TensorFlow

Intro to TensorFlow 2.0
MBL, August 2019

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Agenda 1 of 2

Exercises

- Fashion MNIST with dense layers
- CIFAR-10 with convolutional layers

Concepts (as many as we can intro in this short time)

- Gradient descent, dense layers, loss, softmax, convolution

Games

- QuickDraw

Agenda 2 of 2

Walkthroughs and new tutorials

- Deep Dream and Style Transfer
- Time series forecasting

Games

- Sketch RNN

Learning more

- Book recommendations

Deep Learning is representation learning

Image link

Image link

TensorFlow

Latest tutorials and guides

tensorflow.org/beta

News and updates

medium.com/tensorflow

twitter.com/tensorflow

Demo

PoseNet and BodyPix

bit.ly/pose-net

bit.ly/body-pix

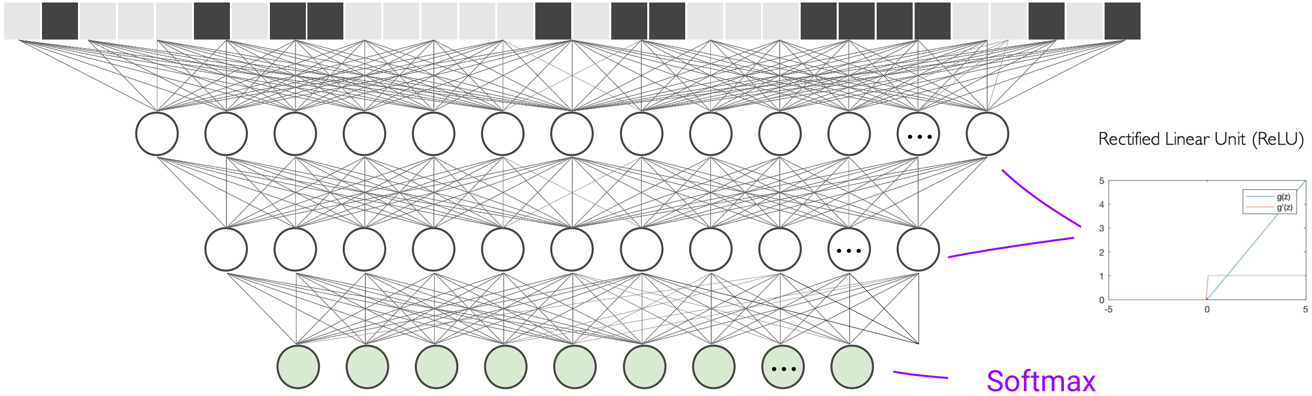
TensorFlow for JavaScript, Sw
Android, and iOS

tensorflow.org/js
tensorflow.org/swift
tensorflow.org/lite

Minimal MNIST in TF 2.0

A linear model, neural network, and deep neural network - then a short exercise.

bit.ly/mnist-seq

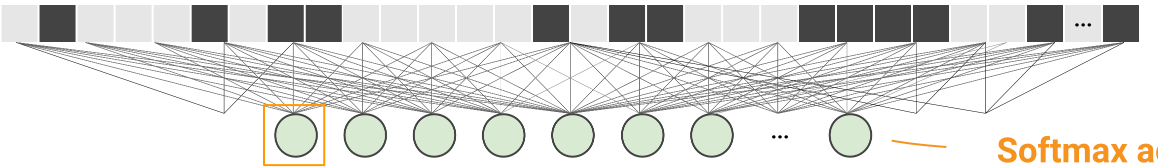



```
model = Sequential()
model.add(Dense(256, activation='relu',input_shape=(784,)))
model.add(Dense(128, activation='relu'))
model.add(Dense(10, activation='softmax'))
```

Linear model $$f(x) = softmax(W_1 x)$$

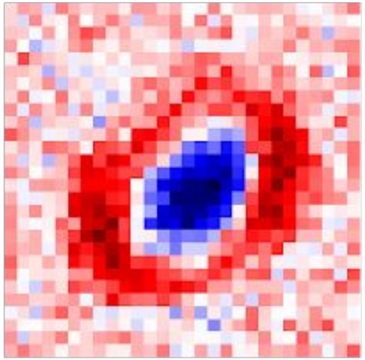
Neural network $$f(x) = softmax(W_2(g(W_1 x)))$$

Deep neural network $$f(x) = softmax(W_3(g(W_2(g(W_1 x)))))$$

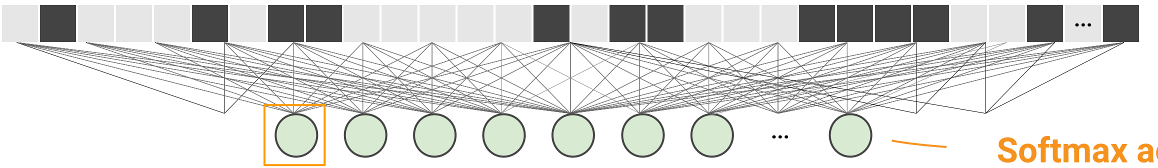


Softmax activation

After training, select all the weights connected to this output.

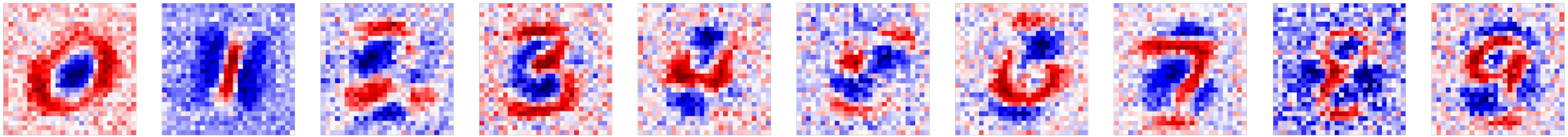


```
model.layers[0].get_weights()

# Your code here
# Select the weights for a single output
# ...

img = weights.reshape(28,28)
plt.imshow(img, cmap = plt.get_cmap('seismic'))
```



Softmax activation

After training, select all the weights connected to this output.



Exercise 1 (option #1)

Exercise: **bit.ly/mnist-seq**

Reference:
tensorflow.org/beta/tutorials/keras/basic_classification

TODO:
Add a validation set. Add code to plot loss vs epochs (next slide).

Exercise 1 (option #2)

bit.ly/ijcav_adv

Answers: next slide.

```python
import matplotlib.pyplot as plt

# Add a validation set
history = model.fit(x_train, y_train, validation_data=(x_test, y_test) ...)

# Get stats from the history object
acc = history.history['accuracy']
val_acc = history.history['val_accuracy']
epochs = range(len(acc))

# Plot accuracy vs epochs
plt.title('Training and validation accuracy')
plt.plot(epochs, acc, color='blue', label='Train')
plt.plot(epochs, val_acc, color='orange', label='Val')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
```

bit.ly/mnist-seq

Exercise 1 (option #2)

bit.ly/ijcav_adv

Answers: next slide.

bit.ly/ijcai_adv_answer

TensorFlow

About TensorFlow 2.0

Install

```
# GPU
!pip install tensorflow-gpu==2.0.0-beta1
```

```
# CPU
!pip install tensorflow==2.0.0-beta1
```

In either case, check your installation (in Colab, you may need to use runtime -> restart after installing).

```
import tensorflow as tf
print(tf.__version__) # 2.0.0-beta1
```

Nightly is available too, but best bet: stick with a named release for stability.

TF2 is imperative by default

```
import tensorflow as tf
print(tf.__version__) # 2.0.0-beta1

x = tf.constant(1)
y = tf.constant(2)
z = x + y

print(z) # tf.Tensor(3, shape=(), dtype=int32)
```

You can interactive explore layers

```
from tensorflow.keras.layers import Dense
layer = Dense(units=1, kernel_initializer='ones', use_bias=False)
data = tf.constant([[1.0, 2.0, 3.0]]) # Note: a batch of data
print(data) # tf.Tensor([[1. 2. 3.]], shape=(1, 3), dtype=float32)

# Call the layer on our data
result = layer(data)

print(result) # tf.Tensor([[6.]], shape=(1, 1), dtype=float32)
print(result.numpy()) # tf.Tensors have a handy .numpy() method
```

TF1: Build a graph, then run it.

```
import tensorflow as tf # 1.14.0
print(tf.__version__)


x = tf.constant(1)
y = tf.constant(2)
z = tf.add(x, y)


print(z)
```

TF1: Build a graph, then run it.

```
import tensorflow as tf # 1.14.0
print(tf.__version__)

x = tf.constant(1)
y = tf.constant(2)
z = tf.add(x, y)

print(z) # Tensor("Add:0", shape=(), dtype=int32)

with tf.Session() as sess:
  print(sess.run(x)) # 3
```

Keras is built-in to TF2

How to import tf.keras

If you want to use **tf.keras** and see the message “Using TensorFlow Backend”, you have accidentally imported Keras (which is installed by default on Colab) from outside of TensorFlow.

Example

```
# !pip install tensorflow==2.0.0-beta1, then

>>> from tensorflow.keras import layers # Right

>>> from keras import layers # Oops

Using TensorFlow backend. # You shouldn’t see this
```

When in doubt, copy the imports from one of the tutorials on tensorflow.org/beta

Notes

A **superset** of the reference implementation. Built-in to TensorFlow 2.0 (no need to install Keras separately).

Documentation and examples

- **Tutorials**: tensorflow.org/beta
- **Guide**: tensorflow.org/beta/guide/keras/

```
!pip install tensorflow==2.0.0-beta1
from tensorflow import keras
```

I'd recommend the examples you find on tensorflow.org/beta over other resources (they are better maintained and most of them are carefully reviewed).

tf.keras adds a bunch of stuff, including… model subclassing (Chainer / PyTorch style model building), custom training loops using a GradientTape, a collection of distributed training strategies, support for TensorFlow.js, Android, iOS, etc.

More notes

TF 2.0 is similar to NumPy, with:

- GPU support
- Autodiff
- Distributed training
- JIT compilation
- A portable format (train in Python on Mac, deploy on iOS using Swift, or in a browser using JavaScript)

Write models in Python, JavaScript or Swift (and run anywhere).

API doc: tensorflow.org/versions/r2.0/api_docs/python/tf
Note: make sure you're looking at version 2.0 (the website still defaults to 1.x)

TensorFlow

Three model building styles

Sequential, Functional, Subclassing

Sequential models

```
model = tf.keras.models.Sequential([
  tf.keras.layers.Flatten(),
  tf.keras.layers.Dense(512, activation='relu'),
  tf.keras.layers.Dropout(0.2),
  tf.keras.layers.Dense(10, activation='softmax')
])
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)
```

TF 1.x

```
model = tf.keras.models.Sequential([
  tf.keras.layers.Flatten(),
  tf.keras.layers.Dense(512, activation='relu'),
  tf.keras.layers.Dropout(0.2),
  tf.keras.layers.Dense(10, activation='softmax')
])
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              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)
```

TF 2.0

```
model = tf.keras.models.Sequential([
  tf.keras.layers.Flatten(),
  tf.keras.layers.Dense(512, activation='relu'),
  tf.keras.layers.Dropout(0.2),
  tf.keras.layers.Dense(10, activation='softmax')
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              metrics=['accuracy'])

model.fit(x_train, y_train, epochs=5)
model.evaluate(x_test, y_test)
```
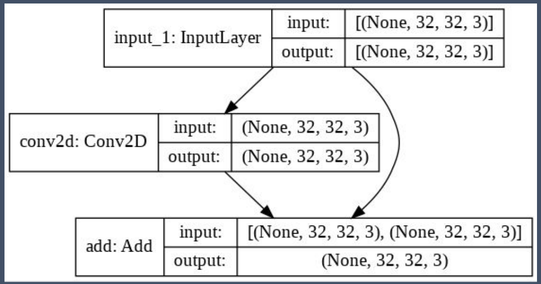

Functional models

```
inputs = keras.Input(shape=(32, 32, 3))

y = layers.Conv2D(3, (3, 3),activation='relu',padding='same')(inputs)
outputs = layers.add([inputs, y])
model = keras.Model(inputs, outputs)

keras.utils.plot_model(model, 'skip_connection.png', show_shapes=True)
```



Subclassed models

```
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='sigmoid')

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

TensorFlow

Two training styles

Built-in and custom

Use a built-in training loop

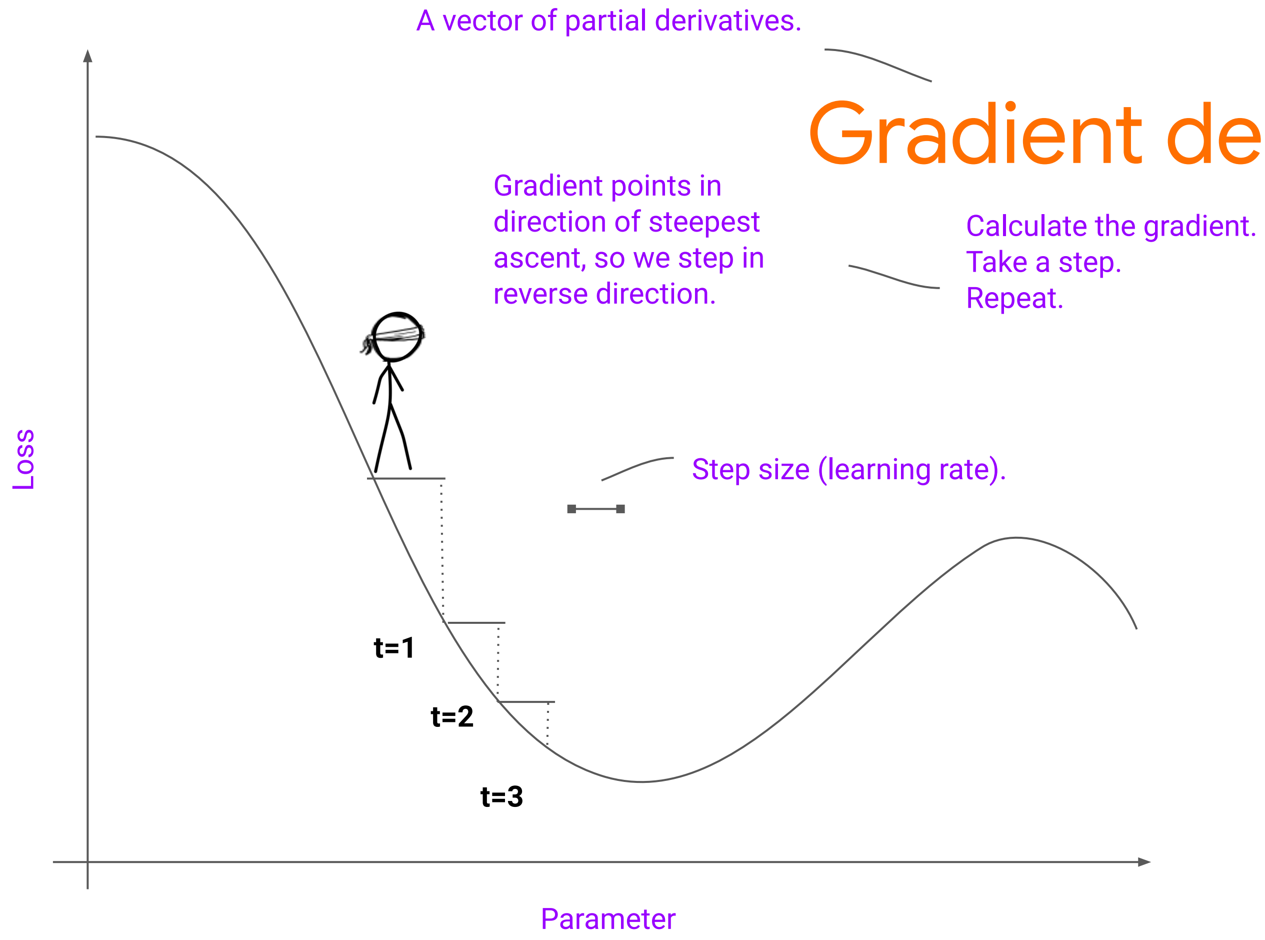
```
model.fit(x_train, y_train, epochs=5)
```

Or, define your own

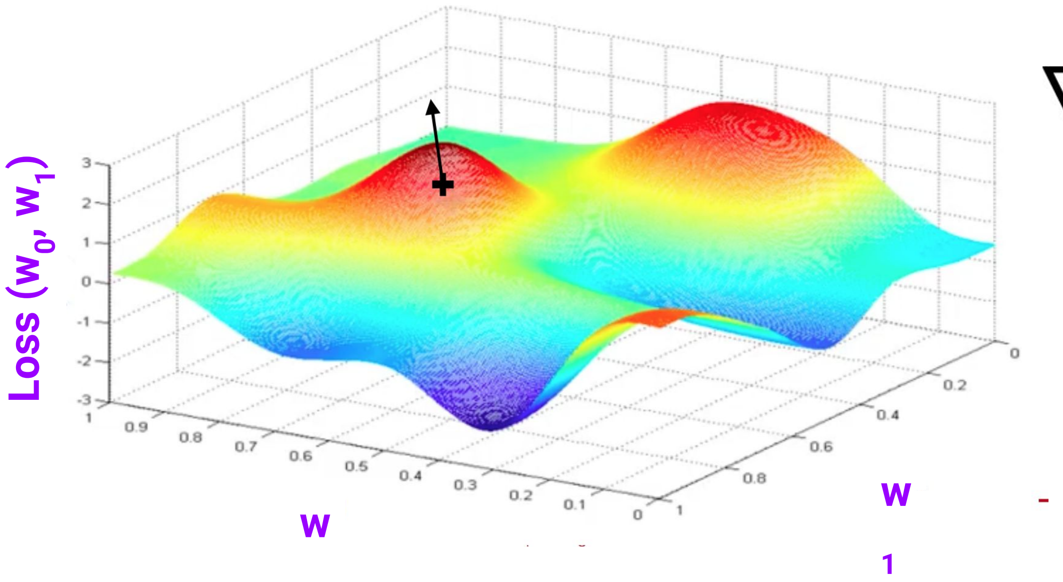
```
model = MyModel()

with tf.GradientTape() as tape:
  logits = model(images)
  loss_value = loss(logits, labels)

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

A few concepts

Gradient descent



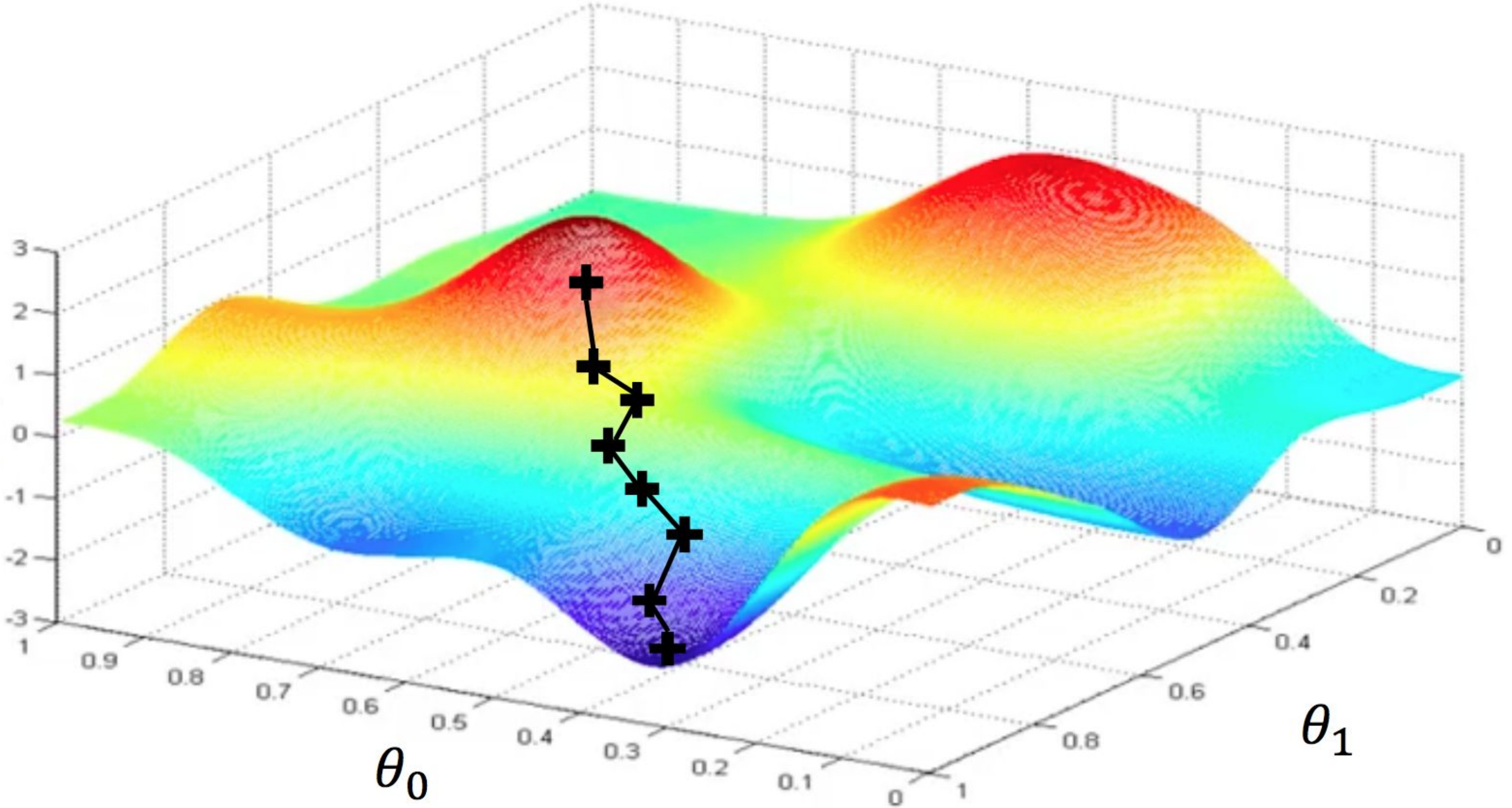
With more than one variable



$$\nabla_w Loss = \frac{\partial Loss}{\partial w_0}, \frac{\partial Loss}{\partial w_1}$$

The gradient is a vector of partial derivatives (the derivative of a function w.r.t. each variable while the others are held constant).

The gradient points in the direction of steepest ascent. We usually want to minimize a function (like loss), so we take a step in the opposite direction..



3
2
1
0
-1
-2
-3
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
θ_0
0
0.2
0.4
0.6
0.8
1
θ_1

Training models with gradient descent

Forward pass

- Linear regression: y=mx +b
- Neural network: $f(x) = \text{softmax}(W_2(g(W_1x)))$

Calculate loss

- Regression: squared error.
- Classification: cross entropy.

Backward pass

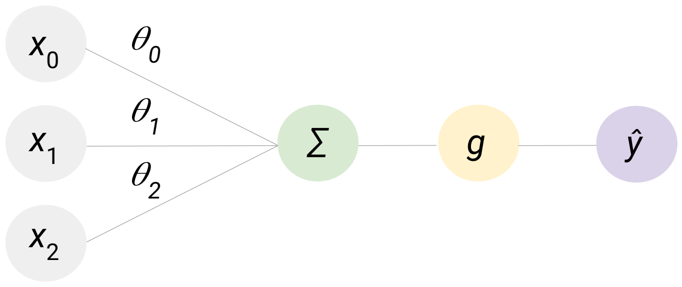
- Backprop: efficient method to calculate gradients
- Gradient descent: nudge parameters a bit in the opposite direction

Try it: Linear regression

bit.ly/tf-ws1

Bonus: Deep Dream training loop will be similar.

A neuron



Inputs **weights** **sum** **activation** **output**

Linear combination of inputs and weights

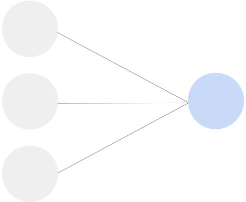
$$\hat{y} = g\left(\sum x_i \theta_i\right)$$

Can rewrite as a dot product

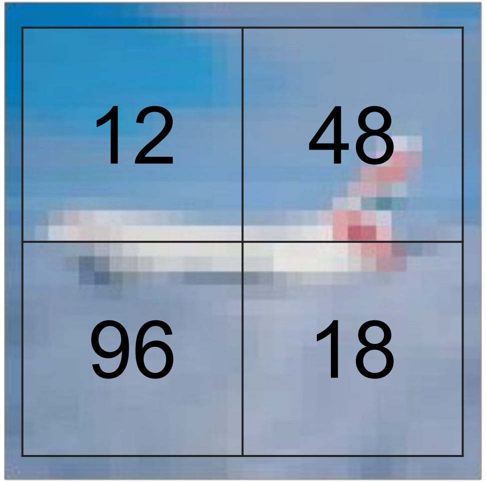
$$\hat{y} = g\left(x^T \theta\right)$$

Bias not drawn (you could set x_1 to be a constant input of 1).

One image and one class

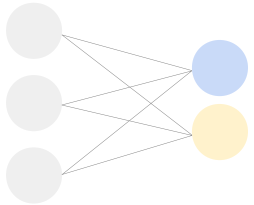


Interpret as “how strongly do you think this image is a plane?”

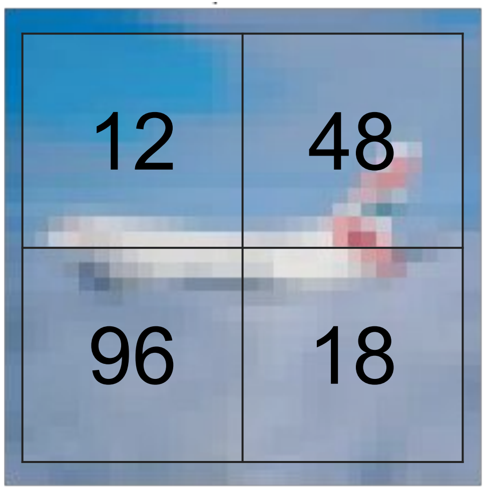


$$\underbrace{\begin{bmatrix}1.4 & 0.5 & 0.7 & 1.2\end{bmatrix}}_{\substack{w \\ \text{Weights}}}\ \underbrace{\begin{bmatrix}12\\48\\96\\18\end{bmatrix}}_{\substack{x \\ \text{Inputs}}} + \underbrace{\begin{bmatrix}0.5\end{bmatrix}}_{\substack{b \\ \text{Bias}}} = \underbrace{\begin{bmatrix}130.1 & \text{Plane}\end{bmatrix}}_{\substack{\text{Output} \\ \text{Scores}}}$$

One image and two classes



Multiple inputs; multiple outputs



$$\begin{bmatrix} 1.4 & 0.5 & 0.7 & 1.2 \\ -2.0 & 0.1 & 0.2 & -0.7 \end{bmatrix} \begin{bmatrix} 12 \\ 48 \\ 96 \\ 18 \end{bmatrix} + \begin{bmatrix} 0.5 \\ 1.2 \end{bmatrix} = \begin{array}{cc} 130.1 & \text{Plane} \\ -11.4 & \text{Car} \end{array}$$

W is now a matrix

W	x	b	Output
Weights	Inputs	Bias	Scores

Two images and two classes

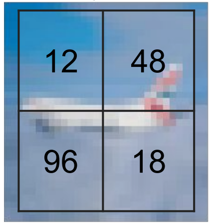


Image 1

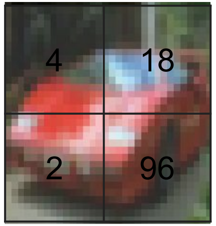


Image 2

W — Weights (N x D)

1.4	**0.5**	**0.7**	**1.2**
-2.0	**0.1**	**0.2**	**-0.7**
0.2	**0.9**	**-0.2**	**0.5**

x — Inputs (D x batch_size)

12	**4**
48	**18**
96	**2**
18	**96**

\+

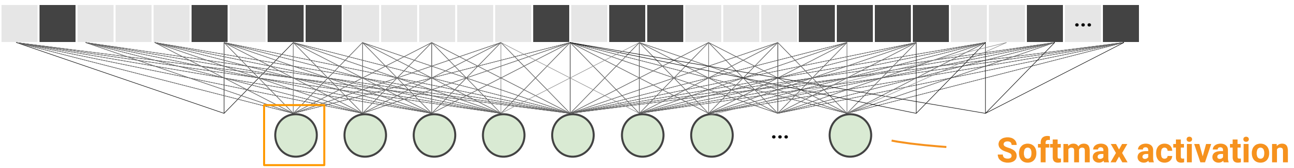
b — Bias (N x 1)

0.5
1.2
0.2

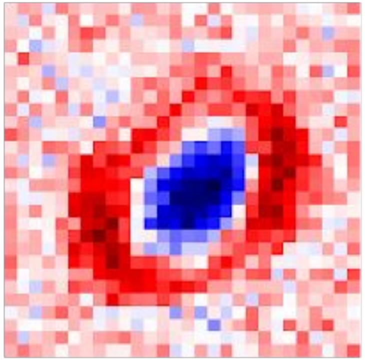
=

Output — Scores (N x batch_size)

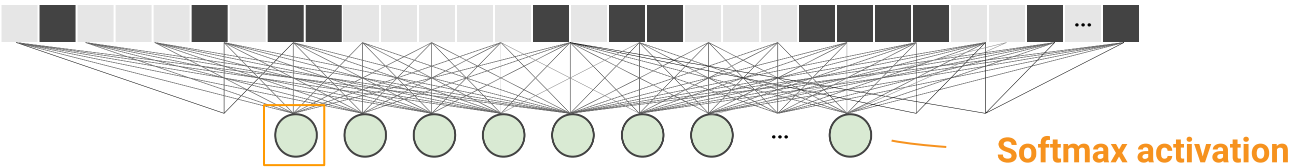
Image 1	**Image 2**	
130.1	**131.7**	**Plane**
-11.4	**-71.7**	**Car**
12.8	**64.8**	**Truck**



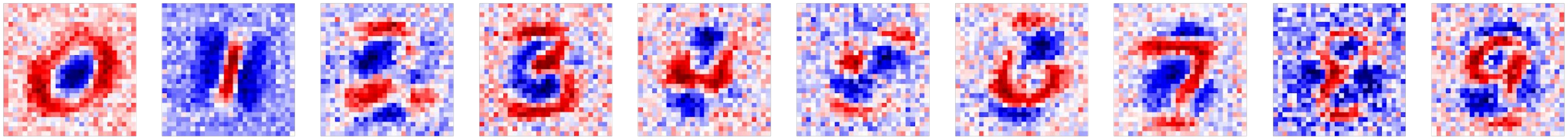
After training, select all the weights connected to this output.



```
model.layers[0].get_weights()

# Your code here
# Select the weights for a single output
# ...

img = weights.reshape(28,28)
plt.imshow(img, cmap = plt.get_cmap('seismic'))
```



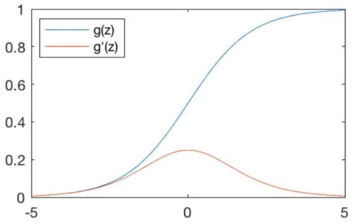
After training, select all the weights connected to this output.



A neural network

$$f = W_2 \boxed{g}(W x)$$

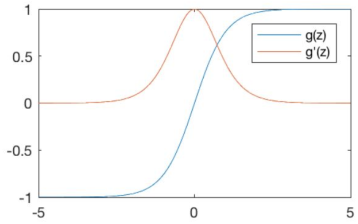
Sigmoid Function



$$g(z) = \frac{1}{1 + e^{-z}}$$

$$g'(z) = g(z)(1 - g(z))$$

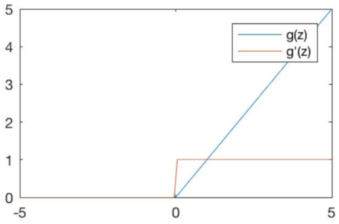
Hyperbolic Tangent



$$g(z) = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}}$$

$$g'(z) = 1 - g(z)^2$$

Rectified Linear Unit (ReLU)



$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$

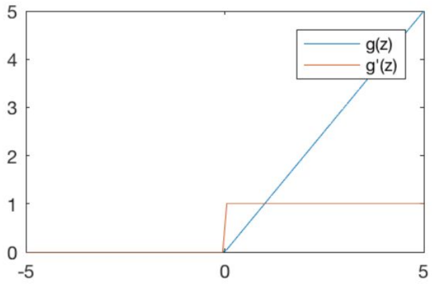
ReLU

130.1	Plane
-11.4	Car
12.8	Truck

Output

Scores

Rectified Linear Unit (ReLU)



$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$

g(130.1)	Plane
g(-11.4)	Car
g(12.8)	Truck

=

?	Plane
?	Car
?	Truck

$$f = W_2 \boxed{g(Wx)}$$

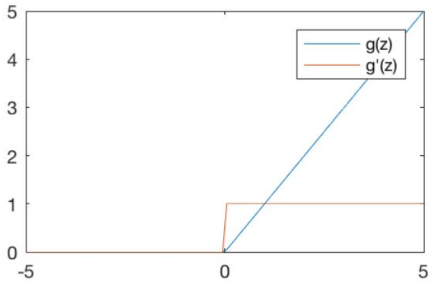
Applied piecewise

130.1	Plane
-11.4	Car
12.8	Truck

Output

Scores

Rectified Linear Unit (ReLU)



$$g(z) = \max(0, z)$$

$$g'(z) = \begin{cases} 1, & z > 0 \\ 0, & \text{otherwise} \end{cases}$$

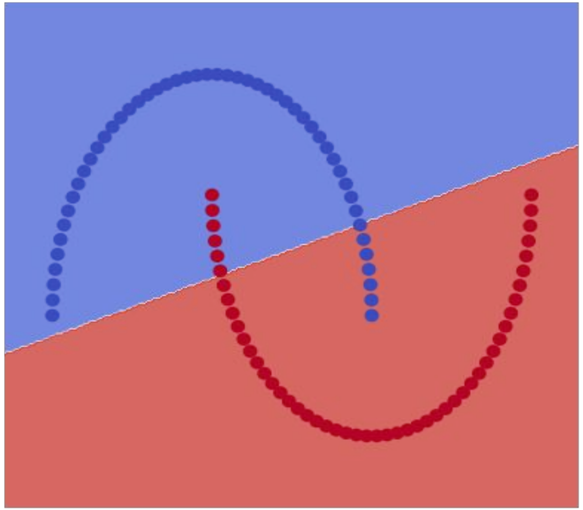
g(130.1)	Plane
g(-11.4)	Car
g(12.8)	Truck

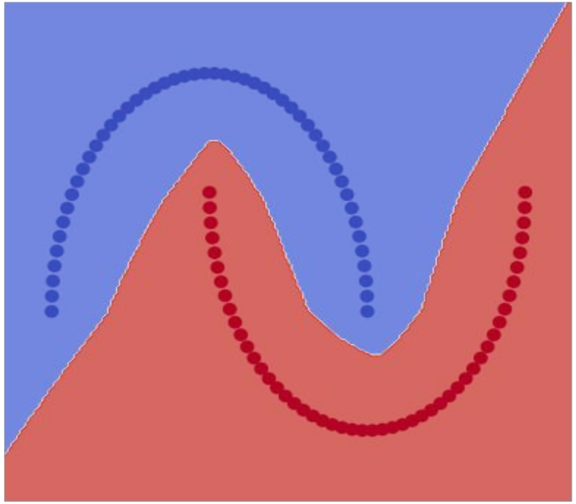
=

130.1	Plane
0	Car
12.8	Truck

$$f = W_2 \boxed{g(Wx)}$$

Activation functions introduce non-linearities





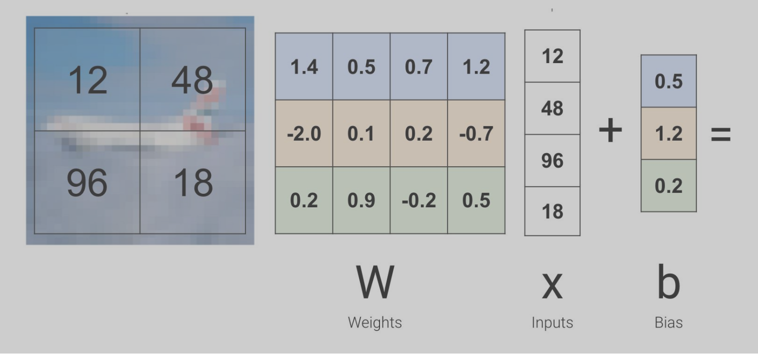
Notes
- You can make similar plots (and more) with this example. Note: from an older version of TF, but should work out of the box in Colab.
- Each of our convolutional layers used an activation as well (not shown in previous slides).
- You can make a demo of this in TensorFlow Playground by setting activation = Linear (or none)

Without activation, many layers are equivalent to one

```
# If you replace 'relu' with 'None', this model ...
model = Sequential([
  Dense(256, activation='relu', input_shape=(2,)),
  Dense(256, activation='relu'),
  Dense(256, activation='relu'),
  Dense(1, activation='sigmoid')
])
```

```
# ... has the same representation power as this one
model = Sequential([Dense(1, activation='sigmoid', input_shape=(2,))])
```

Softmax converts scores to probabilities



130.1	Plane
-11.4	Car
12.8	Truck

Scores

```
softmax([130.1, -11.4, 12.8])
>>> 0.999, 0.001, 0.001
```

Probabilities

Note: these are 'probability like' numbers (do not go to vegas and bet in this ratio).

Cross entropy compares two distributions

Each example has a label in a one-hot format

This is a bird

0	1	2	3	4	5	6	7	8	9	
0	0	1	0	0	0	0	0	0	0	True probabilities
0.1	0.2	0.6	0.2	0.0	0.0	0.0	0.0	0.0	0.0	Predicted probabilities

Rounded! Softmax output is always 0 < x < 1

Cross entropy loss for a batch of examples

True prob (either 1 or 0) in our case!

$$L = -\sum \hat{y}\; ln(y_i)$$

Sum over all examples

Predicted prob (between 0-1)

Exercise

bit.ly/ijcai_1-a

Complete the notebook for Fashion MNIST

Answers: next slide.

Exercise

bit.ly/ijcai_1-a

Complete the notebook for Fashion MNIST

Answers: bit.ly/ijcai_1-a_answers

TensorFlow RFP

jbgordon@google.com

goo.gle/tensorflow-rfp

Convolution

Not a Deep Learning concept

```
import scipy
from skimage import color, data
import matplotlib.pyplot as plt
img = data.astronaut()
img = color.rgb2gray(img)
plt.axis('off')
plt.imshow(img, cmap=plt.cm.gray)
```

Convolution example

-1	-1	-1
-1	8	-1
-1	-1	-1

Notes
Edge detection intuition: dot product of the filter with a region of the image will be zero if all the pixels around the border have the same value as the center.

Does anyone know who this is?

Convolution example

-1	-1	-1
-1	8	-1
-1	-1	-1

Notes
Edge detection intuition: dot product of the filter with a region of the image will be zero if all the pixels around the border have the same value as the center.

Eileen Collins

A simple edge detector

```
kernel = np.array([[-1,-1,-1],
                   [-1,8,-1],
                   [-1,-1,-1]])
result = scipy.signal.convolve2d(img, kernel, 'same')
plt.axis('off')
plt.imshow(result, cmap=plt.cm.gray)
```

Easier to see with seismic

Eileen Collins

-1	-1	-1
-1	8	-1
-1	-1	-1

Notes
Edge detection intuition: dot product of the filter with a region of the image will be zero if all the pixels around the border have the same value as the center.

Example

2	0	1	1
0	1	0	0
0	0	1	0
0	3	0	0

An input image
(no padding)

1	0	1
0	0	0
0	1	0

A filter
(3x3)

Output image
(after convolving with stride 1)

Example

2	0	1	1
0	1	0	0
0	0	1	0
0	3	0	0

An input image
(no padding)

1	0	1
0	0	0
0	1	0

A filter
(3x3)

3	

Output image
(after convolving with stride 1)

2*1 + 0*0 + 1*1 + 0*0 + 1*0 + 0*0 + 0*0 + 0*1 + 1*0

Example

2	0	1	1
0	1	0	0
0	0	1	0
0	3	0	0

An input image
(no padding)

1	0	1
0	0	0
0	1	0

A filter
(3x3)

3	2

Output image
(after convolving with stride 1)

Example

2	0	1	1
0	1	0	0
0	0	1	0
0	3	0	0

An input image
(no padding)

1	0	1
0	0	0
0	1	0

A filter
(3x3)

3	2
3	

Output image
(after convolving with stride 1)

Example

2	0	1	1
0	1	0	0
0	0	1	0
0	3	0	0

An input image
(no padding)

1	0	1
0	0	0
0	1	0

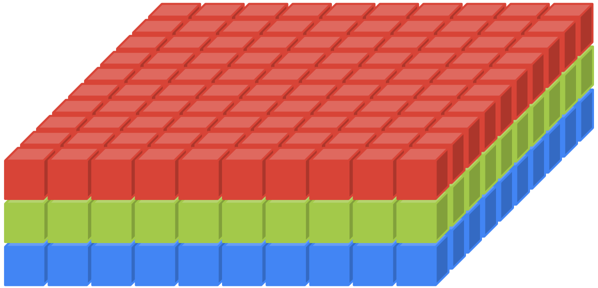
A filter
(3x3)

3	2
3	1

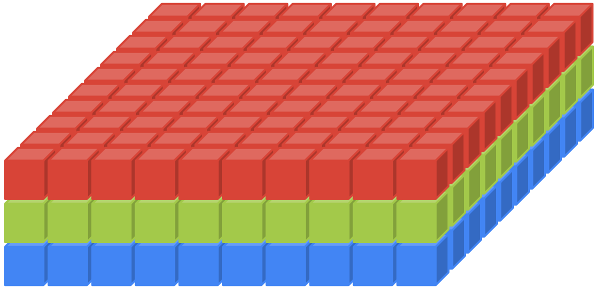
Output image
(after convolving with stride 1)

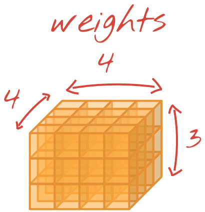
In 3d

```
model = Sequential()

model.add(Conv2D(filters=4,
                 kernel_size=(4,4),
                 input_shape=(10,10,3)))
```

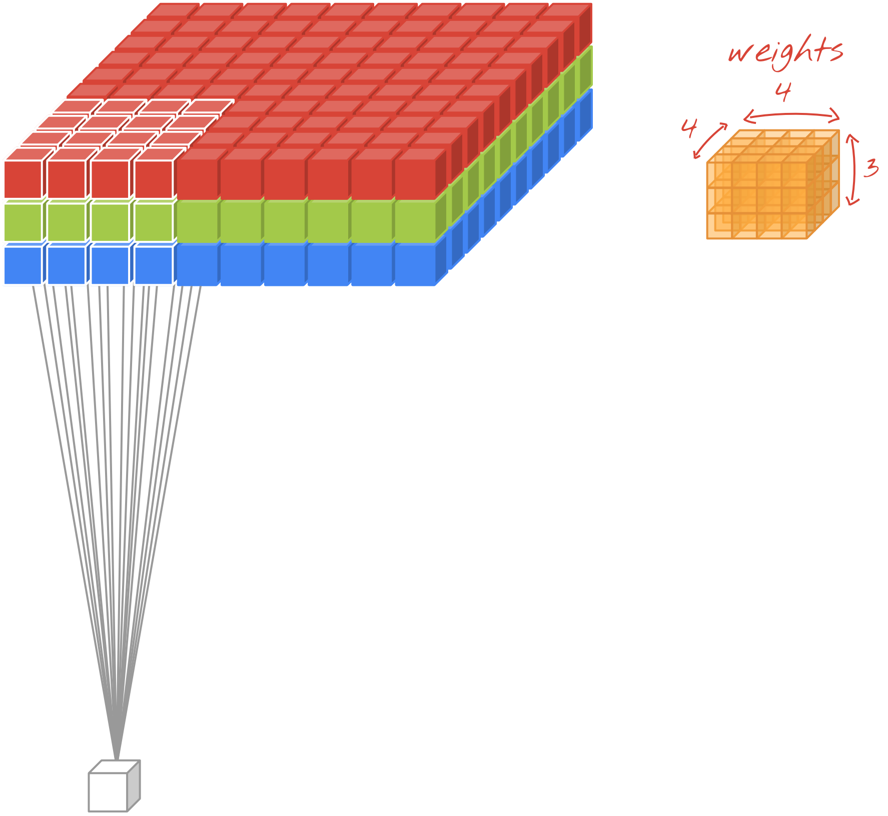


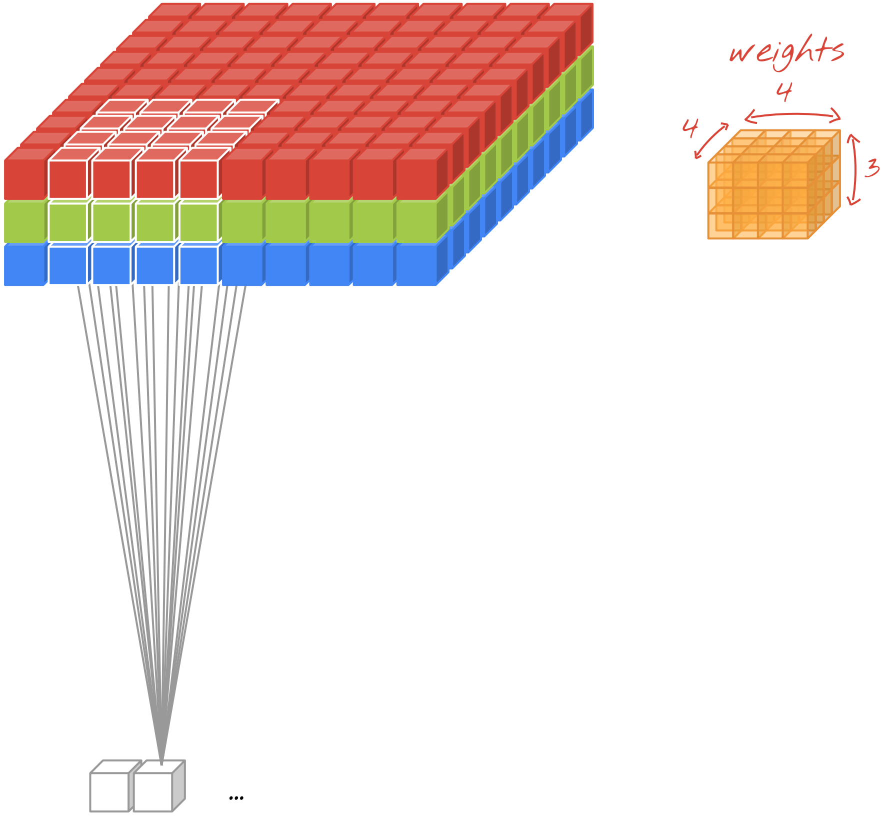
A RGB image as a 3d **volume**.
Each color (or channel) is a layer.



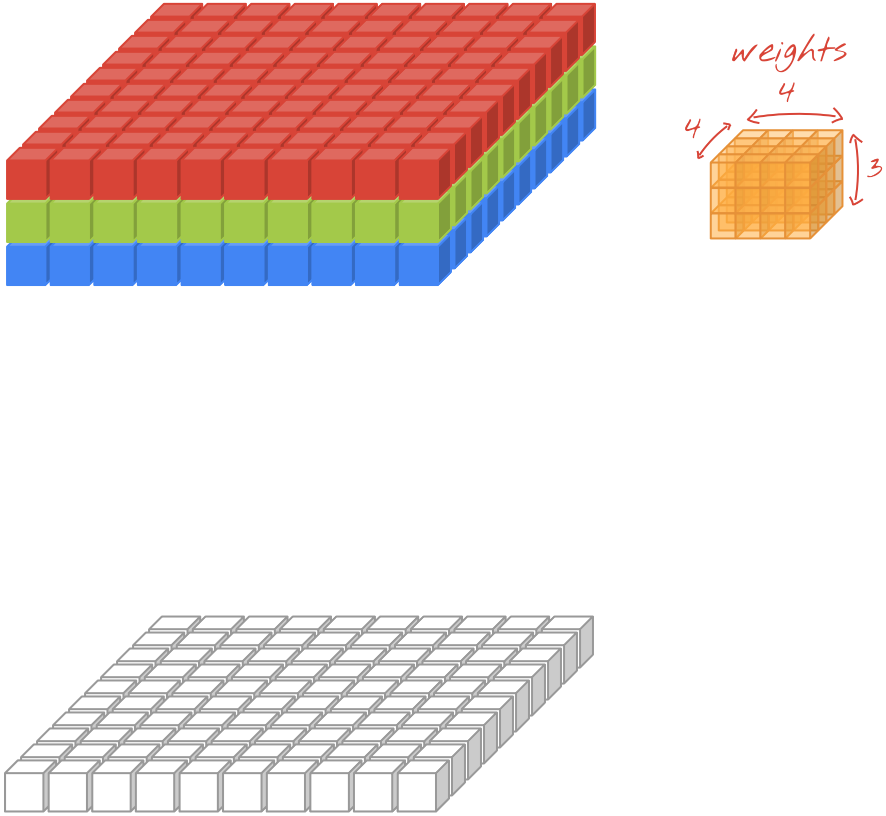


In 3d, our filters have width, height, and depth.

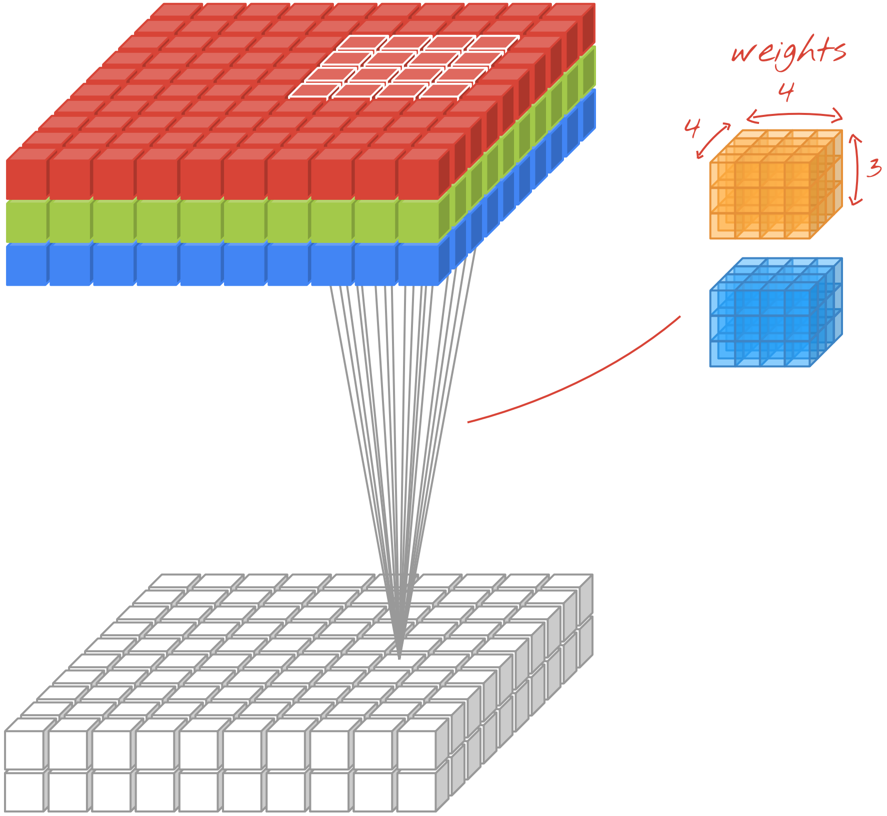

weights
4
4
3



Applied in the same way as 2d (sum of weight * pixel value as they slide across the image).



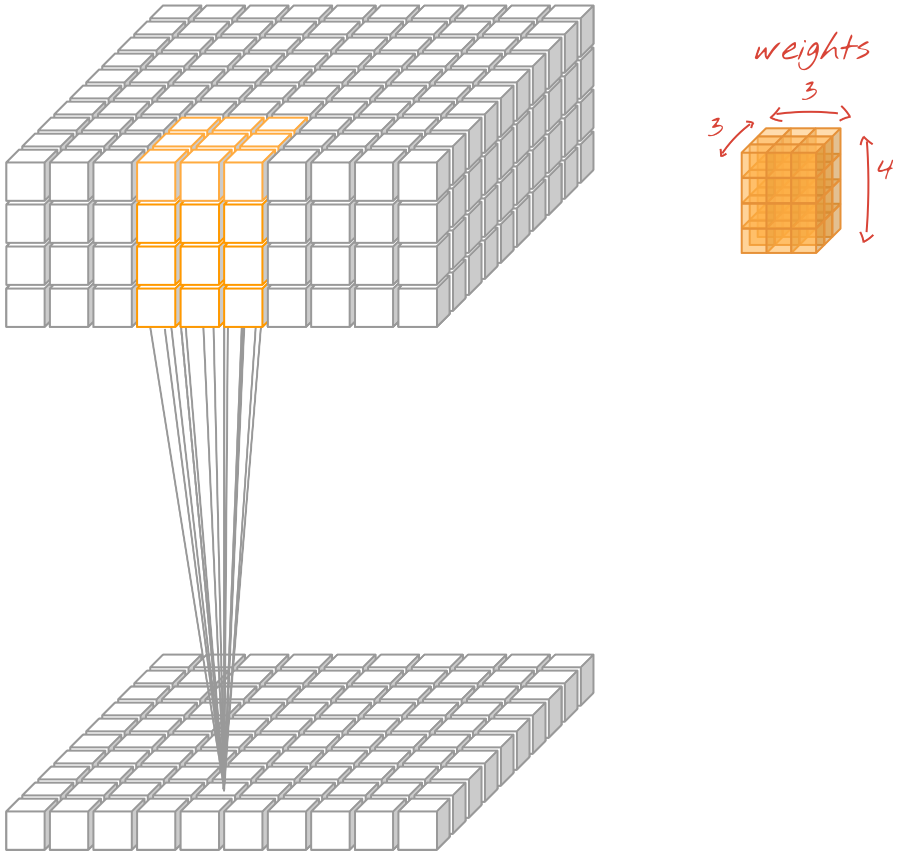
Applying the convolution over the rest of the input image.



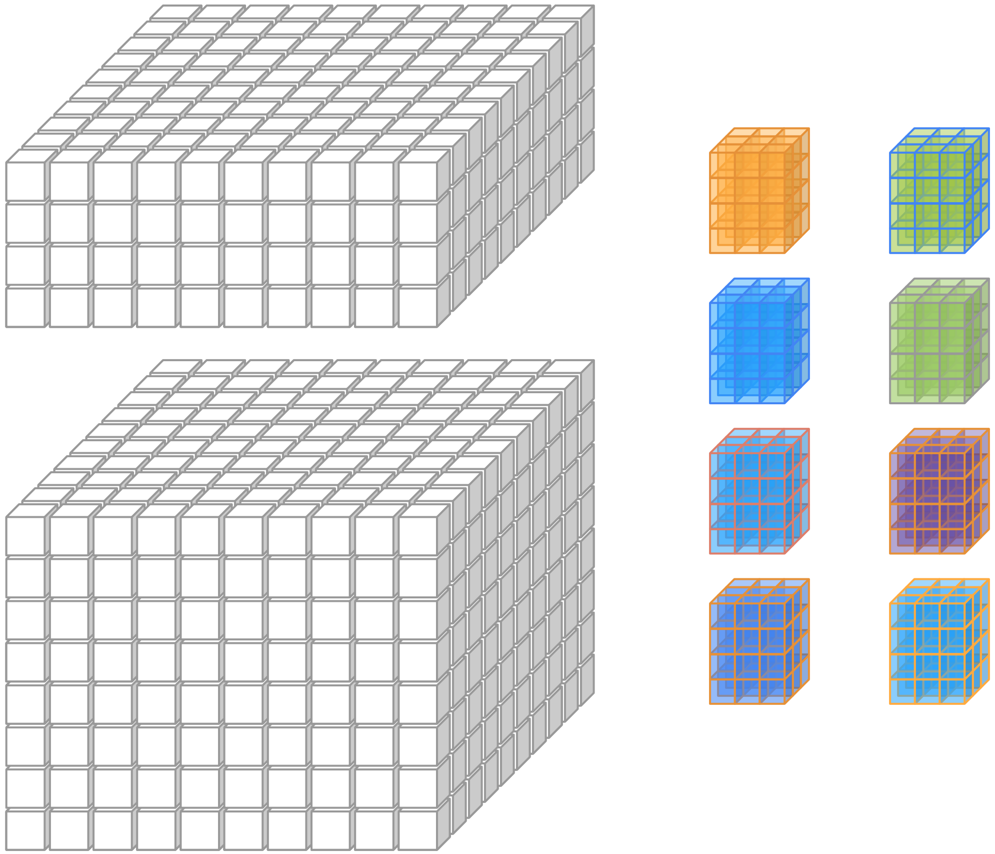
More filters, more output channels.

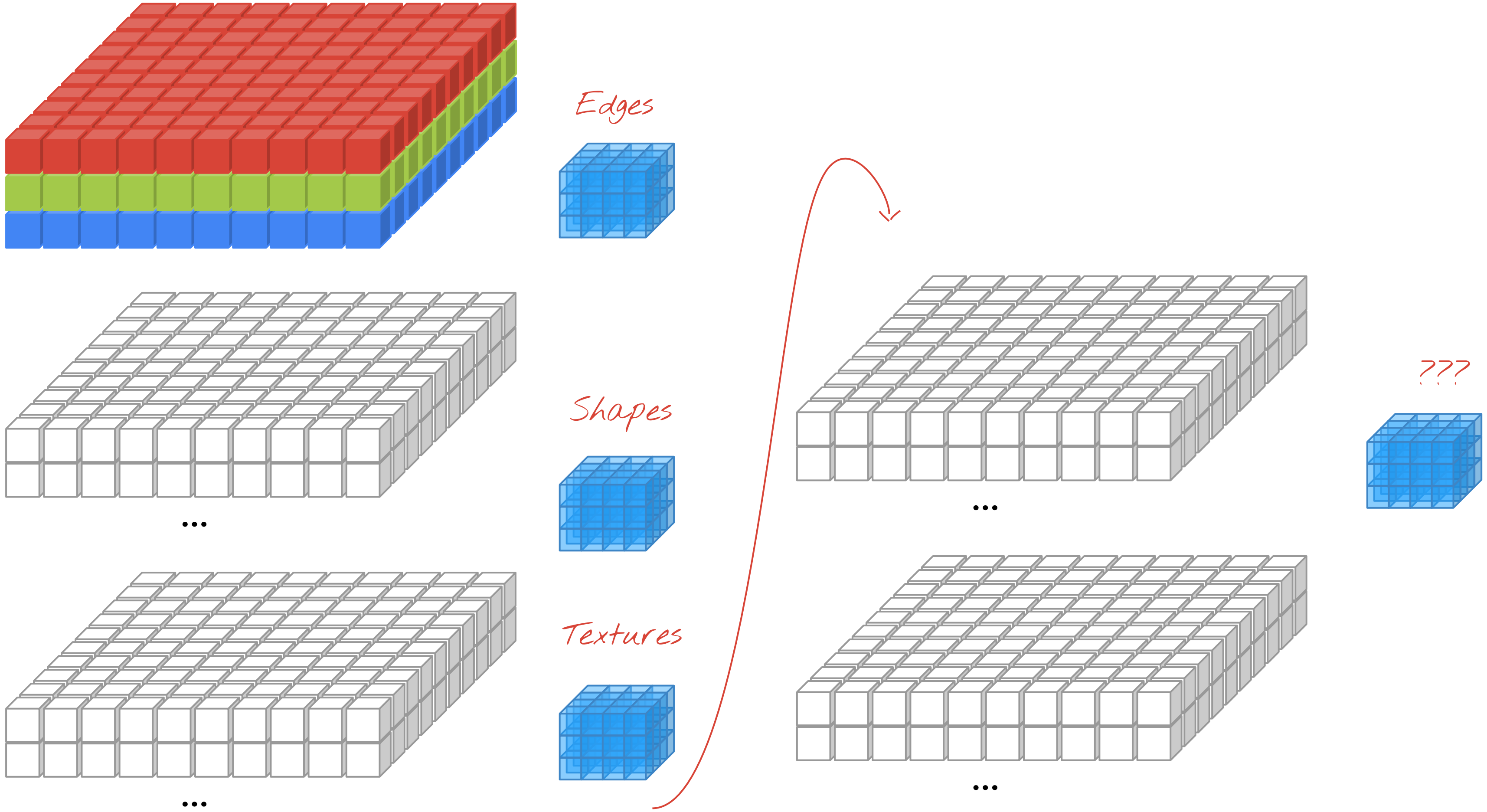
Going deeper

```
model = Sequential()

model.add(Conv2D(filters=4,
                 kernel_size=(4,4),
                 input_shape=(10,10,3))

model.add(Conv2D(filters=8,
                 kernel_size=(3,3))
```

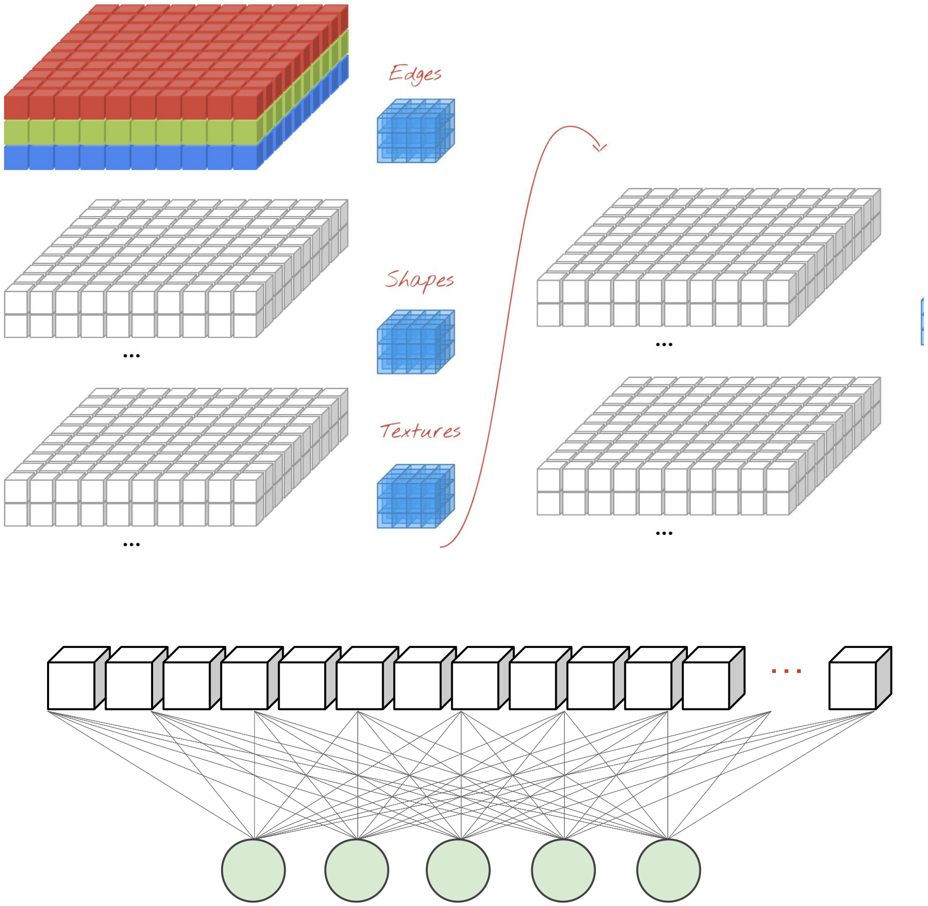


weights
3
3
4





Edges
Shapes
Textures
...
...
???
...
...


Edges
Shapes
Textures

Exercise

bit.ly/ijcai_1_b

Write a CNN from scratch for CIFAR-10.

Answers: next slide.

Ref: tensorflow.org/beta/tutorials/images/intro_to_cnns

Exercise

bit.ly/ijcai_1b

Write a CNN from scratch for CIFAR-10.

Answers: bit.ly/ijcai_1_b_answers

Game 1

Would you like to volunteer?

quickdraw.withgoogle.com

Example: transfer learning

bit.ly/ijcai_2

Transfer learning using a pretrained MobileNet and a Dense layer.

Ref: tensorflow.org/beta/tutorials/images/transfer_learning

Ref: tensorflow.org/beta/tutorials/images/hub_with_keras

Example: transfer learning

bit.ly/ijcai_2

Transfer learning using a pretrained MobileNet and a Dense layer.

Answers: bit.ly/ijcai_2_answers

Deep Dream

New tutorial

bit.ly/dream-wip

Image segmentation

Recent tutorial

bit.ly/im-seg

Timeseries forecasting

Recent tutorial

Game 2

Who would like to volunteer?

magenta.tensorflow.org/assets/sketch_rnn_demo/index.html

CycleGAN

Recent tutorial

Under the hood

Let’s make this faster

```
lstm_cell = tf.keras.layers.LSTMCell(10)



def fn(input, state):
  return lstm_cell(input, state)

input = tf.zeros([10, 10]); state = [tf.zeros([10, 10])] * 2
lstm_cell(input, state); fn(input, state) # warm up

# benchmark
timeit.timeit(lambda: lstm_cell(input, state), number=10) # 0.03
```

Let’s make this faster

```
lstm_cell = tf.keras.layers.LSTMCell(10)

@tf.function
def fn(input, state):
  return lstm_cell(input, state)

input = tf.zeros([10, 10]); state = [tf.zeros([10, 10])] * 2
lstm_cell(input, state); fn(input, state) # warm up

# benchmark
timeit.timeit(lambda: lstm_cell(input, state), number=10) # 0.03
timeit.timeit(lambda: fn(input, state), number=10) # 0.004
```

AutoGraph makes this possible

```
@tf.function
def f(x):
  while tf.reduce_sum(x) > 1:
    x = tf.tanh(x)
  return x

# you never need to run this (unless curious)
print(tf.autograph.to_code(f))
```

Generated code

```
def tf__f(x):
  def loop_test(x_1):
    with ag__.function_scope('loop_test'):
      return ag__.gt(tf.reduce_sum(x_1), 1)
  def loop_body(x_1):
    with ag__.function_scope('loop_body'):
      with ag__.utils.control_dependency_on_returns(tf.print(x_1)):
        tf_1, x = ag__.utils.alias_tensors(tf, x_1)
        x = tf_1.tanh(x)
        return x,
  x = ag__.while_stmt(loop_test, loop_body, (x,), (tf,))
  return x
```

Going big: tf.distribute.Strategy

```
model = tf.keras.models.Sequential([
    tf.keras.layers.Dense(64, input_shape=[10]),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(10, activation='softmax')])

model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

Going big: Multi-GPU

```
strategy = tf.distribute.MirroredStrategy()

with strategy.scope():
  model = tf.keras.models.Sequential([
      tf.keras.layers.Dense(64, input_shape=[10]),
      tf.keras.layers.Dense(64, activation='relu'),
      tf.keras.layers.Dense(10, activation='softmax')])
  model.compile(optimizer='adam', loss='categorical_crossentropy',
              metrics=['accuracy'])
```

Learning more

Latest tutorials and guides

- tensorflow.org/beta

Books

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

For details

- deeplearningbook.org