O'REILLY®
TensorFlow World

PRESENTED WITH TensorFlow

Intro to TensorFlow 2.0

Easier for beginners, more powerful for experts

Josh Gordon

twitter.com/random_forests

These are the slides from this talk

https://www.youtube.com/watch?v=5ECD8J3dvDQ

Functions, not sessions

TF1

```
a = tf.constant(5)

b = tf.constant(3)

c = a * b
```

Symbolic

```
with tf.Session() as sess:

  print(sess.run(c))
```

TF2

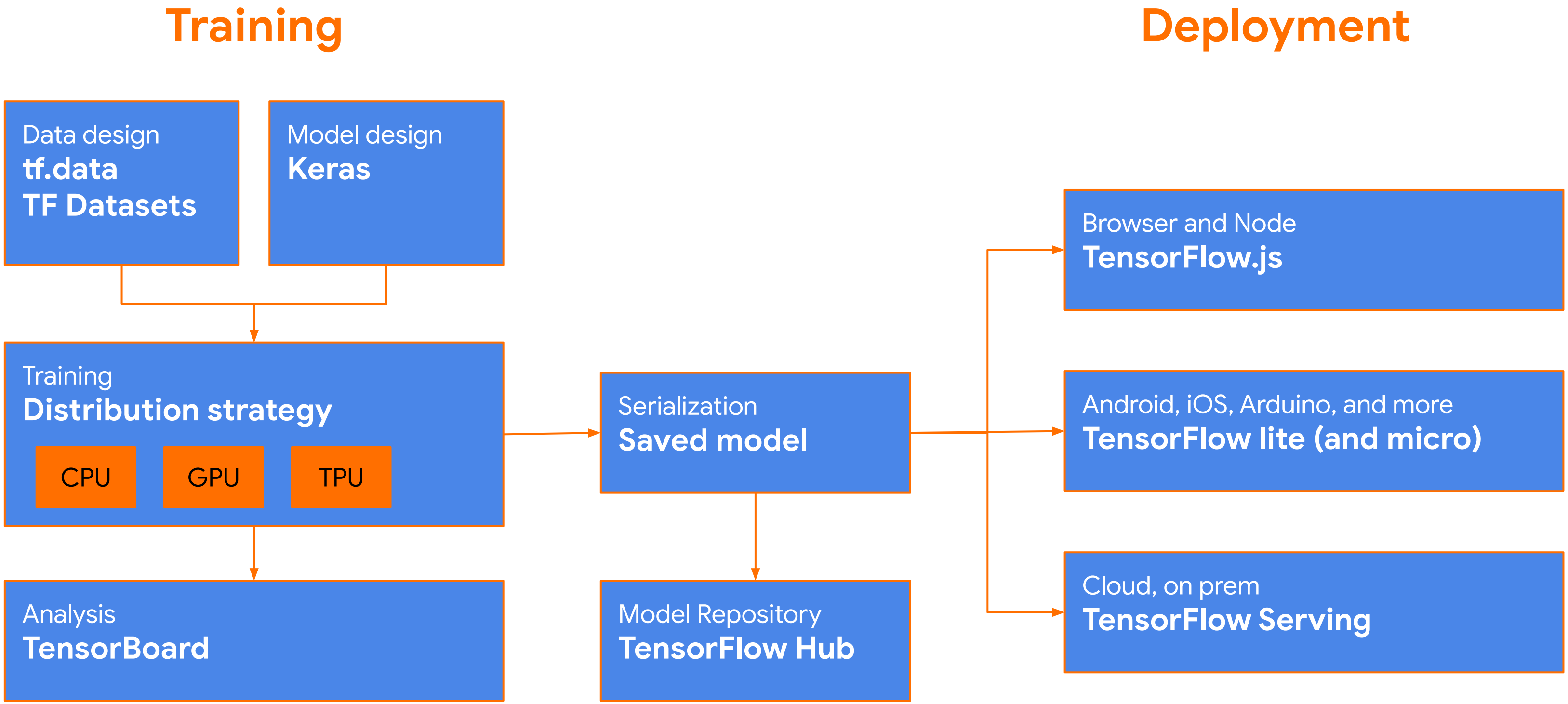
```
a = tf.constant(5)

b = tf.constant(3)

c = a * b
```

Concrete

```
print(c)
```



Training

Deployment

Data design
tf.data
TF Datasets

Model design
Keras

Training
Distribution strategy

CPU
GPU
TPU

Analysis
TensorBoard

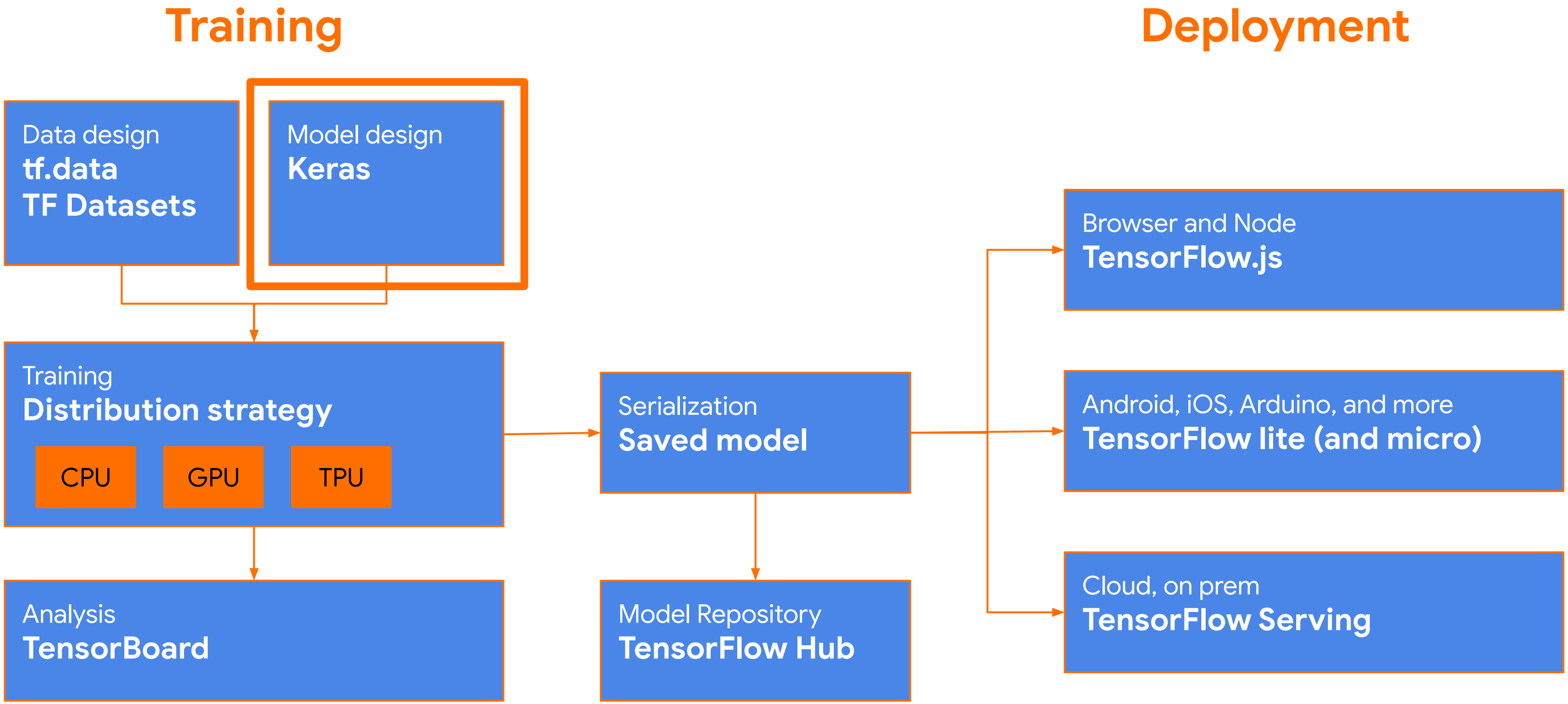
Serialization
Saved model

Model Repository
TensorFlow Hub

Browser and Node
TensorFlow.js

Android, iOS, Arduino, and more
TensorFlow lite (and micro)

Cloud, on prem
TensorFlow Serving



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Model building: from simple to arbitrarily flexible

Progressive disclosure of complexity

Sequential API
+ built-in layers

New users,
simple models

Functional API
+ built-in layers

Engineers with
standard use
cases

Functional API
- **+ Custom layers**
- **+ Custom metrics**
- **+ Custom losses**

Engineers
requiring
increasing
control

Subclassing: write
everything yourself
from scratch

Researchers

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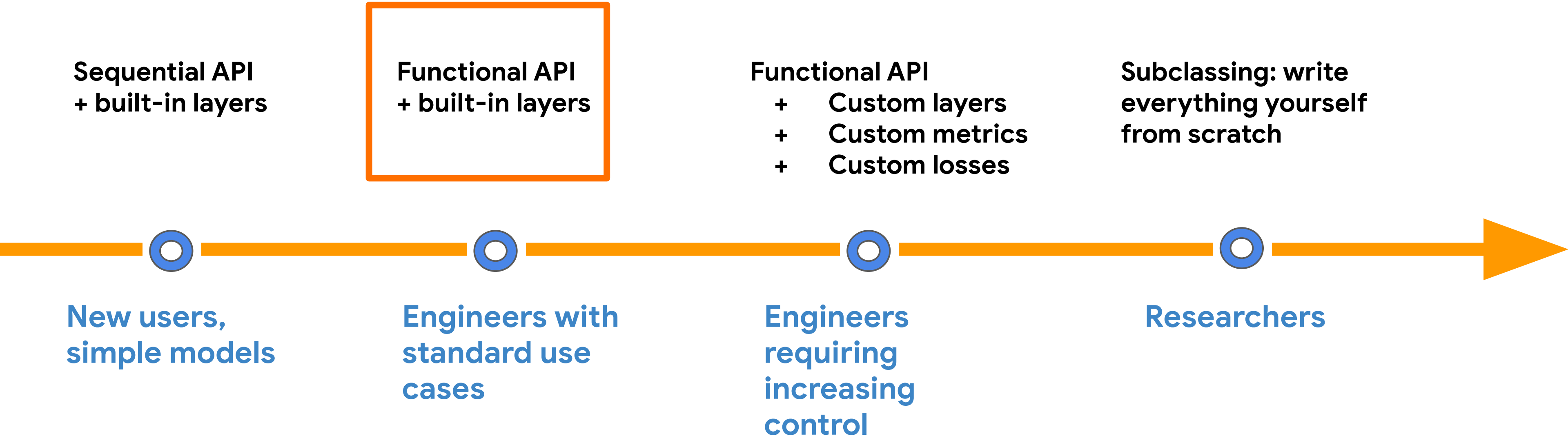
```
model = keras.Sequential()
model.add(layers.Dense(32, activation='relu', input_shape=(784,)))
model.add(layers.Dense(32, activation='relu'))
model.add(layers.Dense(32, activation='softmax'))
```

Model building: from simple to arbitrarily flexible

Progressive disclosure of complexity



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Visual Question Answering

Question: What color is the dog on the right?

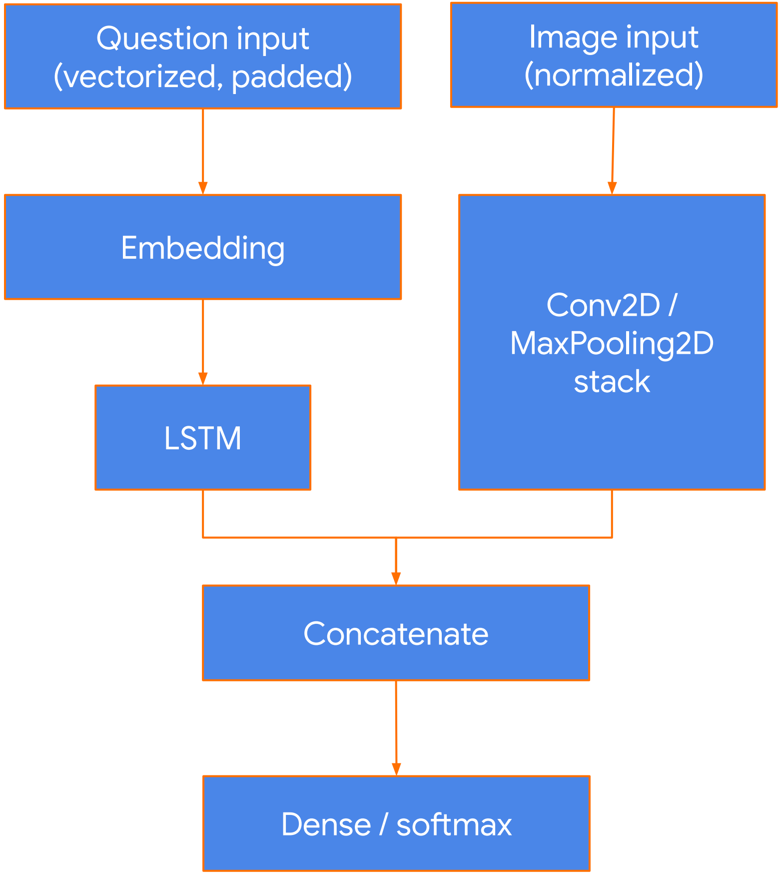
Answer: Golden

https://www.flickr.com/photos/cogdog/3296940/

Workflow

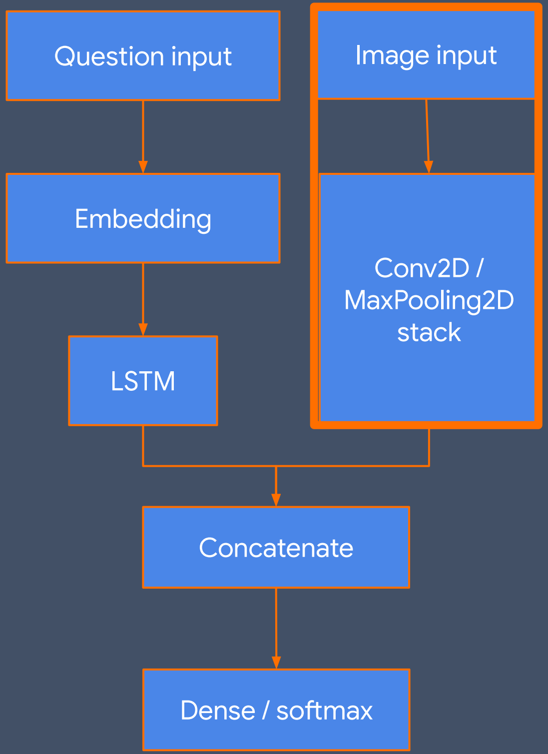
A multi-input model

1. Use a CNN to embed the image
2. Use a LSTM to embed the question
3. **Concatenate**
4. Classify with Dense layers, per usual

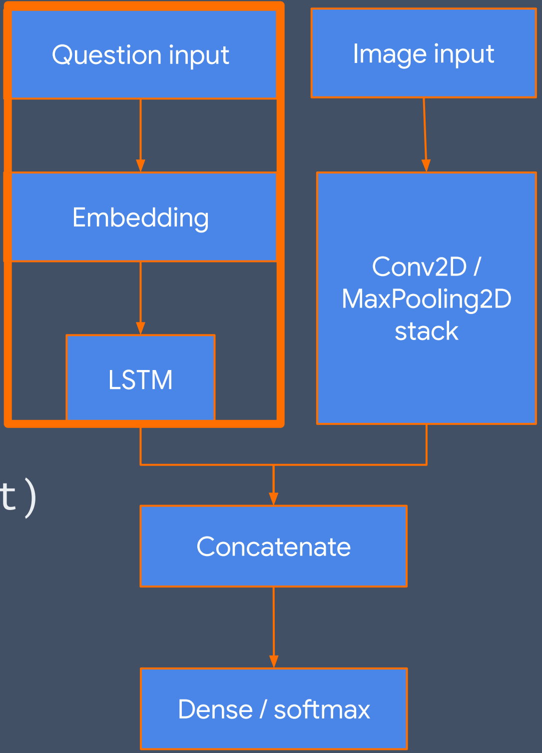


A wonderful thing about Deep Learning: ability to mix data types (text, images, timeseries, structured data) in a single model.

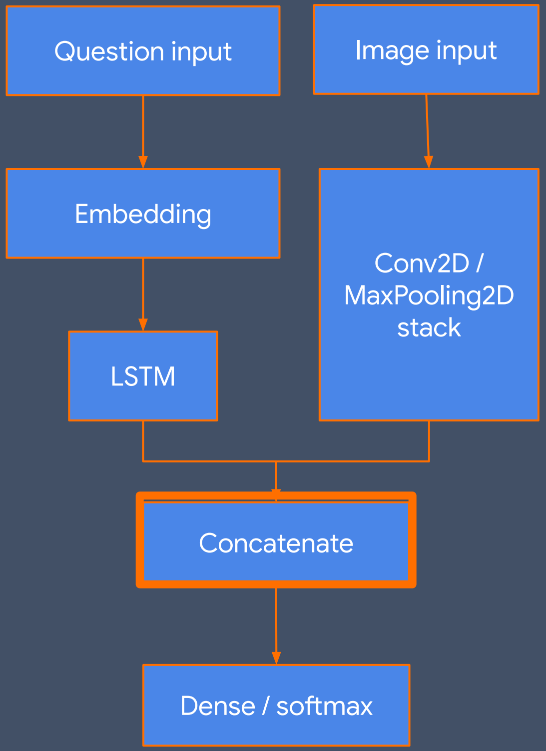
```
# A vision model.
# Encode an image into a vector.
vision_model = Sequential()
vision_model.add(Conv2D(64, (3, 3),
                        activation='relu',
                        input_shape=(224, 224, 3)))
vision_model.add(MaxPooling2D())
vision_model.add(Flatten())

# Get a tensor with the output of your vision model
image_input = Input(shape=(224, 224, 3))
encoded_image = vision_model(image_input)
```



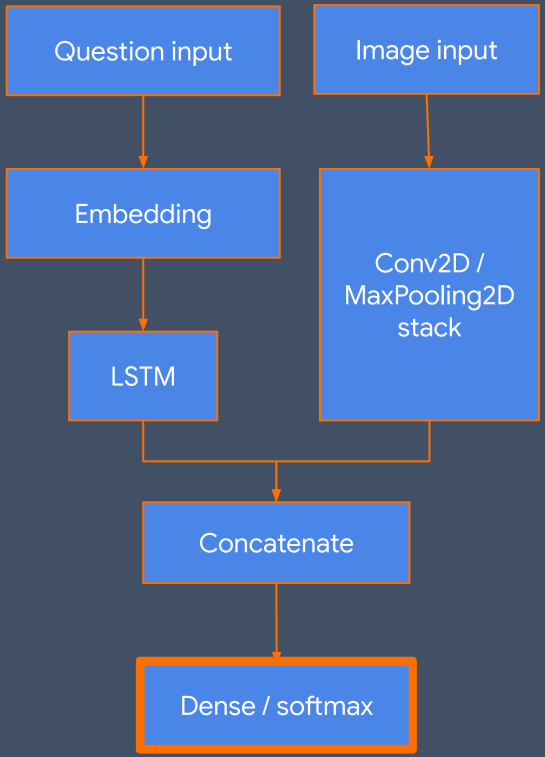
```
# A language model.
# Encode the question into a vector.
question_input = Input(shape=(100,),
                       dtype='int32',
                       name="Question")

embedded = Embedding(input_dim=10000,
                     output_dim=256,
                     input_length=100)(question_input)

encoded_question = LSTM(256)(embedded_question)
```



```
# Concatenate the encoded image and question
merged = layers.concatenate([encoded_image,
                             encoded_question])
```



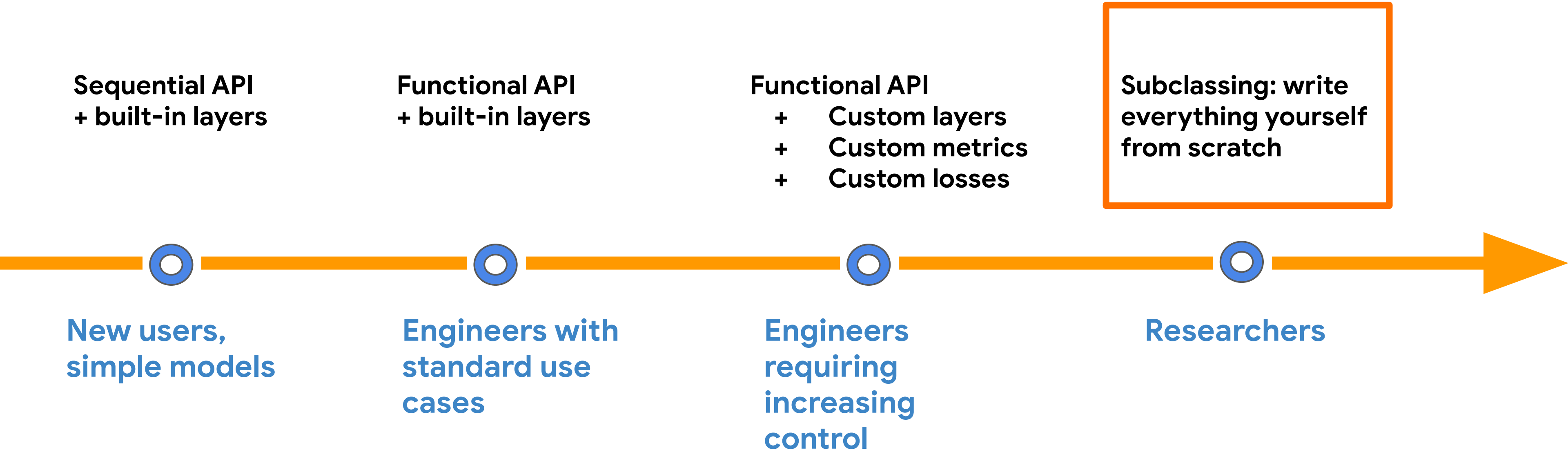
```
# Train a classifier on top.
output = Dense(1000,
               activation='softmax')(merged)


# You can train w/ .fit, .train_on_batch,
# or with a GradientTape.
vqa_model = Model(inputs=[image_input,
                          question_input],
                          outputs=output)
```



```python
from tensorflow.keras.utils import plot_model
plot_model(vqa_model, to_file='model.png')
```

Model building: from simple to arbitrarily flexible

Progressive disclosure of complexity



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Engineers requiring increasing control

Researchers

```
class MyModel(tf.keras.Model):
  def __init__(self, num_classes=10):
    super(MyModel, self).__init__(name='my_model')
    self.dense_1 = layers.Dense(32, activation='relu')
    self.dense_2 = layers.Dense(num_classes,activation='softmax')

  def call(self, inputs):
    # Define your forward pass here
    x = self.dense_1(inputs)
    return self.dense_2(x)
```

```
class MyModel(tf.keras.Model):
  def __init__(self, num_classes=10):
    super(MyModel, self).__init__(name='my_model')
    self.dense_1 = layers.Dense(32)
    self.dense_2 = layers.Dense(num_classes,activation='softmax')

  def call(self, inputs):
    # Define your forward pass here
    x = self.dense_1(inputs)
    x = tf.nn.relu(x)
    return self.dense_2(x)
```

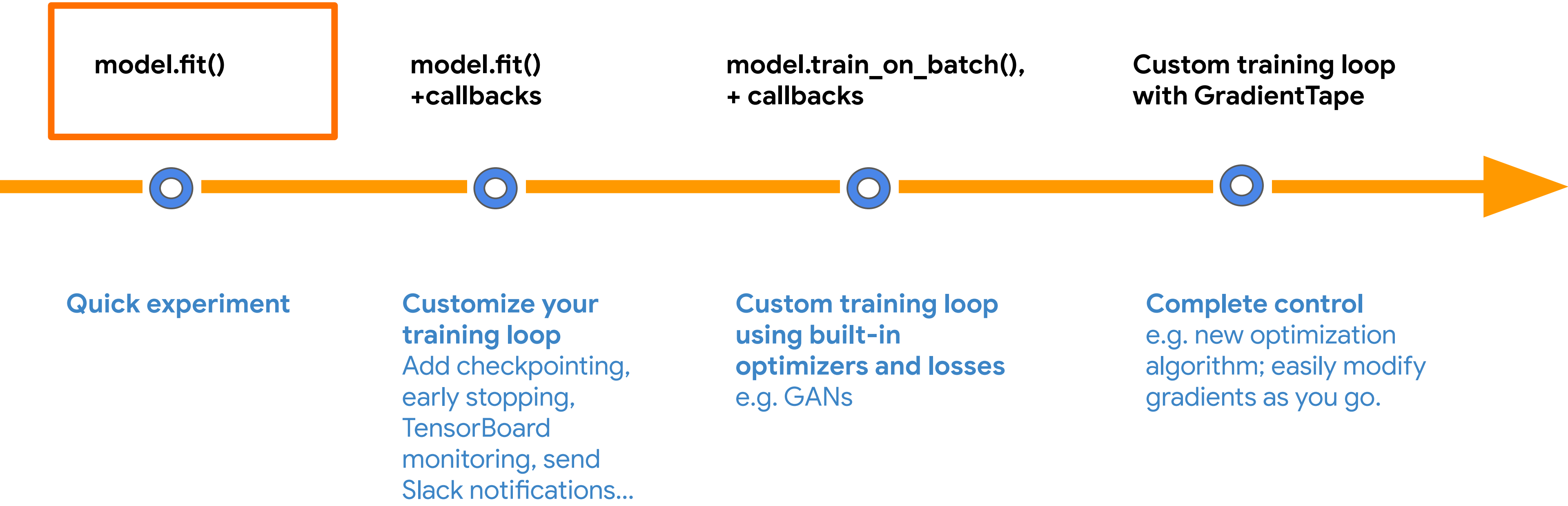
Helpful references

Guides
tensorflow.org/guide/keras/overview
tensorflow.org/guide/keras/functional
tensorflow.org/guide/keras/train_and_evaluate
tensorflow.org/guide/keras/custom_layers_and_models

Examples
tensorflow.org/tutorials/images/segmentation
tensorflow.org/tutorials/generative/pix2pix
tensorflow.org/tutorials/generative/adversarial_fgsm

Model training: from simple to arbitrarily flexible

Progressive disclosure of complexity



model.fit()

Quick experiment

model.fit()
+callbacks

Customize your training loop
Add checkpointing, early stopping, TensorBoard monitoring, send Slack notifications...

model.train_on_batch(),
+ callbacks

Custom training loop using built-in optimizers and losses
e.g. GANs

Custom training loop
with GradientTape

Complete control
e.g. new optimization algorithm; easily modify gradients as you go.

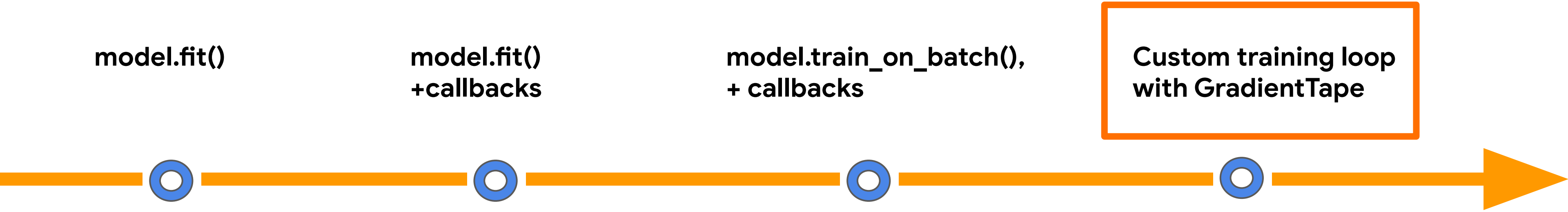
```
model.compile(optimizer=Adam(),
              loss=BinaryCrossentropy(),
              metrics=[AUC(), Precision(), Recall()])

model.fit(data,
          epochs=10,
          validation_data=val_data,
          callbacks=[EarlyStopping(),
                     TensorBoard(),
                     ModelCheckpoint()])
```

...or write your own callbacks!

Model training: from simple to arbitrarily flexible

Progressive disclosure of complexity



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Customize your training loop
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model.train_on_batch(),
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Custom training loop with GradientTape

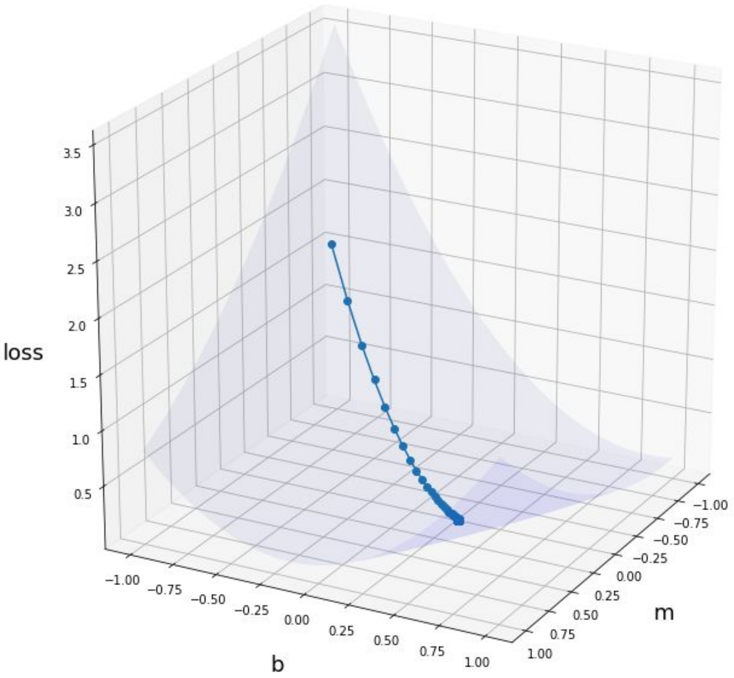
Complete control
e.g. new optimization algorithm; easily modify gradients as you go.

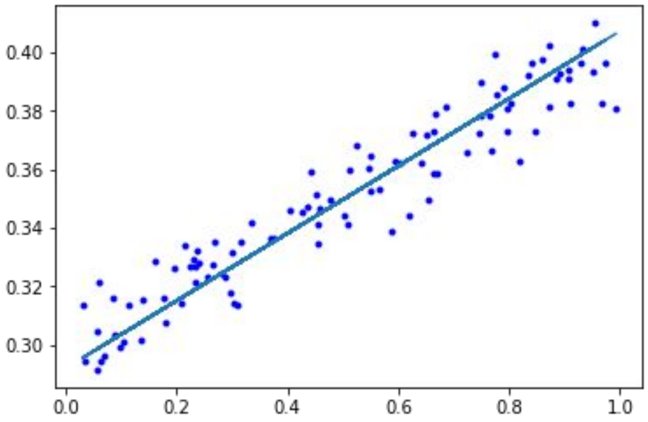
Graphs with one LOC

```python
@tf.function
def train_step(features, labels):
  with tf.GradientTape() as tape:
    logits = model(features, training=True)
    loss = loss_fn(labels, logits)

  grads = tape.gradient(loss, model.trainable_variables)
  optimizer.apply_gradients(zip(grads, model.trainable_variables))
  return loss
```

Low-level details:
Linear regression





Constants

```
x = tf.constant([[5, 2], [1, 3]])
print(x)
```

```
tf.Tensor(
[[5 2]
 [1 3]], shape=(2, 2), dtype=int32)
```

Tensors to NumPy

```
x.numpy()
```

```
array([[5, 2],
       [1, 3]], dtype=int32)
```

Shape and dtype

```
print('shape:', x.shape)
print('dtype:', x.dtype)
```

```
shape: (2, 2)

dtype: <dtype: 'int32'>
```

Distributions

```
print(tf.random.normal(shape=(2, 2), mean=0., stddev=1.))

<tf.Tensor: id=1652819, shape=(2, 2), dtype=float32, numpy=
array([[-0.5636922,  2.6130383],
       [ 0.2622066,  0.7773327]], dtype=float32)>
```

Math in TF2 feels like NumPy

```
a = tf.random.normal(shape=(2, 2))
b = tf.random.normal(shape=(2, 2))
c = a + b
d = tf.square(c)
```

Gradients

```
x = tf.constant(3.0)
with tf.GradientTape() as g:
  g.watch(x)
  y = x * x
dy_dx = g.gradient(y, x) # 6.0
```

Variables are automatically tracked

```
dense1 = tf.keras.layers.Dense(32)
dense2 = tf.keras.layers.Dense(32)



with tf.GradientTape() as tape:
  result = dense2(dense1(tf.zeros([1, 10])))
  tape.gradient(result, dense1.variables)
```

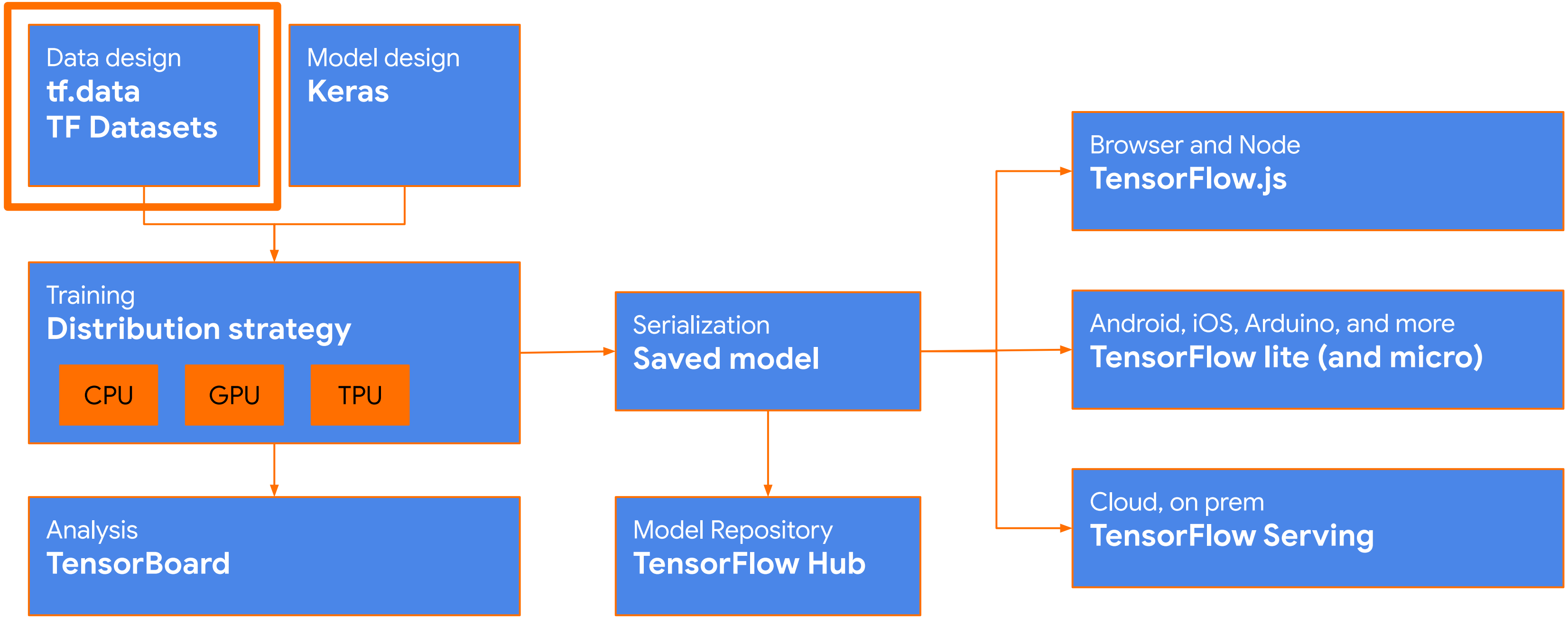
As we saw previously, you can get the gradients for model.trainable_variables as well in one go.

Quick demo

[Link]

Training

Deployment



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```
# Keras datasets
from tensorflow.keras import datasets
(train_images, train_labels), \
  (test_images, test_labels) = datasets.cifar10.load_data()


# TensorFlow Datasets
import tensorflow_datasets as tfds
dataset, metadata = tfds.load('cycle_gan/horse2zebra',
                               with_info=True,
                               as_supervised=True)
```

Helpful reference (on tf.data, loading images, and caching): tensorflow.org/tutorials/load_data/images
List of TensorFlow Datasets: tensorflow.org/datasets/catalog/overview

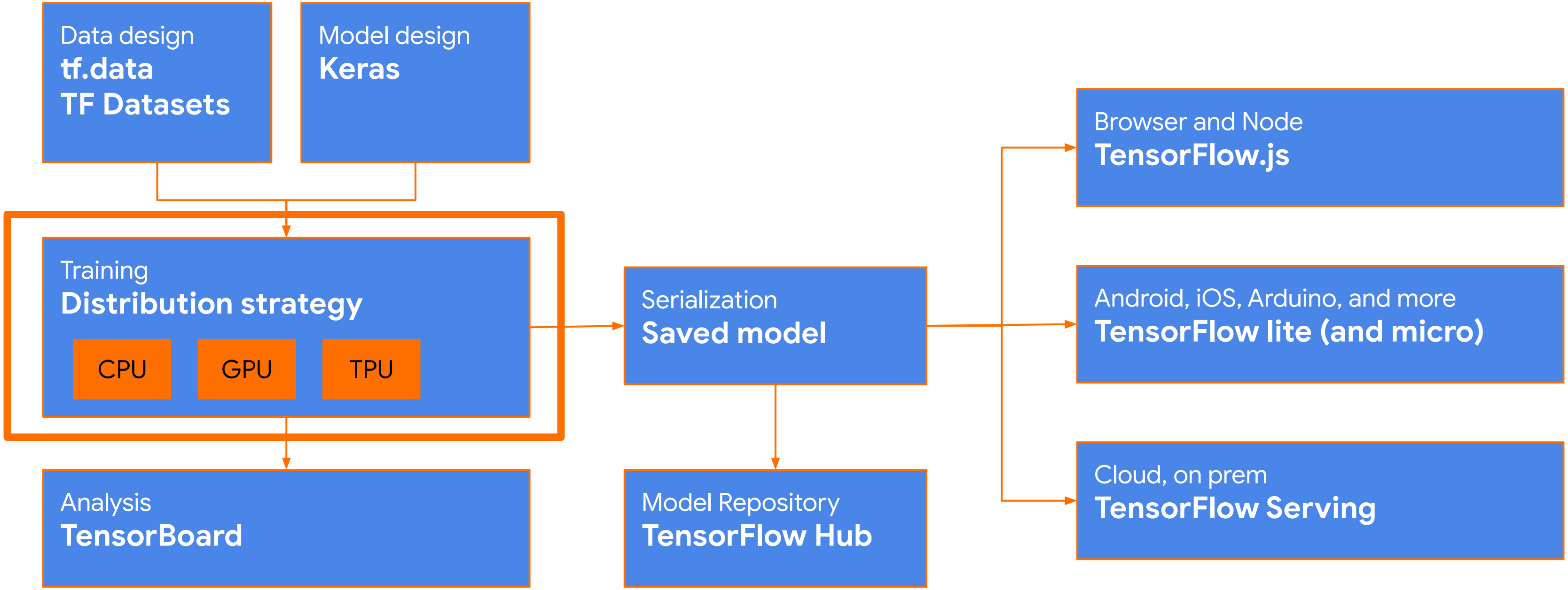
```
# If you’re using TensorFlow Datasets
# Either load your dataset into memory, or
# write a performant input pipeline to load it off disk.
dataset, metadata = tfds.load('mnist',
                              with_info=True,
                              as_supervised=True,
                              in_memory=True)
```

Helpful reference (on tf.data, loading images, and caching): tensorflow.org/tutorials/load_data/images
List of TensorFlow Datasets: tensorflow.org/datasets/catalog/overview

```python
# Caching is important to avoid repeated work
# Use either an in-memory cache, or a cache file
def preprocess(img):
  img = tf.cast(image, tf.float32)
  img = (img / 127.5) - 1
  img = tf.image.resize(img, [286, 286])
  # ...
  return img

image_ds = image_ds.map(
    preprocess, num_parallel_calls=AUTOTUNE).cache()
```

Note: order is important. Cache before shuffling and batching.
Helpful reference (on tf.data, loading images, and caching): tensorflow.org/tutorials/load_data/images
List of TensorFlow Datasets: tensorflow.org/datasets/catalog/overview



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Distribute, without changing your code

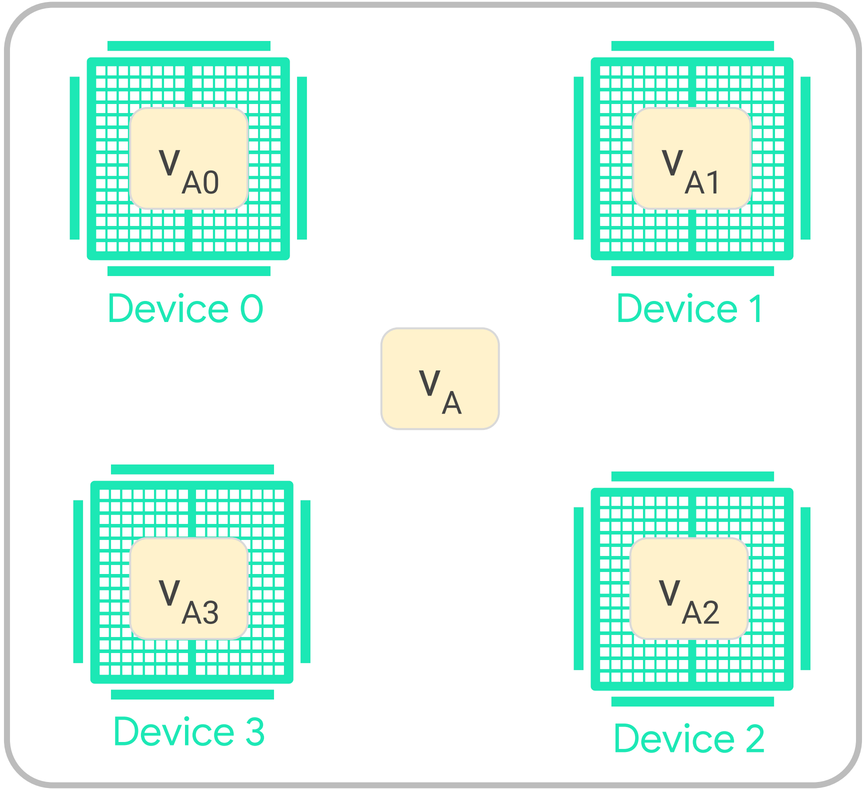
- No code changes for single machine, multi-GPU training
- No code changes for multi-machine, multi-GPU training

Synchronous data parallelism via efficient all reduce.

MirroredStrategy

Multi-GPU training

- Synchronous data parallelism.
- Variables mirrored on each GPU.
- Replicas are run in lock-step..
- All-reduce: network efficient way to aggregate gradients.



```
import tensorflow as tf



  model = tf.keras.applications.ResNet50()
  optimizer = tf.keras.optimizers.SGD(learning_rate=0.1)
  model.compile(..., optimizer=optimizer)
  model.fit(train_dataset, epochs=10)
```

tensorflow.org/tutorials/distribute/keras
tensorflow.org/guide/distributed_training

```
import tensorflow as tf

strategy = tf.distribute.MirroredStrategy()
with strategy.scope():
  model = tf.keras.applications.ResNet50()
  optimizer = tf.keras.optimizers.SGD(learning_rate=0.1)
  model.compile(..., optimizer=optimizer)
  model.fit(train_dataset, epochs=10)
```

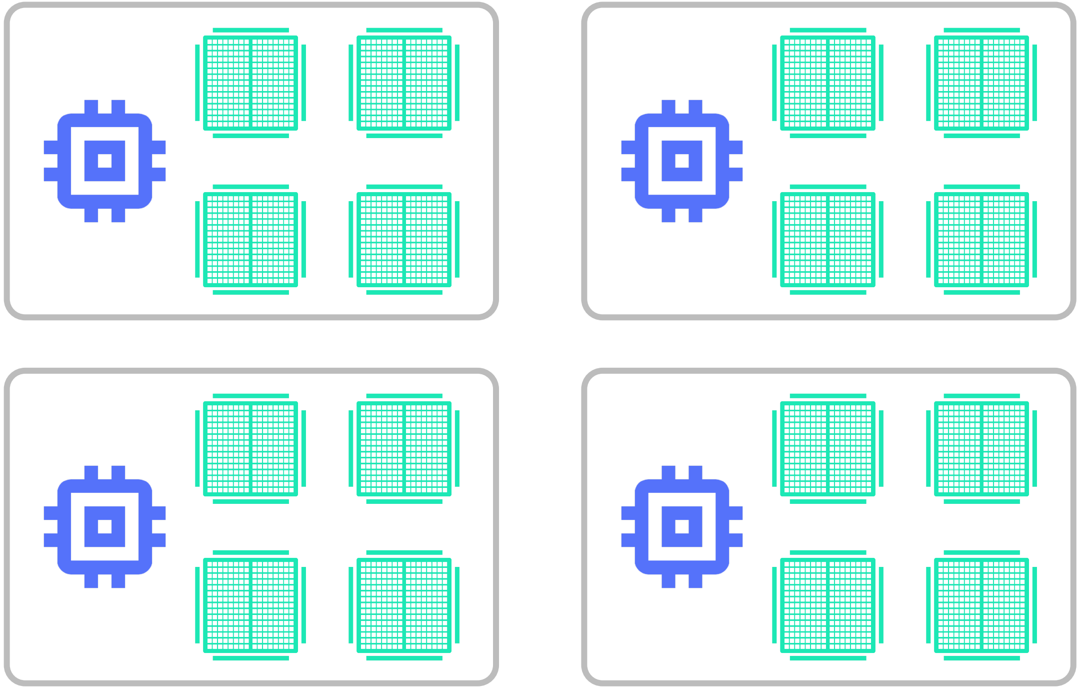
Distribute-aware

tensorflow.org/tutorials/distribute/keras
tensorflow.org/guide/distributed_training

MultiWorkerMirroredStrategy

Multi-machine, multi-GPU training

- Efficient all reduce across multiple machines
- No additional code changes
- Cluster config environment variable



Training

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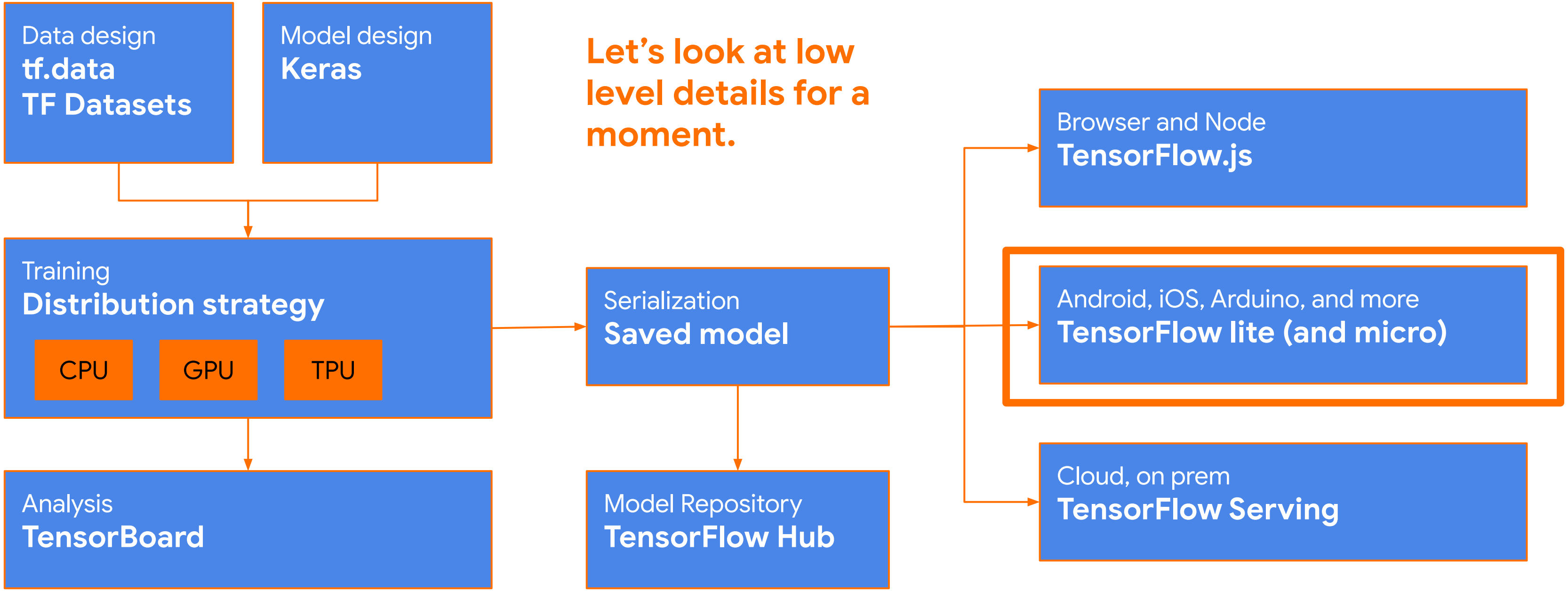

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Project suggestion: TinyML

Train with Python; Deploy with Arduino

Gesture classification (on-device!)

How-to Get Started with Machine Learning on Arduino, by Sandeep Mistry & Dominic Pajak

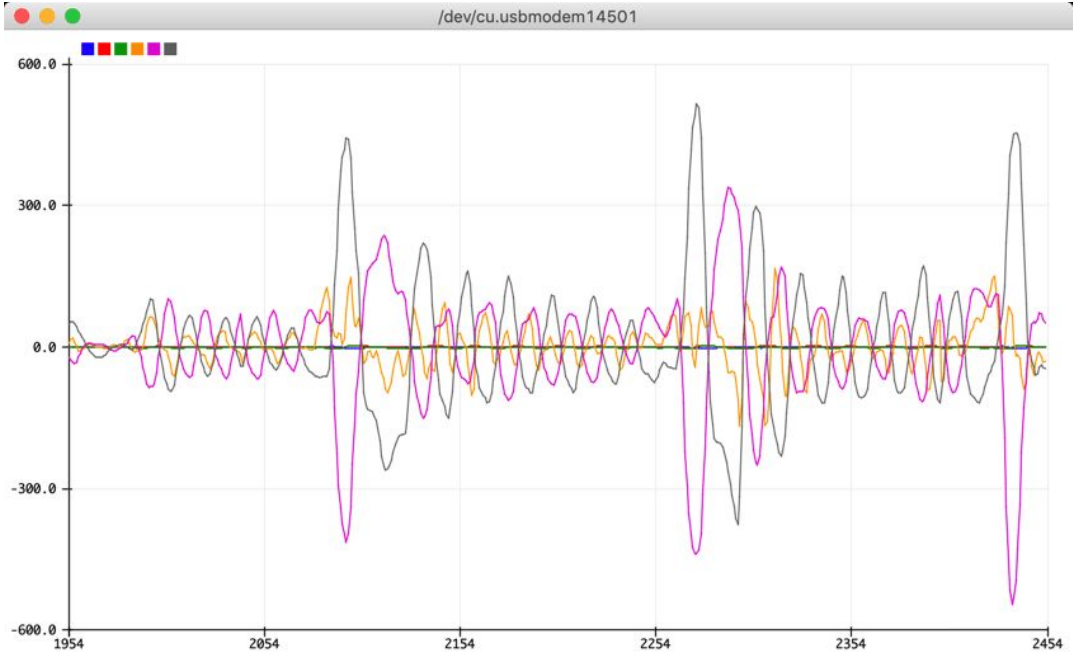
tensorflow.org/lite/microcontrollers/overview

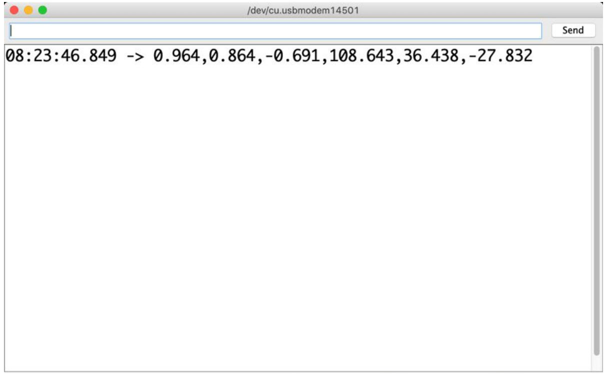
Workflow

1. Capture data with the Arduino IDE for each gesture
2. Save CSVs (e.g. punch.csv, wave.csv)
3. Upload to Colab
4. Train a model with TF2 using Keras
5. Convert your model to TFLite
6. Install on device (walkthrough provided)

How-to Get Started with Machine Learning on Arduino, by Sandeep Mistry & Dominic Pajak

Capturing data





```
08:23:46.849 -> 0.964,0.864,-0.691,108.643,36.438,-27.832
```

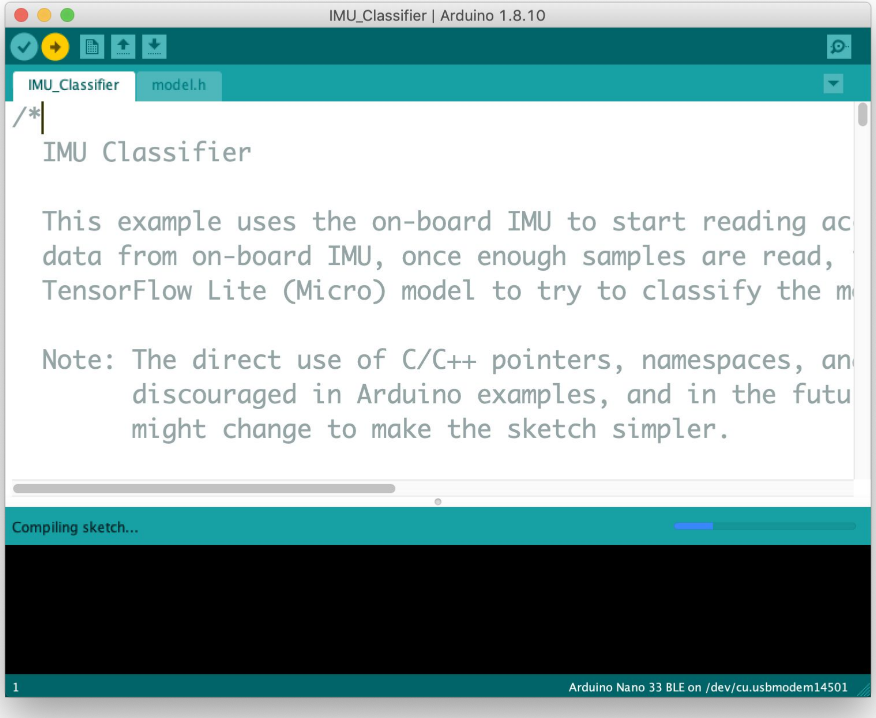
[How-to Get Started with Machine Learning on Arduino, by Sandeep Mistry & Dominic Pajak]

```python
# Convert the model to the TFLite format without quantization
converter = tf.lite.TFLiteConverter.from_keras_model(model)
tflite_model = converter.convert()

# Save the model to disk
open("gesture_model.tflite", "wb").write(tflite_model)

# Check the size
import os
basic_model_size = os.path.getsize("gesture_model.tflite")
print("Model is %d bytes" % basic_model_size)
```

Deploying on device



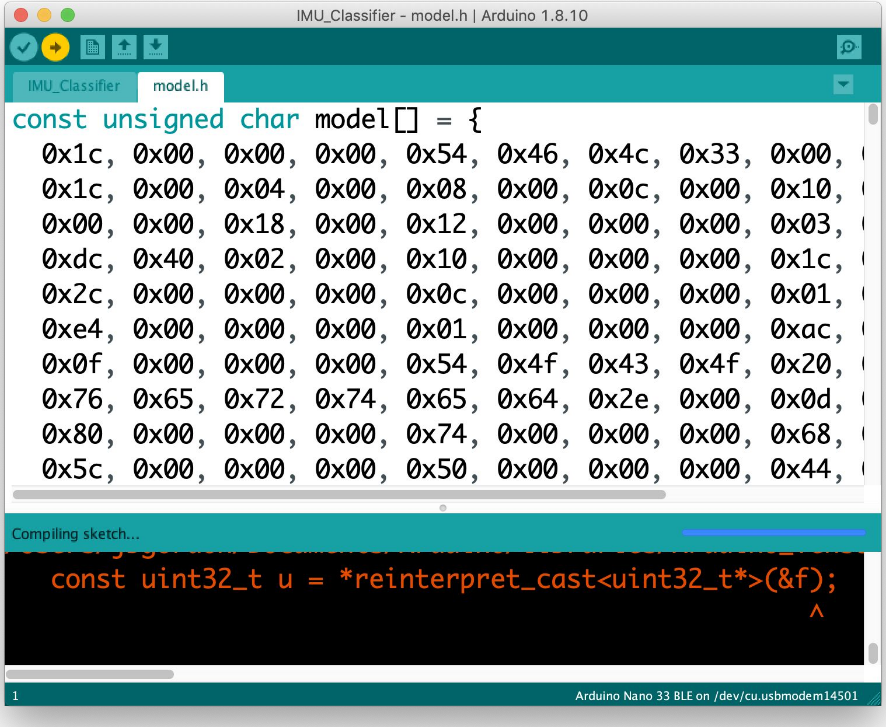
```
/*
  IMU Classifier

  This example uses the on-board IMU to start reading ac
  data from on-board IMU, once enough samples are read,
  TensorFlow Lite (Micro) model to try to classify the m

  Note: The direct use of C/C++ pointers, namespaces, an
        discouraged in Arduino examples, and in the futu
        might change to make the sketch simpler.
```

Compiling sketch...

1 Arduino Nano 33 BLE on /dev/cu.usbmodem14501



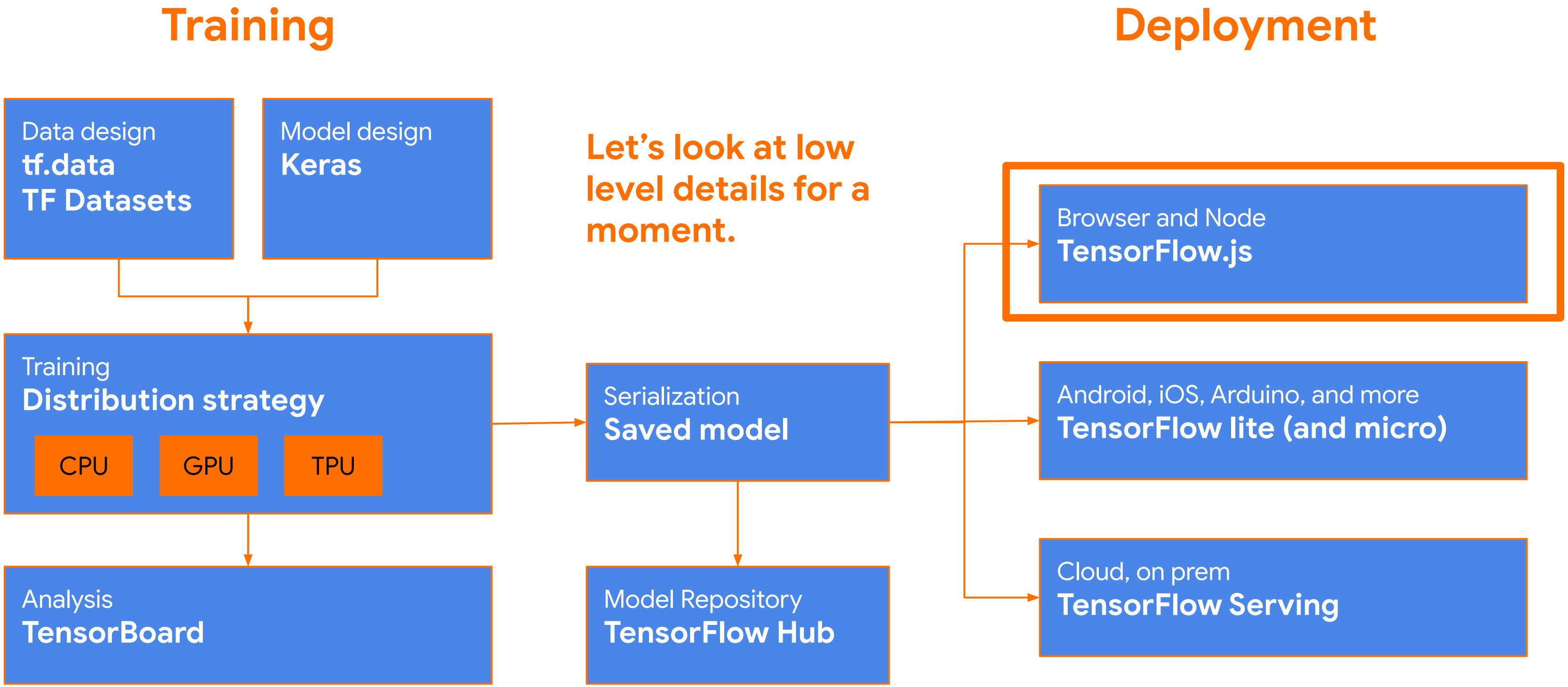
```
const unsigned char model[] = {
  0x1c, 0x00, 0x00, 0x00, 0x54, 0x46, 0x4c, 0x33, 0x00,
  0x1c, 0x00, 0x04, 0x00, 0x08, 0x00, 0x0c, 0x00, 0x10,
  0x00, 0x00, 0x18, 0x00, 0x12, 0x00, 0x00, 0x00, 0x03,
  0xdc, 0x40, 0x02, 0x00, 0x10, 0x00, 0x00, 0x00, 0x1c,
  0x2c, 0x00, 0x00, 0x00, 0x0c, 0x00, 0x00, 0x00, 0x01,
  0xe4, 0x00, 0x00, 0x00, 0x01, 0x00, 0x00, 0x00, 0xac,
  0x0f, 0x00, 0x00, 0x00, 0x54, 0x4f, 0x43, 0x4f, 0x20,
  0x76, 0x65, 0x72, 0x74, 0x65, 0x64, 0x2e, 0x00, 0x0d,
  0x80, 0x00, 0x00, 0x00, 0x74, 0x00, 0x00, 0x00, 0x68,
  0x5c, 0x00, 0x00, 0x00, 0x50, 0x00, 0x00, 0x00, 0x44,
```

Compiling sketch...

```
  const uint32_t u = *reinterpret_cast<uint32_t*>(&f);
                                                     ^
```

1 Arduino Nano 33 BLE on /dev/cu.usbmodem14501

[How-to Get Started with Machine Learning on Arduino, by Sandeep Mistry & Dominic Pajak]



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Project suggestion: TF.js

Train with Python; Deploy with JS

Sentiment analysis in the browser

STATUS

Inference result (0 - negative; 1 - positive): 0.653573 (elapsed: 5.88 ms)

[TensorFlow.js sentiment analysis example]

Workflow

1. **Train a model in Python**
2. Save and convert your model (and metadata) to TF.js format
3. Upload to GitHub pages (or serve locally)
4. Run in the browser following the HTML and JS in the example

TensorFlow.js sentiment analysis example

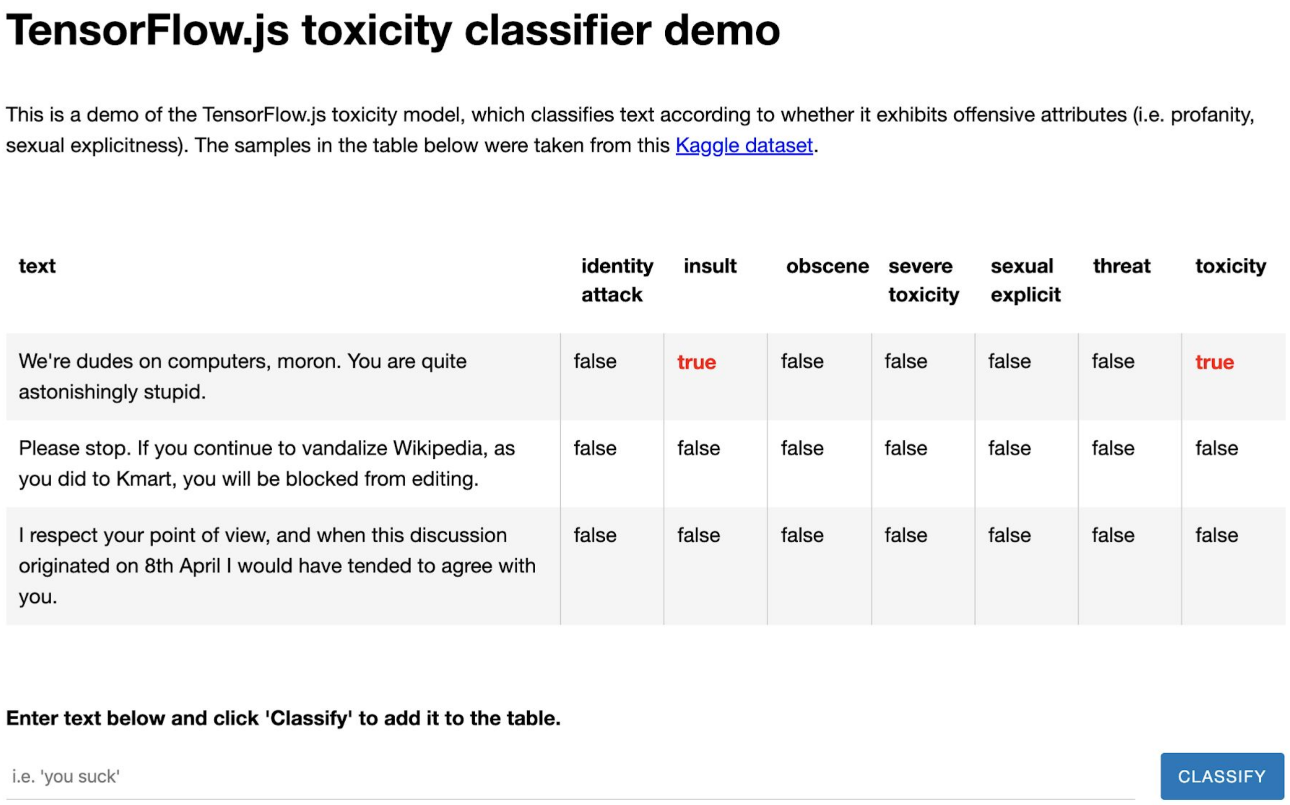
```
import tensorflowjs as tfjs

metadata = {
  'word_index': tokenizer.word_index,
  # …
}

# Save metadata
metadata_json_path = os.path.join(FLAGS.artifacts_dir, 'metadata.json')
json.dump(metadata, open(metadata_json_path, 'wt'))

# Convert your model to TF.js format
tfjs.converters.save_keras_model(model, FLAGS.artifacts_dir)
```

Tip: you must preprocess text in the browser exactly as you do in Python.



TensorFlow.js toxicity classifier demo

This is a demo of the TensorFlow.js toxicity model, which classifies text according to whether it exhibits offensive attributes (i.e. profanity, sexual explicitness). The samples in the table below were taken from this Kaggle dataset.

text	identity attack	insult	obscene	severe toxicity	sexual explicit	threat	toxicity
We're dudes on computers, moron. You are quite astonishingly stupid.	false	**true**	false	false	false	false	**true**
Please stop. If you continue to vandalize Wikipedia, as you did to Kmart, you will be blocked from editing.	false	false	false	false	false	false	false
I respect your point of view, and when this discussion originated on 8th April I would have tended to agree with you.	false	false	false	false	false	false	false

Enter text below and click 'Classify' to add it to the table.

Applications

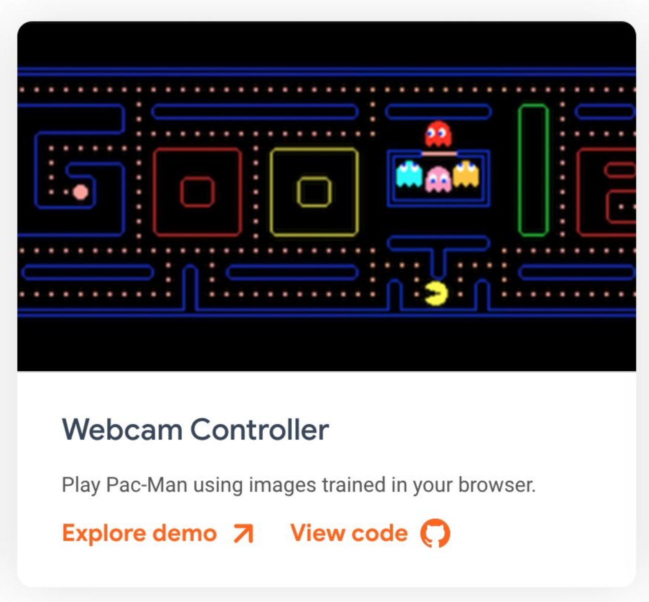
Imagine a tool to assist moderators.

Or, to prompt users.

All data stays client side.

github.com/tensorflow/tfjs-models/tree/master/toxicity

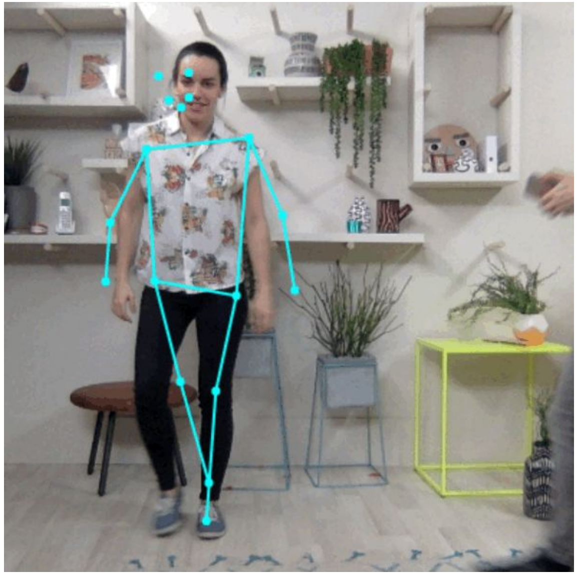
Demos



Webcam Controller

Play Pac-Man using images trained in your browser.

Explore demo ↗ **View code**



bit.ly/pose-net

tensorflow.org/js/

Notes

Installing TF2

In Colab, run this command at the top of your notebook:

%tensorflow_version 2.x

To install locally, you can use pip.

- Visit tensorflow.org/install

Keras vs tf.keras

In TF2, instead of writing “import keras” you write “from tensorflow import keras”.

In Colab, if you ever see the message “Using TensorFlow Backend”, you’ve imported the incorrect version.

Learning more

Learning more

Practical books

- Hands-on ML with Scikit-Learn, Keras and TensorFlow **(2nd edition)**
- Deep Learning with Python
- Deep Learning with JavaScript
- TinyML

Latest tutorials and guides

- tensorflow.org/tutorials
- tensorflow.org/guide

Thank you!

Josh Gordon

twitter.com/random_forests