Learning Systems 2018:
Lecture 3 – Keras Overview

Crescat scientia; vita excolatur

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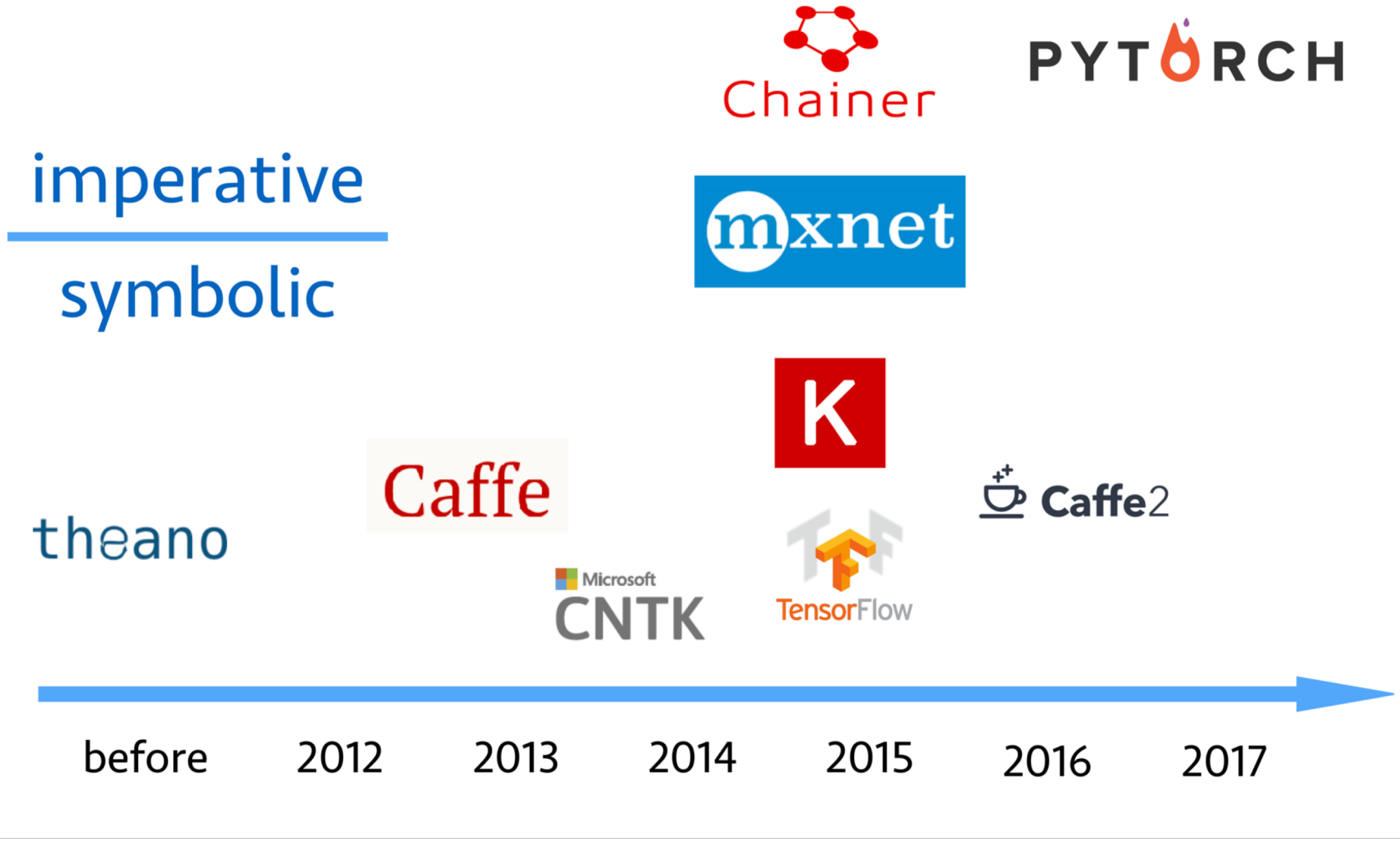
Argonne National Laboratory
The University of Chicago

Many of these slides are adapted from talks from François Chollet and others


Chainer
PYTORCH
imperative
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Caffe
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theano
Microsoft
CNTK
TensorFlow
before
2012
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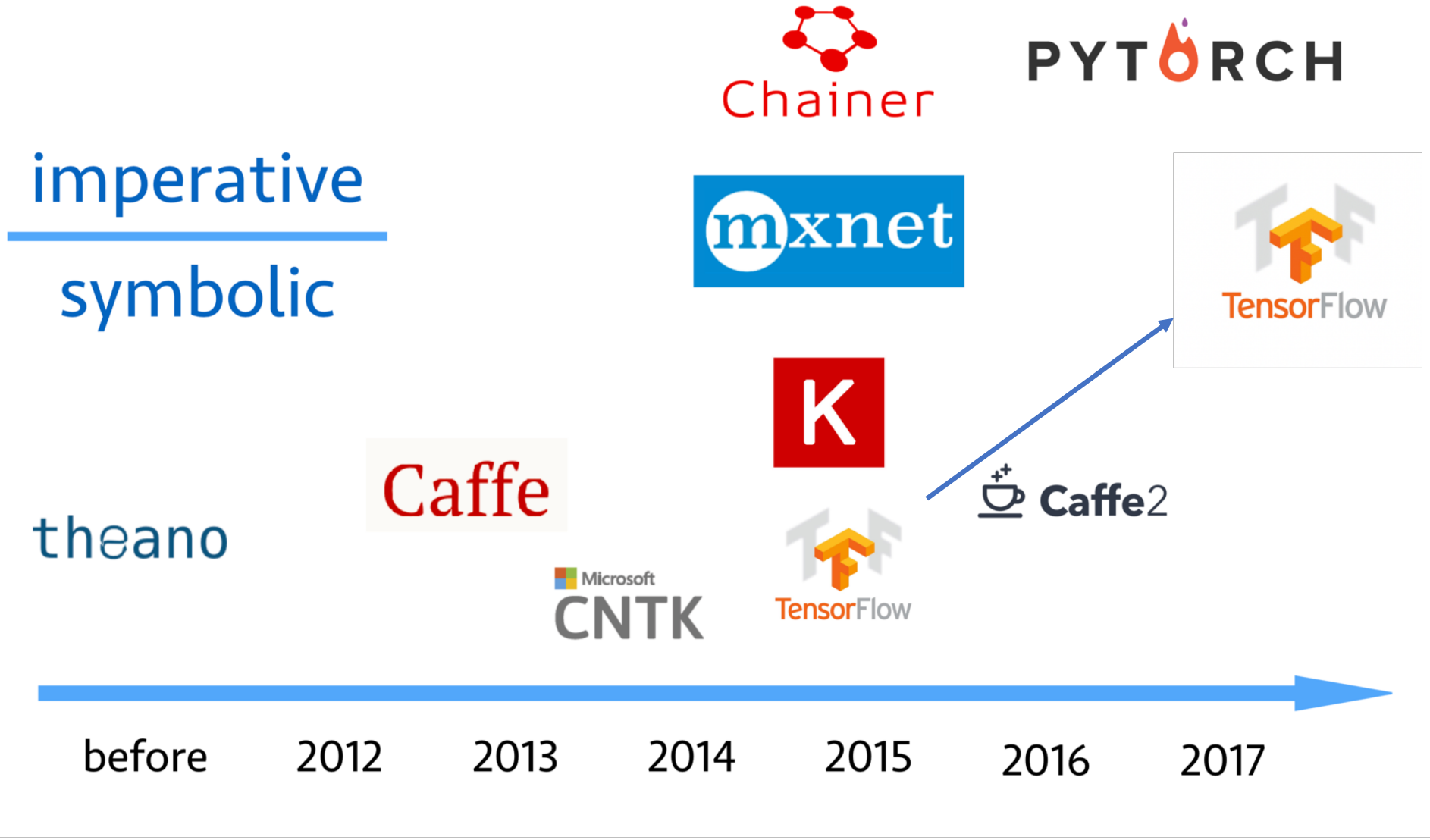
2014
2015
2016
2017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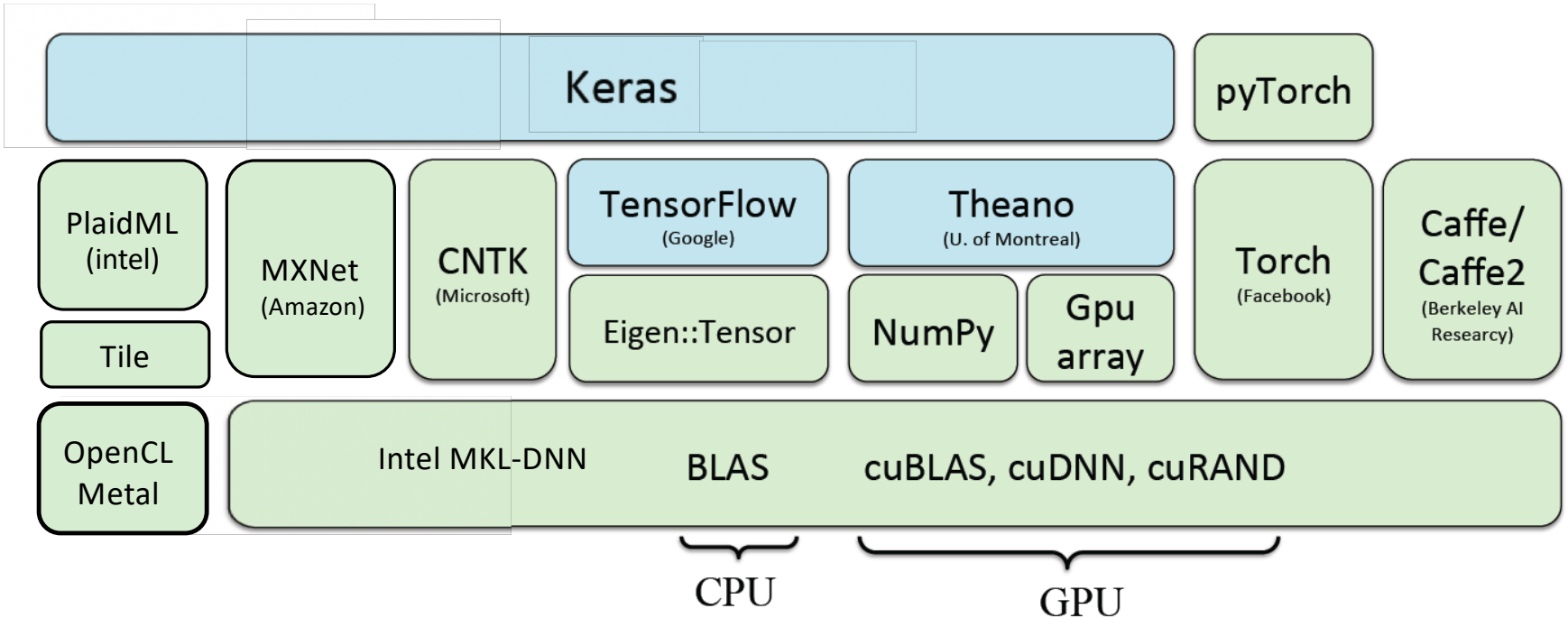
Deep Learning Software Stacks



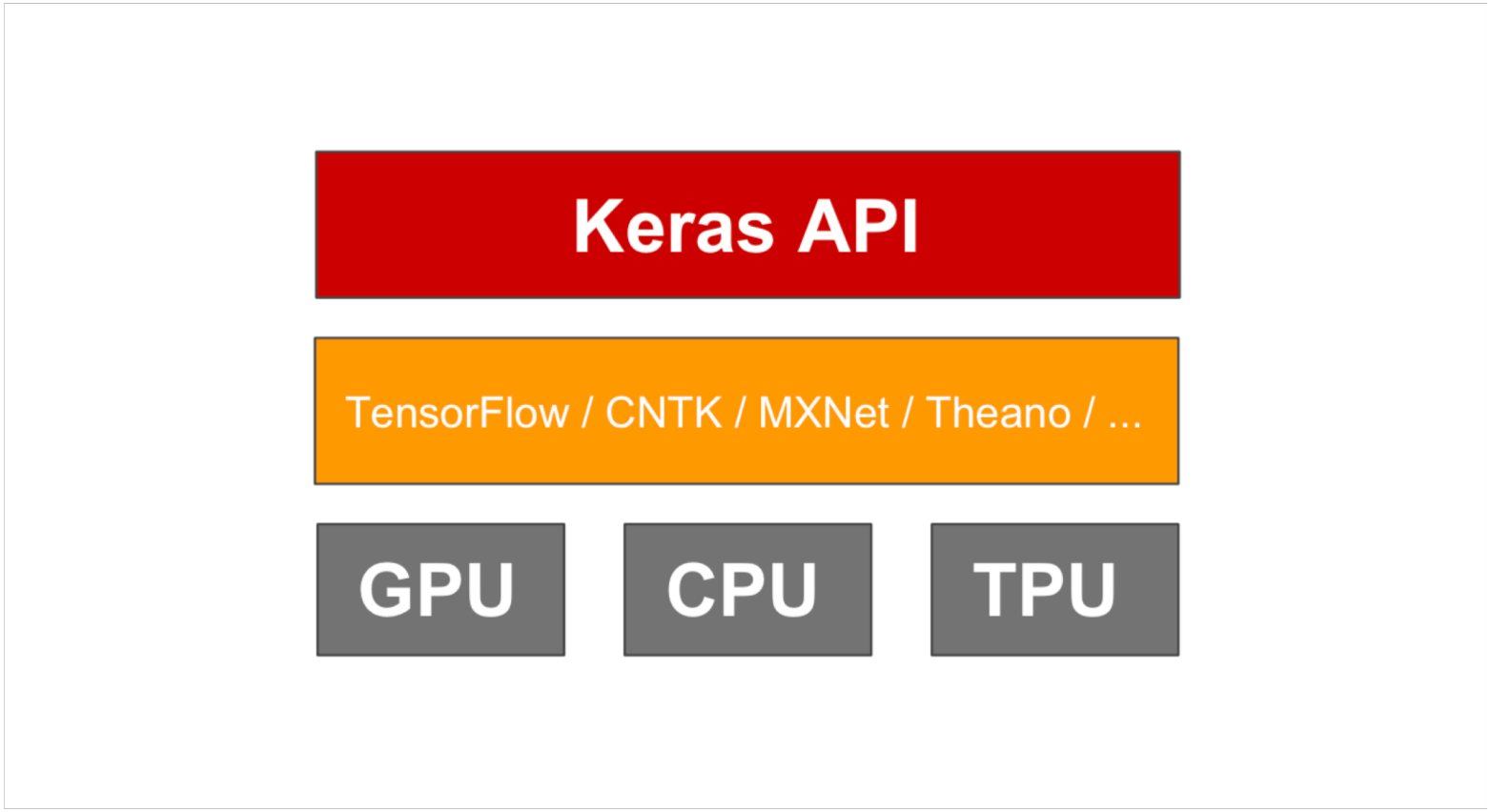
Open Source Framework Comparison

	Languages	Tutorials and training materials	CNN modeling capability	RNN modeling capability	Architecture: easy-to-use and modular front end	Speed	Multiple GPU support	Keras compatible
Theano	Python, C++	++	++	++	+	++	+	+
Tensor-Flow	Python	+++	+++	++	+++	++	++	+
Torch	Lua, Python (new)	+	+++	++	++	+++	++	
Caffe	C++	+	++		+	+	+	
MXNet	R, Python, Julia, Scala	++	++	+	++	++	+++	+
Neon	Python	+	++	+	+	++	+	
CNTK	C++	+	+	+++	+	++	+	+

Introduction to Keras

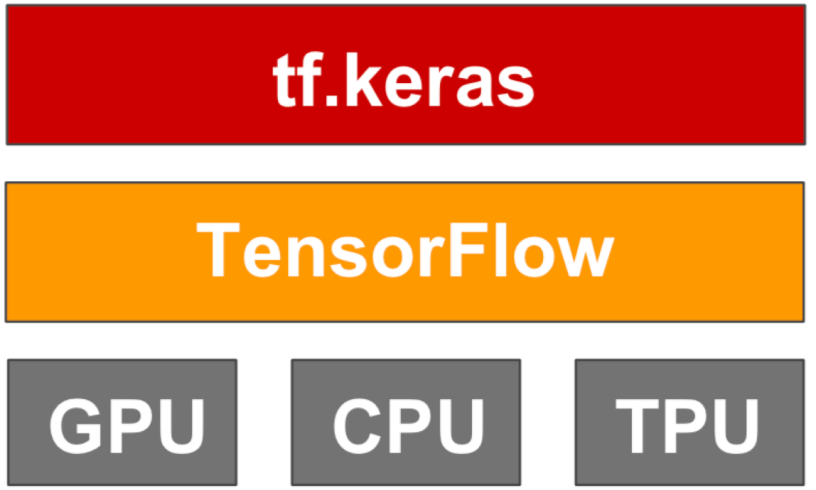
- What is Keras?
  - What are the target use cases
  - TensorFlow Integration
  - Backends for other frameworks
- How to use Keras
  - 3 API Styles
- Distributed, Multi-GPU and TPU Training
- Eager execution (define-by-run, aka dynamic graphs)

Keras: an API for specifying and training differentiable programs



Keras is the “Official” high-level API of TensorFlow (but not the only one)

- 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.



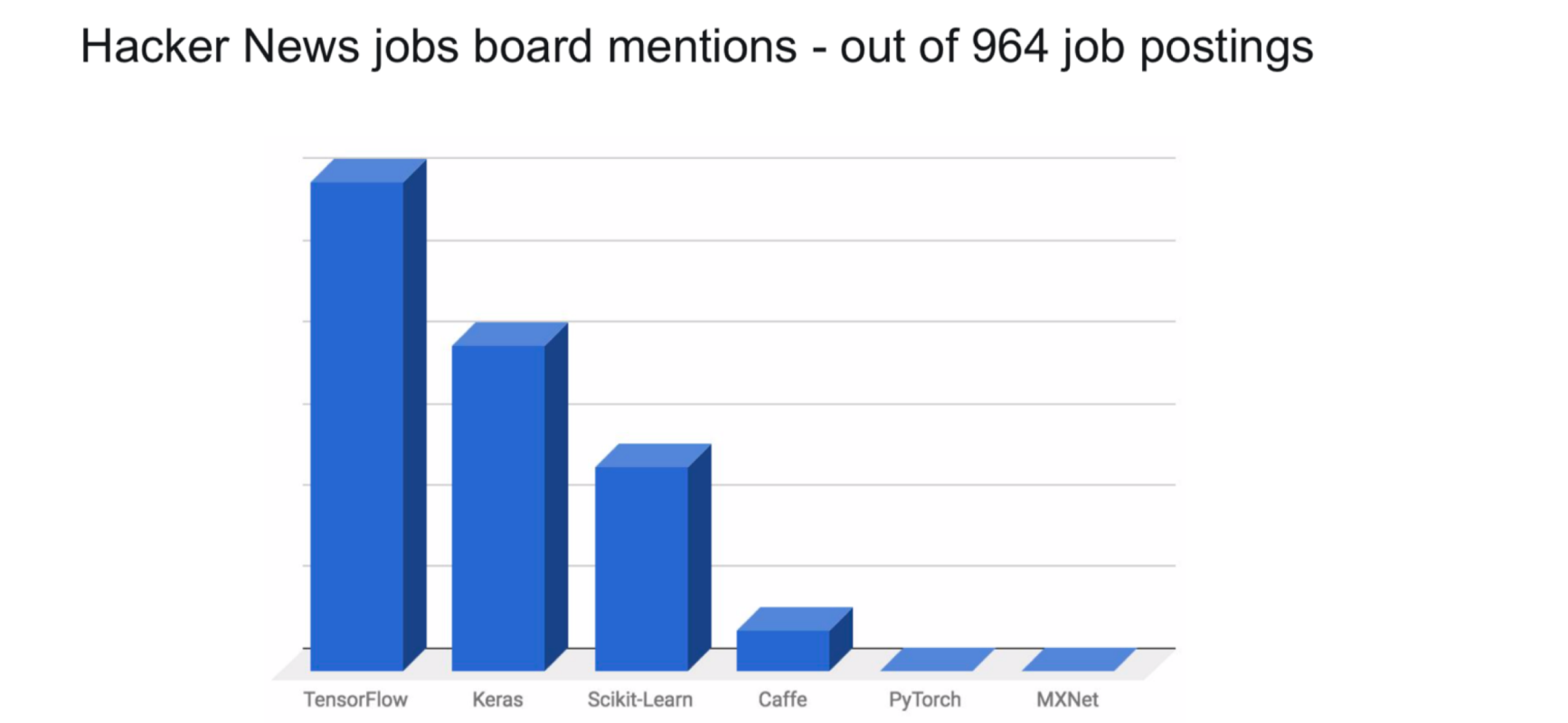
Who makes Keras? Contributors and Backers

How is Keras different?

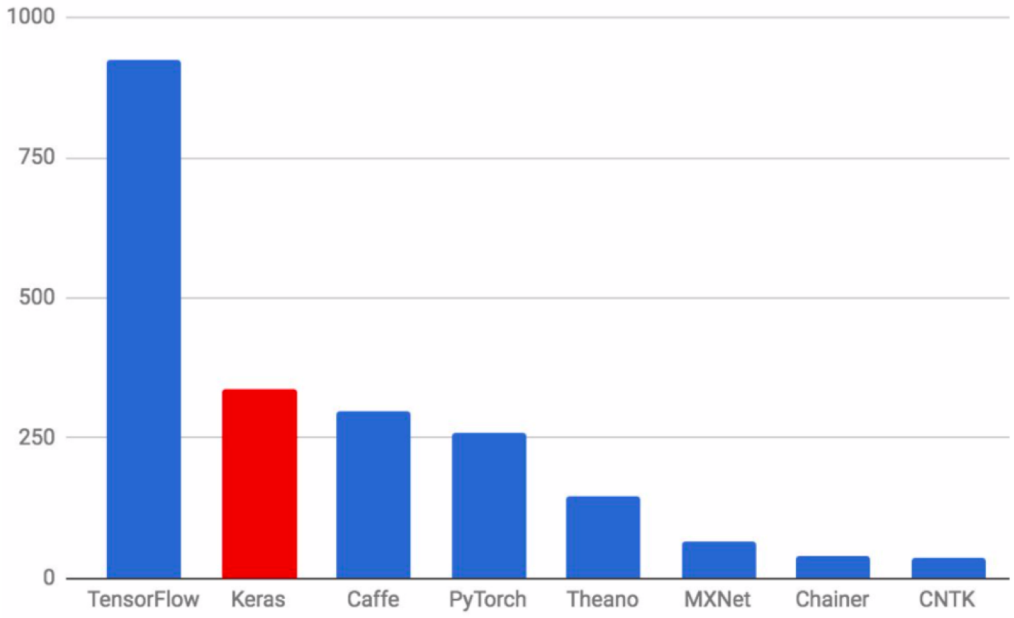
- A focus on user experience
- Large adoption in industry and research community > 250,000 devs
- Multi-backend, multi-platform
- Easy path to productization of models
- Easy learning curve
- Well documented
- Good examples library
- Good pre-trained model library

Adoption by Industry

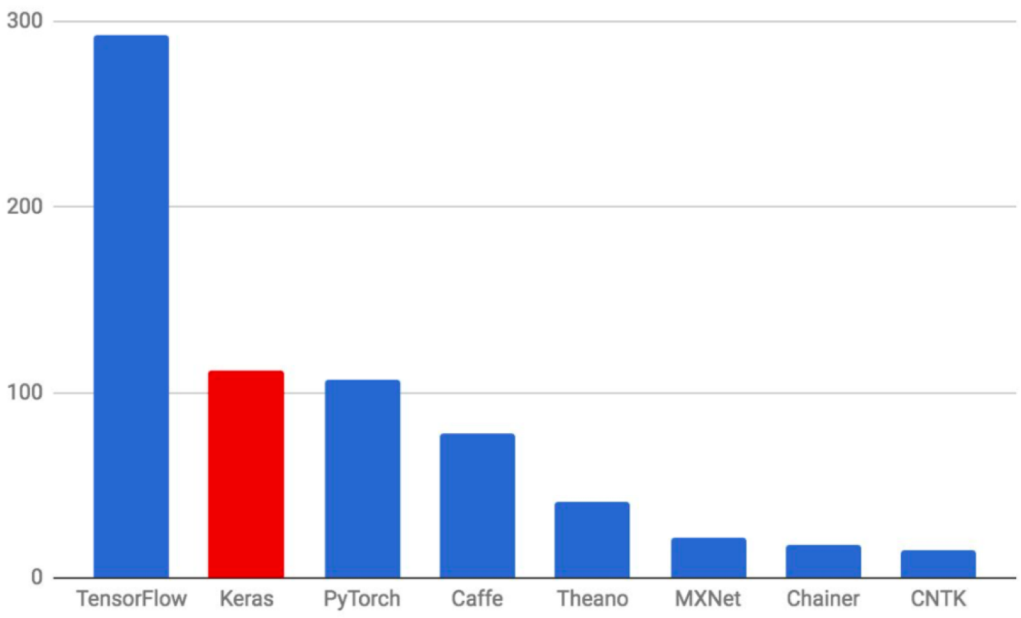
High-Adoption in Startup Land



Adoption in Research Community



arXiv mentions as of 2018/03/07 (past 3 months)



arXiv mentions as of 2018/03/07 (past 1 month)

User Experience is the Primary Goal

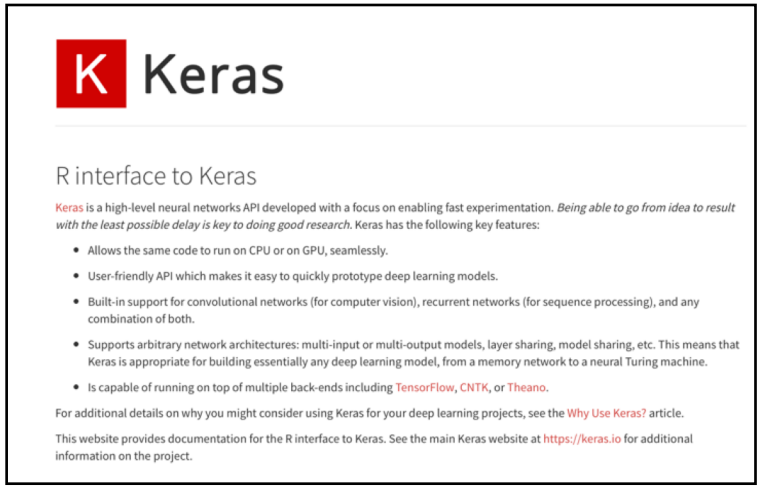
Keras is an API designed for human beings, not machines. Keras follows best practices for reducing cognitive load: it offers consistent & simple APIs, it minimizes the number of user actions required for common use cases, and it provides clear and actionable feedback upon user error.

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 or R
  - Unix, OSX and Windows
- Run the same code (nearly true) on
  - TensorFlow
  - Theano
  - MXNet
  - CNTK
  - PlaidML (☺) (Vertex.ai → Intel Machine Learning Group now)
- Backends run on nearly everything
  - X86/ARM CPU, NVIDIA GPUs, AMD GPUs, TPU, (custom accelerators…)



Large number of options for moving models to production

- TF-serving
- In-Browser with GPU acceleration (WebKeras, Keras.js, WebDNN, …)
- Android (TF, TF Lite), iPhone (native CoreML support)
- Raspberry Pi
- JVM
- via ONNX to other systems

  https://github.com/onnx/onnxmltools

Ex, AR apps with Keras + TF + CoreML + ARKit

How to use Keras: An introduction

Implementing a neural network in Keras

- **Five major steps**
  - Preparing the input and specify the input dimension (size)
  - Define the model architecture and build the computational graph
  - Specify the optimizer and configure the learning process
  - Specify the Inputs, Outputs of the computational graph (model) and the Loss function
  - Train and test the model on the dataset

Note: Gradient calculations are taken care by Auto – Differentiation and parameter updates are done automatically in the backend

Three API styles

- The Sequential Model
  - Super simple
  - Only for single-input, single-output, sequential layer stacks
  - Good for 70+% of use cases
- The functional API
  - Like Lego bricks
  - Multi-input, multi-output, arbitrary static graph topologies
  - Good for 95% of use cases
- Model subclassing (for OO folks that want to drop down)
  - Maximum flexibility
  - Large 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 Sequential API

You need data in X and Y for training

Typically X_train, Y_train and X_test, Y_test

```
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)
```

Compile call, and choice of Optimizer and Loss are omitted here

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):

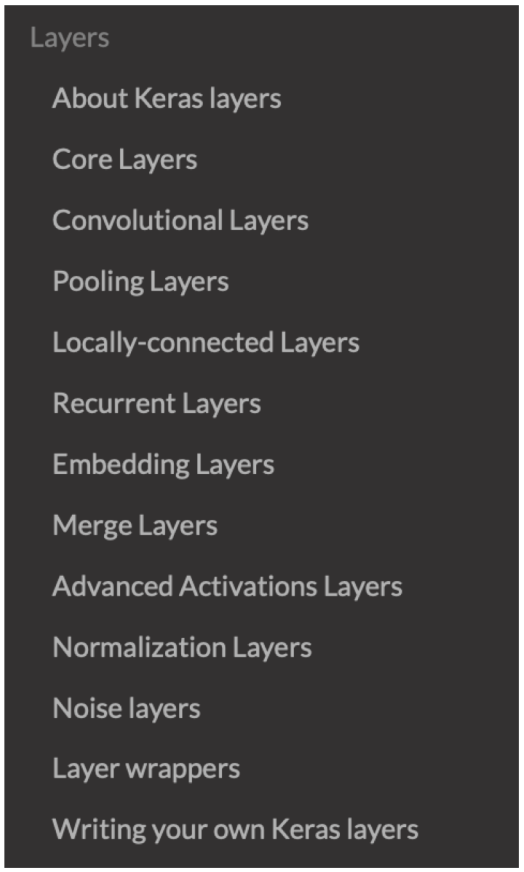
    def __init__(self):
        super(MyModel, self).__init__()
        self.dense1 = layers.Dense(20, activation='relu')
        self.dense2 = layers.Dense(20, activation='relu')
        self.dense3 = layers.Dense(10, activation='softmax')

    def call(self, inputs):
        x = self.dense1(x)
        x = self.dense2(x)
        return self.dense3(x)

model = MyModel()
model.fit(x, y, epochs=10, batch_size=32)
```

High-Level Keras Elements

- Models
- Layers
- Preprocessing Data
- Loss functions
- Metrics (for reporting)
- Optimizers
- Activations
- Callbacks
- Datasets
- Applications



Losses

- Usage of loss functions
- Available loss functions
- mean_squared_error
- mean_absolute_error
- mean_absolute_percentage_error
- mean_squared_logarithmic_error
- squared_hinge
- hinge
- categorical_hinge
- logcosh
- categorical_crossentropy
- sparse_categorical_crossentropy
- binary_crossentropy
- kullback_leibler_divergence
- poisson
- cosine_proximity

Metrics

- Usage of metrics
- Arguments
- Returns
- Available metrics
- binary_accuracy
- categorical_accuracy
- sparse_categorical_accuracy
- top_k_categorical_accuracy
- sparse_top_k_categorical_accuracy
- Custom metrics

Utils

- CustomObjectScope
- HDF5Matrix
- Sequence
- to_categorical
- normalize
- get_file
- print_summary
- plot_model
- multi_gpu_model

Preprocessing

- Sequence Preprocessing
- Text Preprocessing
- Image Preprocessing

Optimizers

- Usage of optimizers
- Parameters common to all Keras optimizers
- SGD
- RMSprop
- Adagrad
- Adadelta
- Adam
- Adamax
- Nadam

Activations

- Usage of activations
- Available activations
- softmax
- elu
- selu
- softplus
- softsign
- relu
- tanh
- sigmoid
- hard_sigmoid
- exponential
- linear
- On "Advanced Activations"

Callbacks

- Usage of callbacks
- Callback
- BaseLogger
- TerminateOnNaN
- ProgbarLogger
- History
- ModelCheckpoint
- EarlyStopping
- RemoteMonitor
- LearningRateScheduler
- TensorBoard
- ReduceLROnPlateau
- CSVLogger
- LambdaCallback
- Create a callback
- Example: recording loss history
- Example: model checkpoints

Datasets

- Datasets
- CIFAR10 small image classification
- CIFAR100 small image classification
- IMDB Movie reviews sentiment classification
- Reuters newswire topics classification
- MNIST database of handwritten digits
- Fashion-MNIST database of fashion articles
- Boston housing price regression dataset

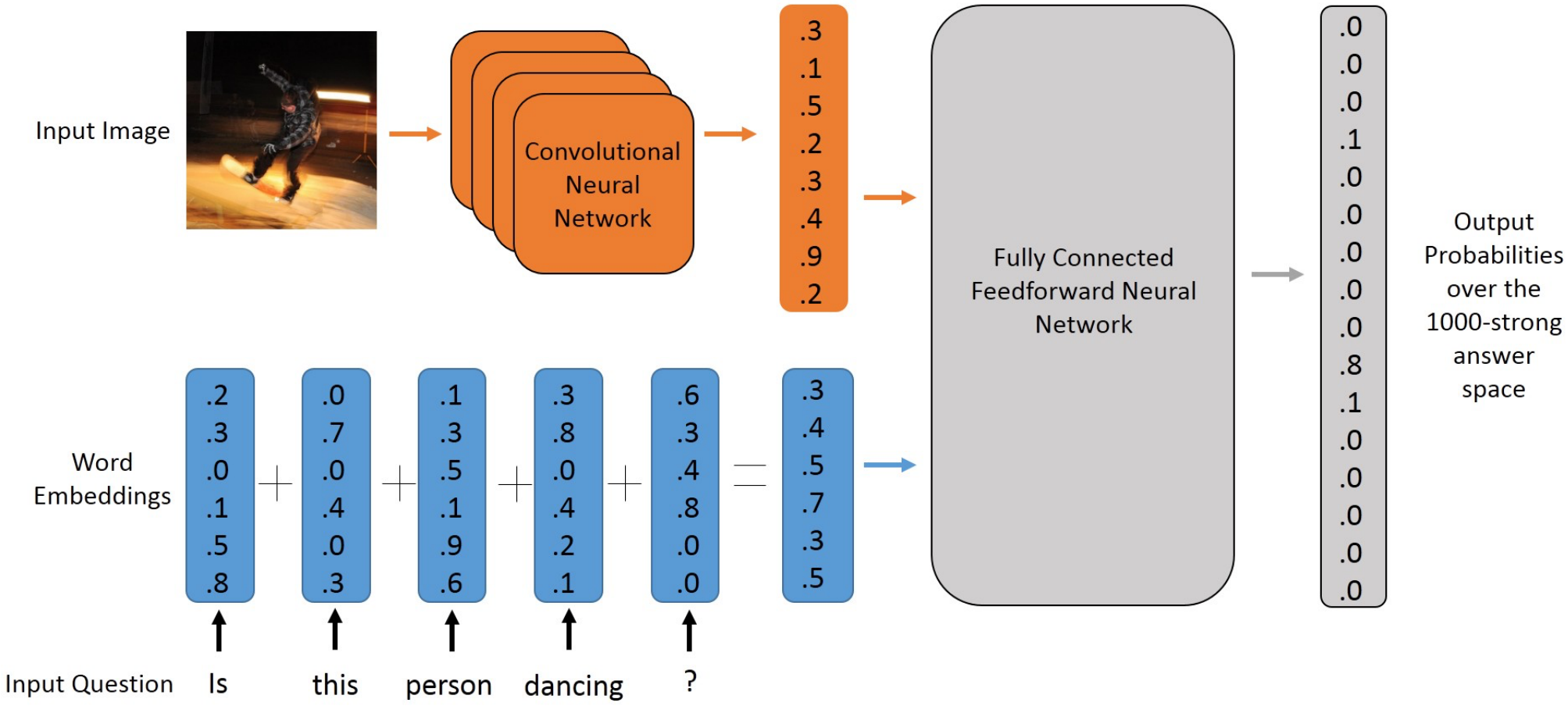
Applications

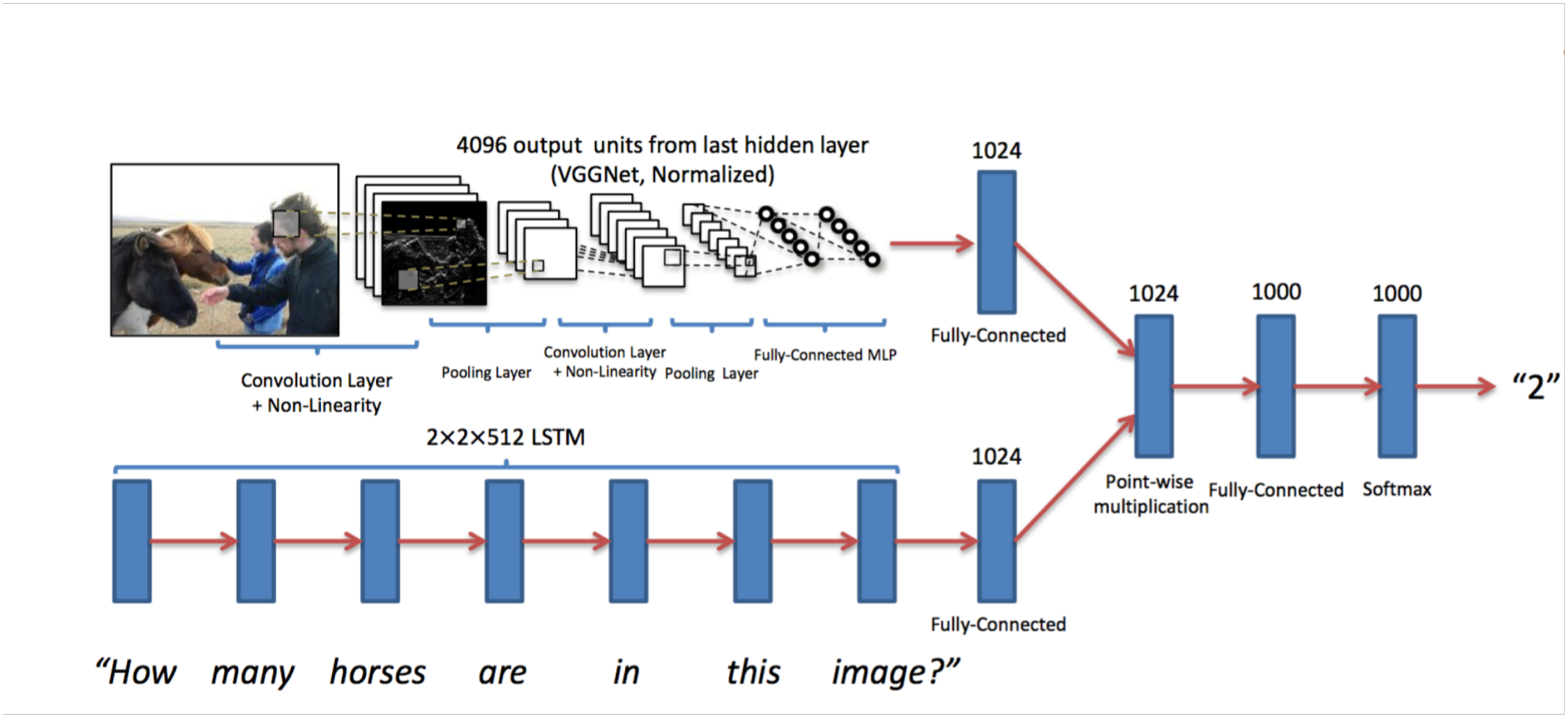
- Applications
- Available models
- Usage examples for image classification models
- Documentation for individual models
- Xception
- VGG16
- VGG19
- ResNet50
- InceptionV3
- InceptionResNetV2
- MobileNet
- DenseNet
- NASNet
- MobileNetV2

Initializers

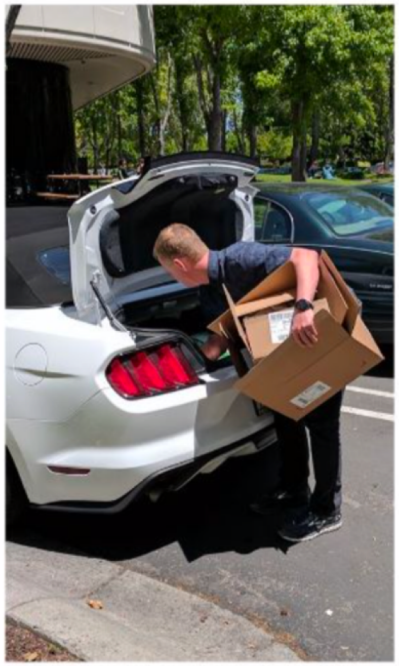
- Usage of initializers
- Available initializers
- Initializer
- Zeros
- Ones
- Constant
- RandomNormal
- RandomUniform
- TruncatedNormal
- VarianceScaling
- Orthogonal
- Identity
- lecun_uniform
- glorot_normal
- glorot_uniform
- he_normal
- lecun_normal
- he_uniform
- Using custom initializers

Example: building a video captioning model


Input Image
Convolutional Neural Network
.3
.1
.5
.2
.3
.4
.9
.2
Fully Connected Feedforward Neural Network
.0
.0
.0
.1
.0
.0
.0
.0
.0
.8
.1
.0
.0
.0
.0
Output Probabilities over the 1000-strong answer space
Word Embeddings
.2 .3 .0 .1 .5 .8
.0 .7 .0 .4 .0 .3
.1 .3 .5 .1 .9 .6
.3 .8 .0 .4 .2 .1
.6 .3 .4 .8 .0 .0
.3 .4 .5 .7 .3 .5
Input Question
Is
this
person
dancing
?

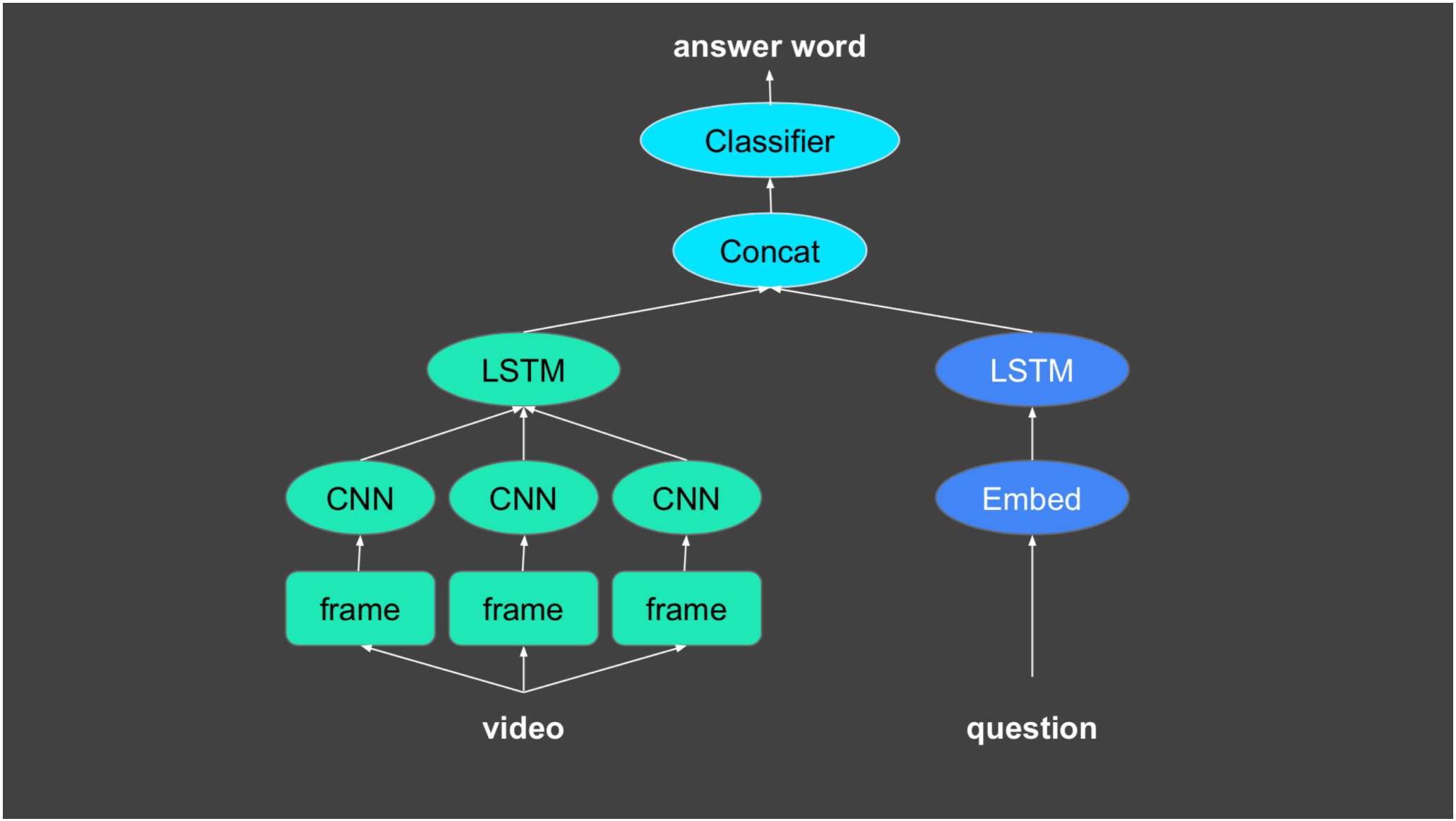

4096 output units from last hidden layer
(VGGNet, Normalized)
1024
Convolution Layer
+ Non-Linearity
Pooling Layer
Convolution Layer
+ Non-Linearity
Pooling Layer
Fully-Connected MLP
Fully-Connected
1024
1000
1000
"2"
2×2×512 LSTM
1024
Point-wise
multiplication
Fully-Connected
Softmax
Fully-Connected
"How many horses are in this image?"

Toy video-QA problem

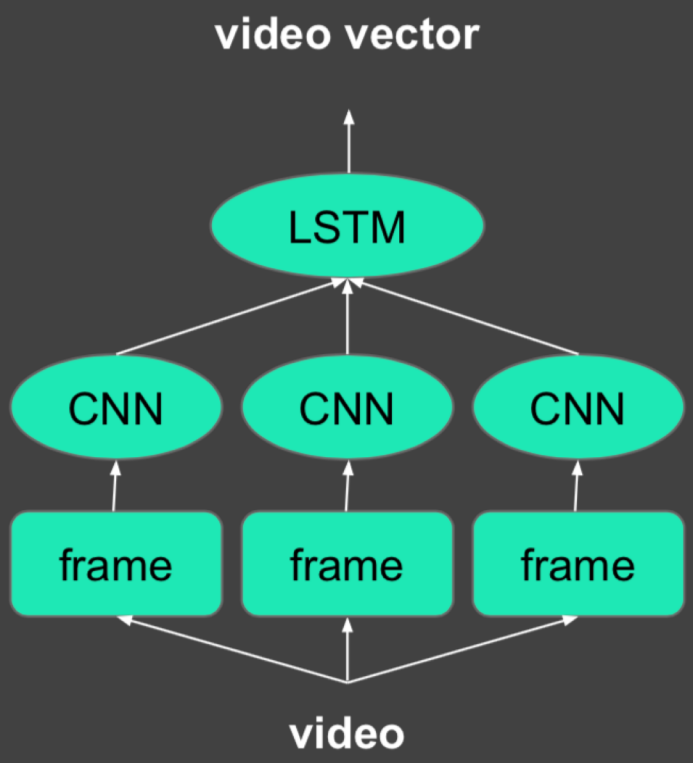



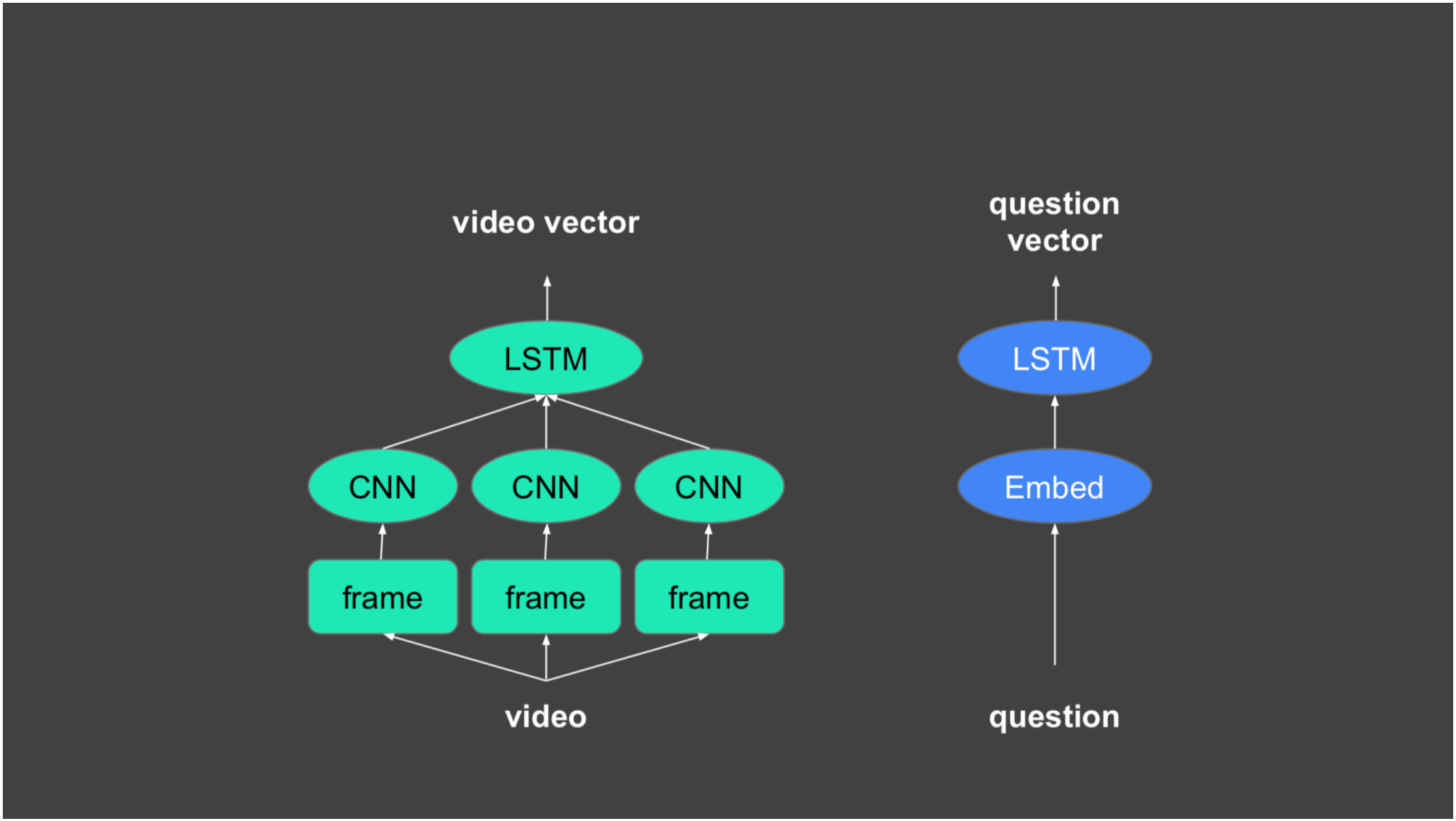

> ***"What is the man doing?"***
> packing

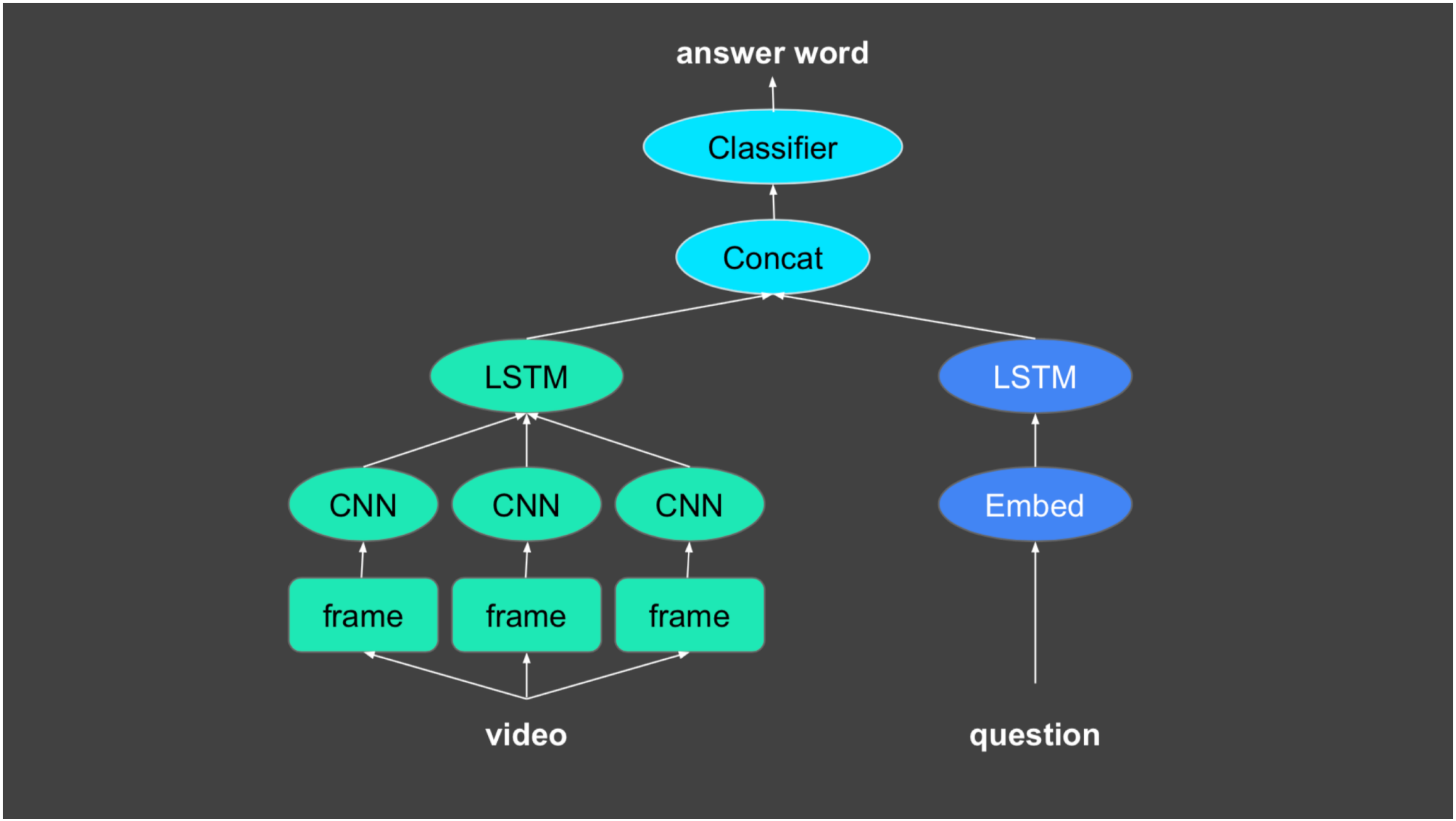
> ***"What color is his shirt?"***
> blue

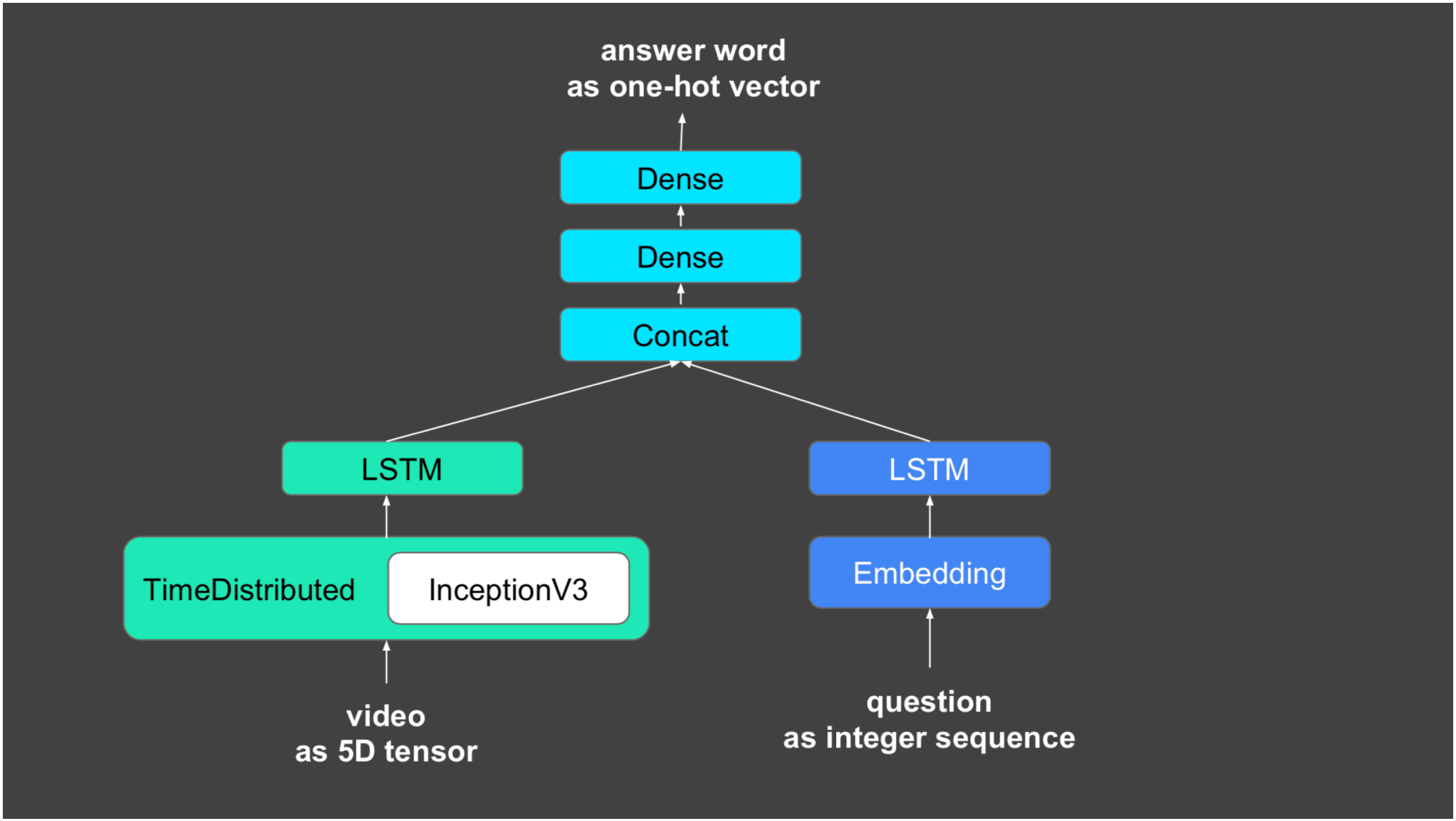

answer word
Classifier
Concat
LSTM
LSTM
CNN
CNN
CNN
Embed
frame
frame
frame
video
question

from frames to a vector




video vector
LSTM
CNN
CNN
CNN
frame
frame
frame
video
question vector
LSTM
Embed
question


answer word
Classifier
Concat
LSTM
LSTM
CNN
CNN
CNN
Embed
frame
frame
frame
video
question


answer word
as one-hot vector
Dense
Dense
Concat
LSTM
LSTM
TimeDistributed
InceptionV3
Embedding
video
as 5D tensor
question
as integer sequence

Turning frames into a vector, with pre-trained representations

Keras Functional API

```
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)
```

Pretrained “Application”

“Application” read only

Built in layer types

Turning frames into a vector, with pre-trained representations

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"Application" read only

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"Application" read only

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"Application" read only

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                  include_top=False,
                  pooling='avg')
cnn.trainable = False
frame_features = 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 = layers.Embedding(input_voc_size, 256)(question)
question_vector = layers.LSTM(128)(embedded_words)
```

Predicting an answer word

```
x = layers.concatenate([video_vector, question_vector])
x = layers.Dense(128, activation=tf.nn.relu)(x)
predictions = layers.Dense(output_voc_size,
                           activation='softmax',
                           name='predictions')(x)
```

Tensorflow call

Setting up the training configuration

```
model = keras.models.Model([video, question], predictions)
model.compile(optimizer=tf.AdamOptimizer(),
              loss=keras.losses.categorical_crossentropy)

model.fit_generator(data_generator,
                    steps_per_epoch=1000,
                    epochs=100)
```

Tensorflow call

Data_generator streams data too large to fit into memory

https://stanford.edu/~shervine/blog/keras-how-to-generate-data-on-the-fly

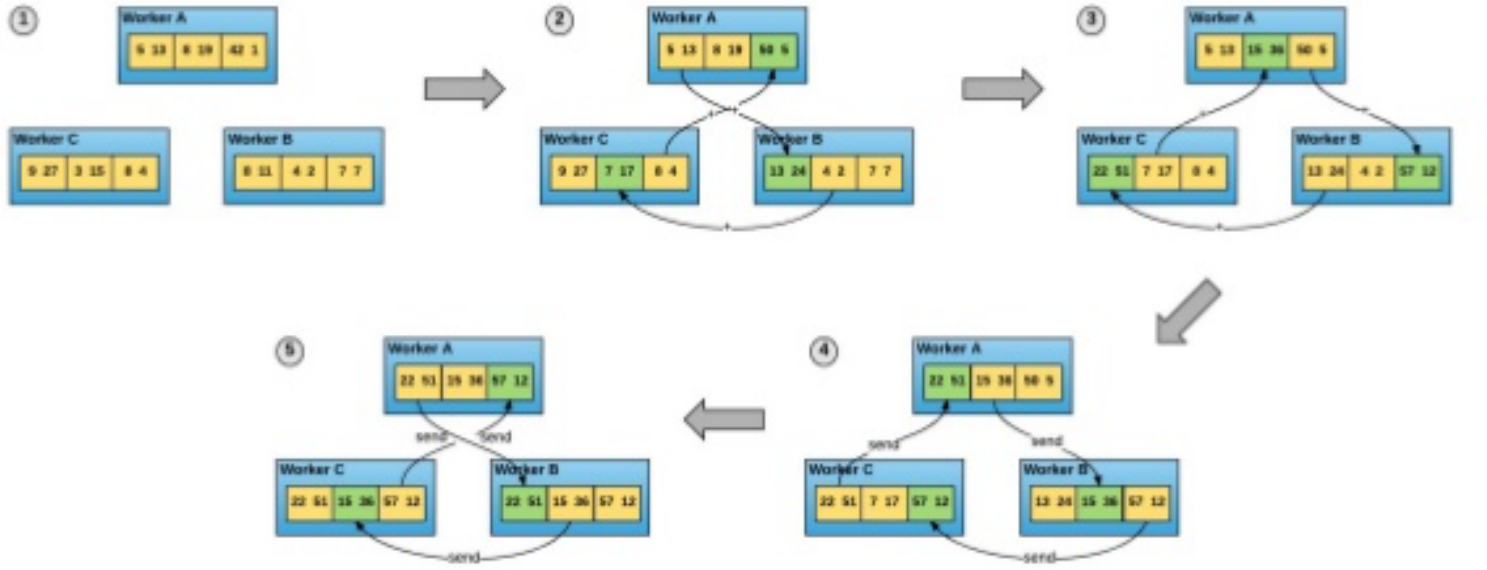

Distributed,
multi-GPU,
& TPU training

Data Parallel (Distributed Training)

- Horovod (from Uber)
- Estimator API (TF built-in option)
- Dist-Keras (Spark)
  - Elephas (Spark)

- Built-in Muli-GPU support (requires multiple GPUs in one address space, such as on a DGX workstation

Horovod Technique



Patarasuk, P., & Yuan, X. (2009). Bandwidth optimal all-reduce algorithms for clusters of workstations. *Journal of Parallel and Distributed Computing*, 69(2), 117-124. doi:10.1016/j.jpdc.2008.09.002

UBER

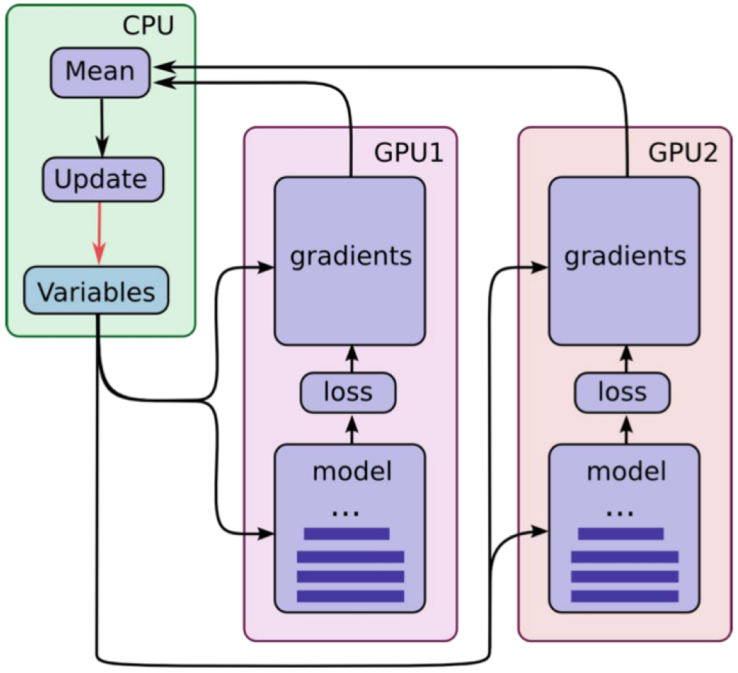
Built-in Multi-GPU support

```
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)
```

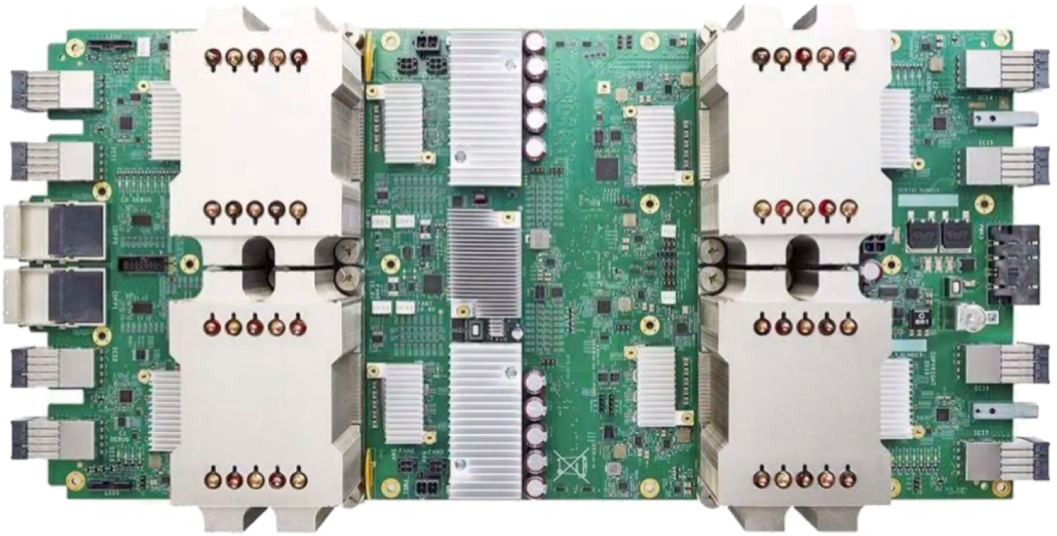



DGX STATION
TESLA
TESLA
TESLA
TESLA
NVIDIA

TPU support

Training + inference

Via Estimator API




A
B
C
D

Deferred (symbolic) vs eager (Imperative)

- **Deferred**: you use Python to build a computational graph that gets executed later
- **Eager**: the Python runtime is the execution runtime (like Numpy)

- In brief:
  - 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 dynamics topologies (tree-RNNs, etc.)

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

- Eager execution is a flexible machine learning platform for research and experimentation, providing:
- *An intuitive interface*—Structure your code naturally and use Python data structures. Quickly iterate on small models and small data.
- *Easier debugging*—Call ops directly to inspect running models and test changes. Use standard Python debugging tools for immediate error reporting.
- *Natural control flow*—Use Python control flow instead of graph control flow, simplifying the specification of dynamic models.

Dynamic Network Surgery for Efficient DNNs

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Abstract

Deep learning has become a ubiquitous technology to improve machine intelligence. However, most of the existing deep models are structurally very complex, making them difficult to be deployed on the mobile platforms with limited computational power. In this paper, we propose a novel network compression method called dynamic network surgery, which can remarkably reduce the network complexity by making on-the-fly connection pruning. Unlike the previous methods which accomplish this task in a greedy way, we properly incorporate connection splicing into the whole process to avoid incorrect pruning and make it as a continual network maintenance. The effectiveness of our method is proved with experiments. Without any accuracy loss, our method can efficiently compress the number of parameters in LeNet-5 and AlexNet by a factor of $\mathbf{108}\times$ and $\mathbf{17.7}\times$ respectively, proving that it outperforms the recent pruning method by considerable margins. Code and some models are available at https://github.com/yiwenguo/Dynamic-Network-Surgery.

1 Introduction

As a family of brain inspired models, deep neural networks (DNNs) have substantially advanced a variety of artificial intelligence tasks including image classification [13, 19, 11], natural language processing, speech recognition and face recognition.

Despite these tremendous successes, recently designed networks tend to have more stacked layers, and thus more learnable parameters. For instance, AlexNet [13] designed by Krizhevsky et al. has 61 million parameters to win the ILSVRC 2012 classification competition, which is over 100 times more than that of LeCun's conventional model [15] (e.g., LeNet-5), let alone the much more complex models like VGGNet [19]. Since more parameters means more storage requirement and more floating-point operations (FLOPs), it increases the difficulty of applying DNNs on mobile platforms with limited memory and processing units. Moreover, the battery capacity can be another bottleneck [9].

Although DNN models normally require a vast number of parameters to guarantee their superior performance, significant redundancies have been reported in their parameterizations [4]. Therefore, with a proper strategy, it is possible to compress these models without significantly losing their prediction accuracies. Among existing methods, network pruning appears to be an outstanding one due to its surprising ability of accuracy loss prevention. For instance, Han et al. [9] recently propose to