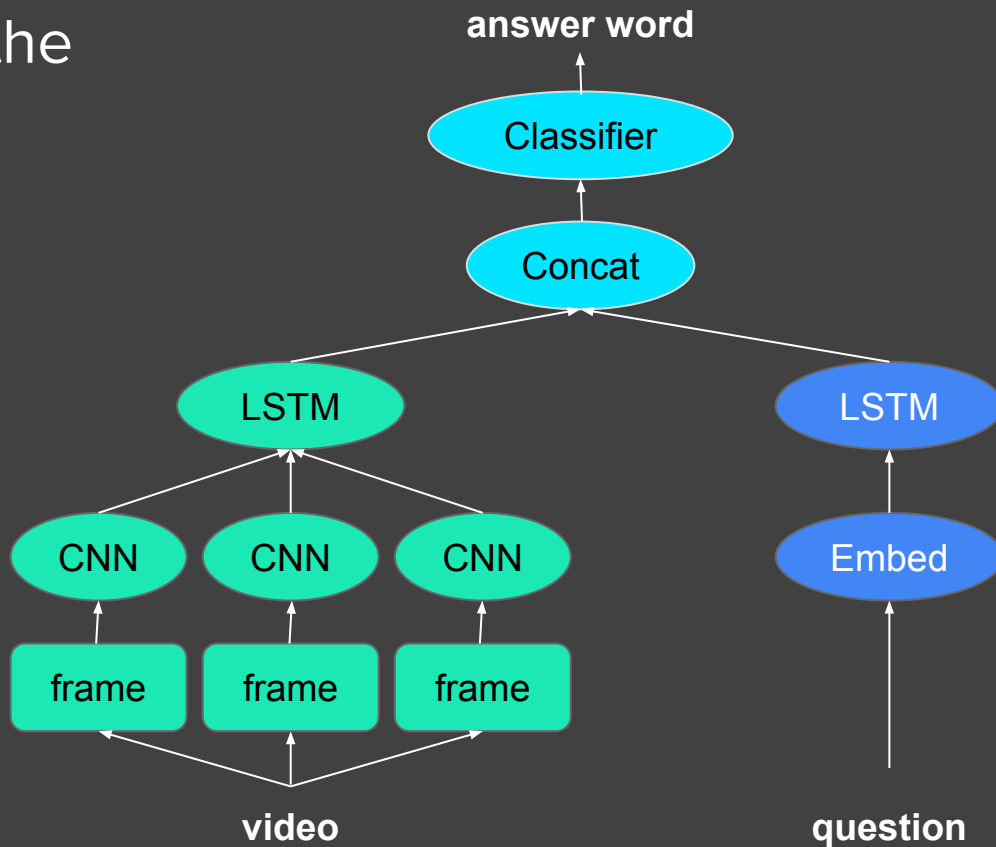
> ***"What color is his shirt?"***

> **blue**

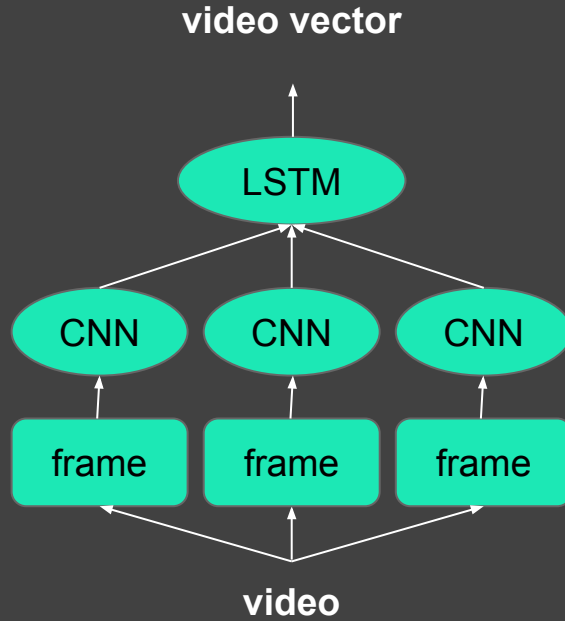
Overview of solution

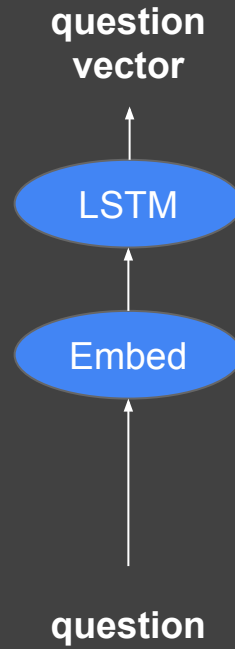
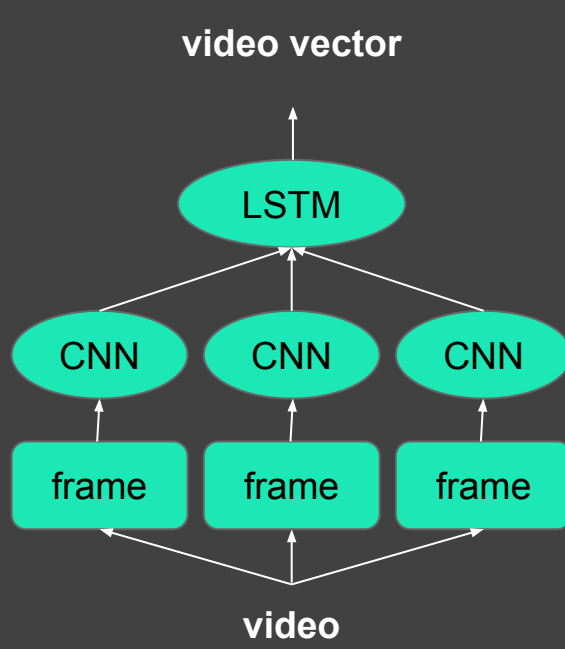
- Design network
- Write `model.py` implementing it (with `tf.keras`)
 - 15 lines for model definition
 - 12 lines for data/training handling
- Package it as a binary
- Upload binary to Google Cloud ML Engine
- Train on arbitrary number of GPUs using asynchronous data parallelism
 - From data stored on Google Cloud

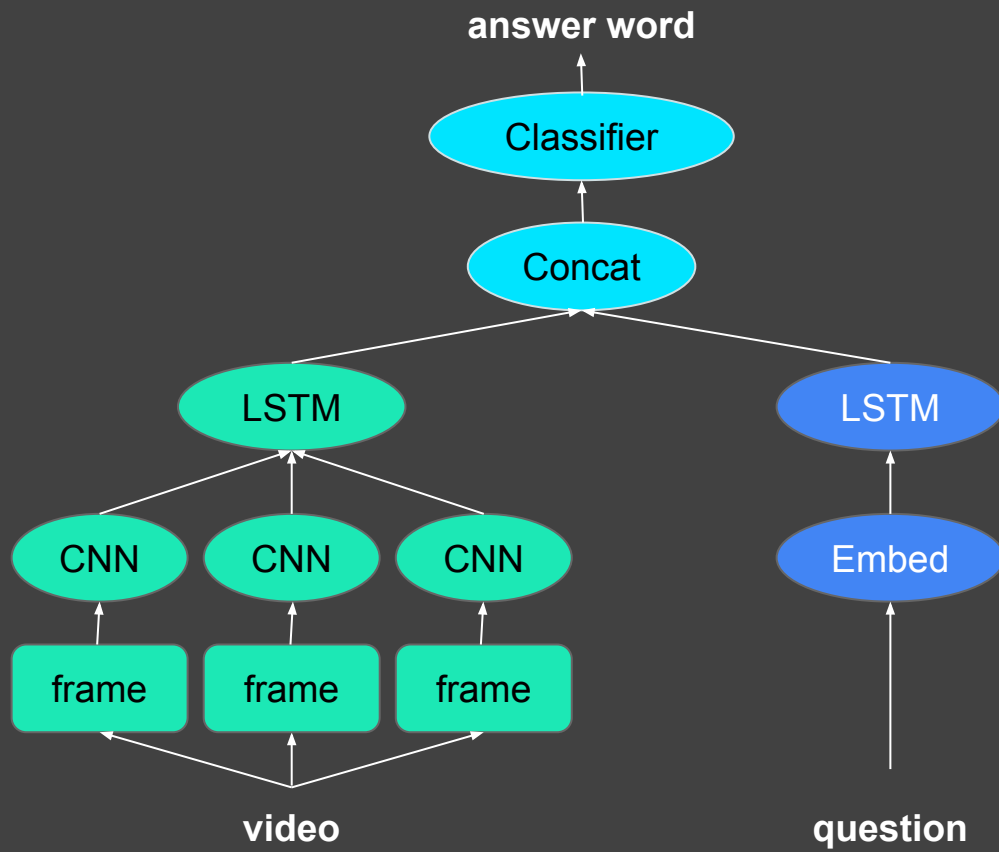
Designing the network

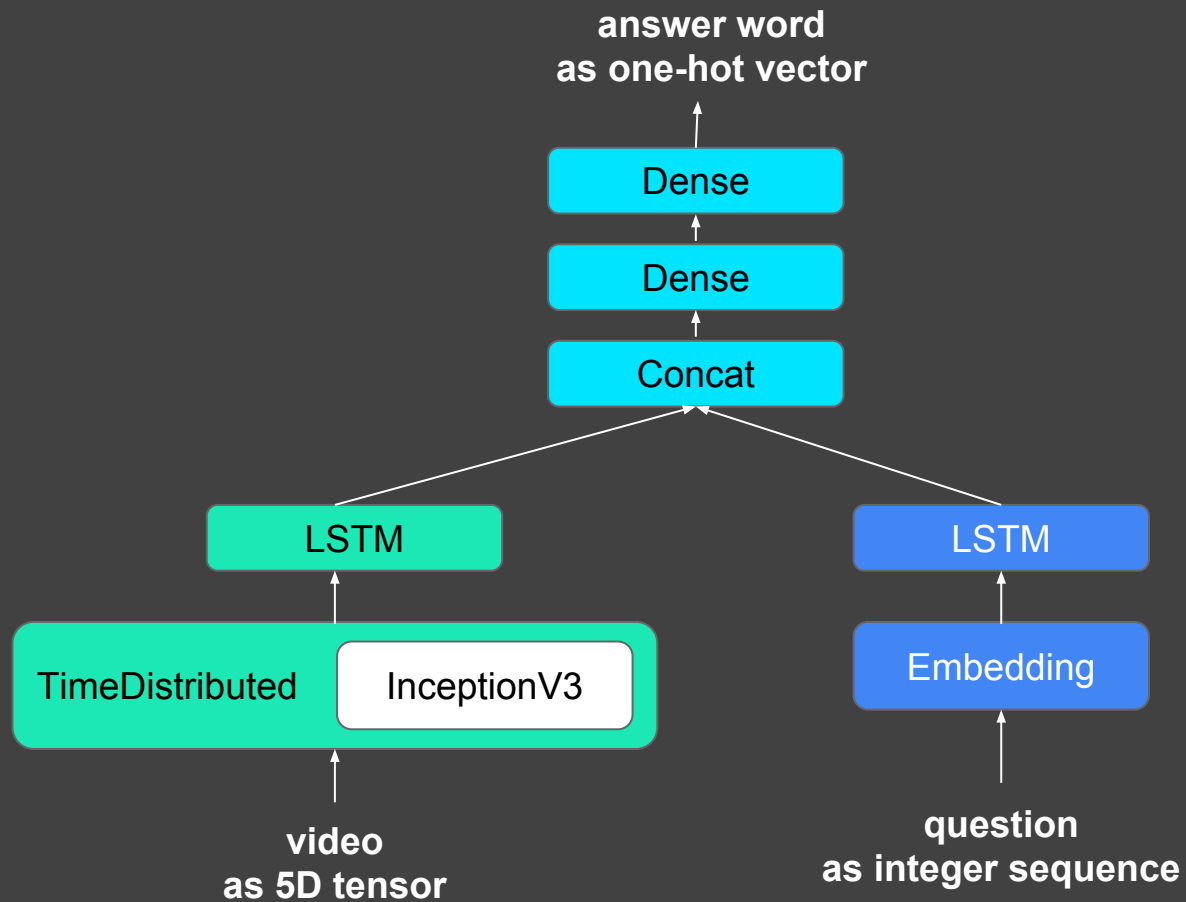


From frames to a vector









Turning frames into a vector,
with pre-trained representations

```
import keras
from keras import layers
from keras.applications import InceptionV3

video = keras.Input(shape=(None, 150, 150, 3), name='video')
cnn = InceptionV3(weights='imagenet',
                  include_top=False,
                  pooling='avg')
cnn.trainable = False
frame_features = layers.TimeDistributed(cnn)(video)
video_vector = layers.LSTM(256)(frame_features)
```

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cnn.trainable = False
frame_features = keras.layers.TimeDistributed(cnn)(video)
video_vector = layers.LSTM(256)(frame_features)
```

Turning a sequence of words into a vector

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


Creating the input function with the TF Dataset API

```
def input_fn(filenamees,  
             epochs=100,  
             batch_size=8):  
    # Parse files and create dataset (omitted)  
    dataset = tf.data.from_tensor_slices(...)  
  
    dataset = dataset.repeat(epochs)  
    dataset = dataset.batch(batch_size)  
    iterator = dataset.make_one_shot_iterator()  
    video, question, labels = iterator.get_next()  
    return {'video': video, 'question': question}, labels
```

Distributed training and evaluation

```
train_input = lambda: input_fn(TRAIN_FILES, batch_size=8)
train_spec = tf.estimator.TrainSpec(train_input, max_steps=10000)

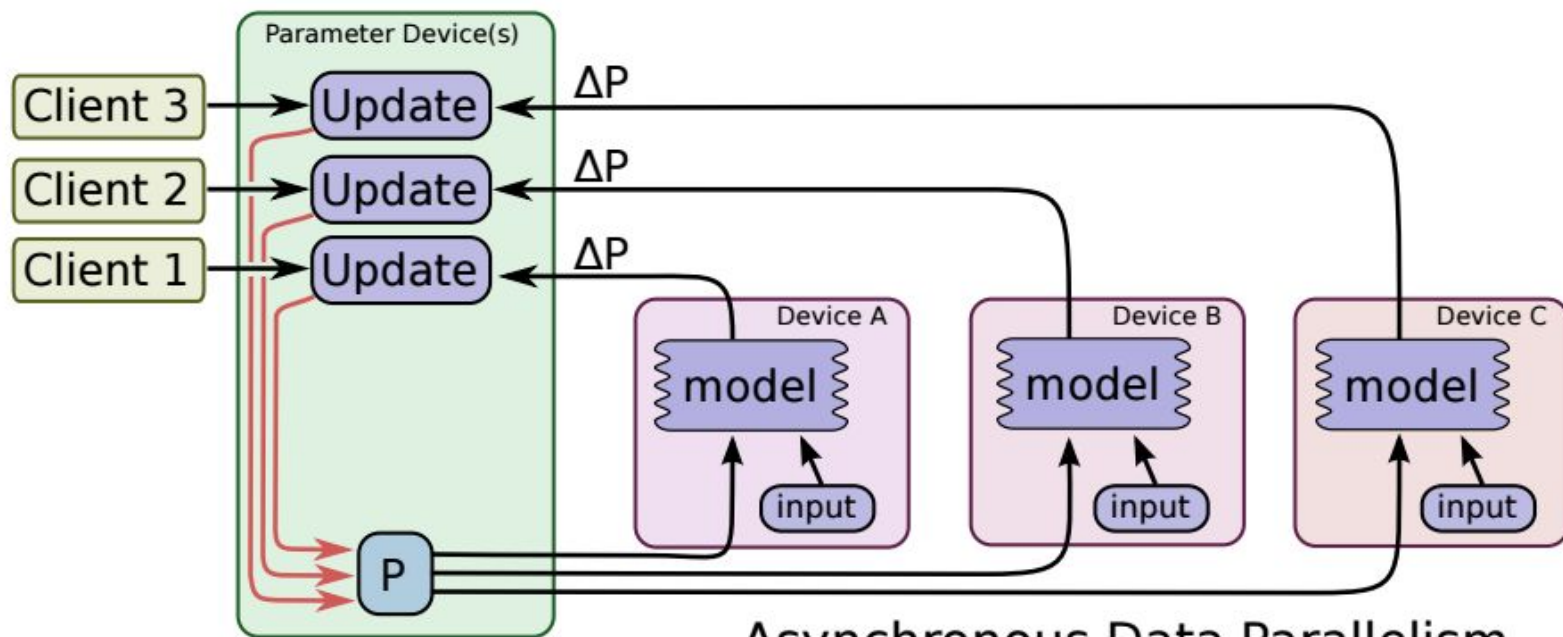
eval_input = lambda: input_fn(EVAL_FILES, batch_size=8)
eval_spec = tf.estimator.TrainSpec(eval_input, steps=100)

tf.estimator.train_and_evaluate(estimator, train_spec, eval_spec)
```

Next: packaging and upload

We'll use a single `gcloud` command to:

- Package our code (and dependencies) into a binary
- Upload the binary to CMLE
- Specify the location of the training data (on GCS)
- Specify a number/type of workers & parameter servers
- Start distributed asynchronous training



Asynchronous Data Parallelism

Start job on Google Cloud

First, we create a project folder:

```
trainer/  
...model.py -> train_and_evaluate  
...task.py -> parses arguments, calls model.py
```

```
gcloud ml-engine jobs submit training $JOB_NAME \  
  --config scaling_config.yaml \  
  --runtime-version 1.4 \  
  --job-dir $GCS_JOB_DIR \  
  --package-path trainer/ \  
  --module-name trainer.task \  
  --region us-central1 \  
  --train-files $GCS_TRAIN_FILE \  
  --eval-files $GCS_EVAL_FILE
```

Scaling configuration in scaling_config.yaml

```
trainingInput:  
  scaleTier: CUSTOM  
  masterType: standard_p100  
  workerType: standard_p100  
  parameterServerType: standard  
  workerCount: 16  
  parameterServerCount: 8
```


Main takeaways from this example

- Concise, easy model definitions with `tf.keras`
 - Including mix-and-matching existing pre-trained models)
- Concise, easy distributed training with TF Estimator API
 - Just configure and call `train_and_evaluate`
- CMLE gives you access to easy scaling of your training jobs
 - Just specify the number & type of workers, parameter servers
- The same code can be run on your own cluster (no lock-in)
 - Can also be run locally for debugging
- Alternatively, you can use Uber's Horovod

Thank you!