Deep Learning with Python and Friends

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Indy.Code() 2019

Polyglot ninja

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Pluralsight Author

Watch for carefully placed marketing through the talk!

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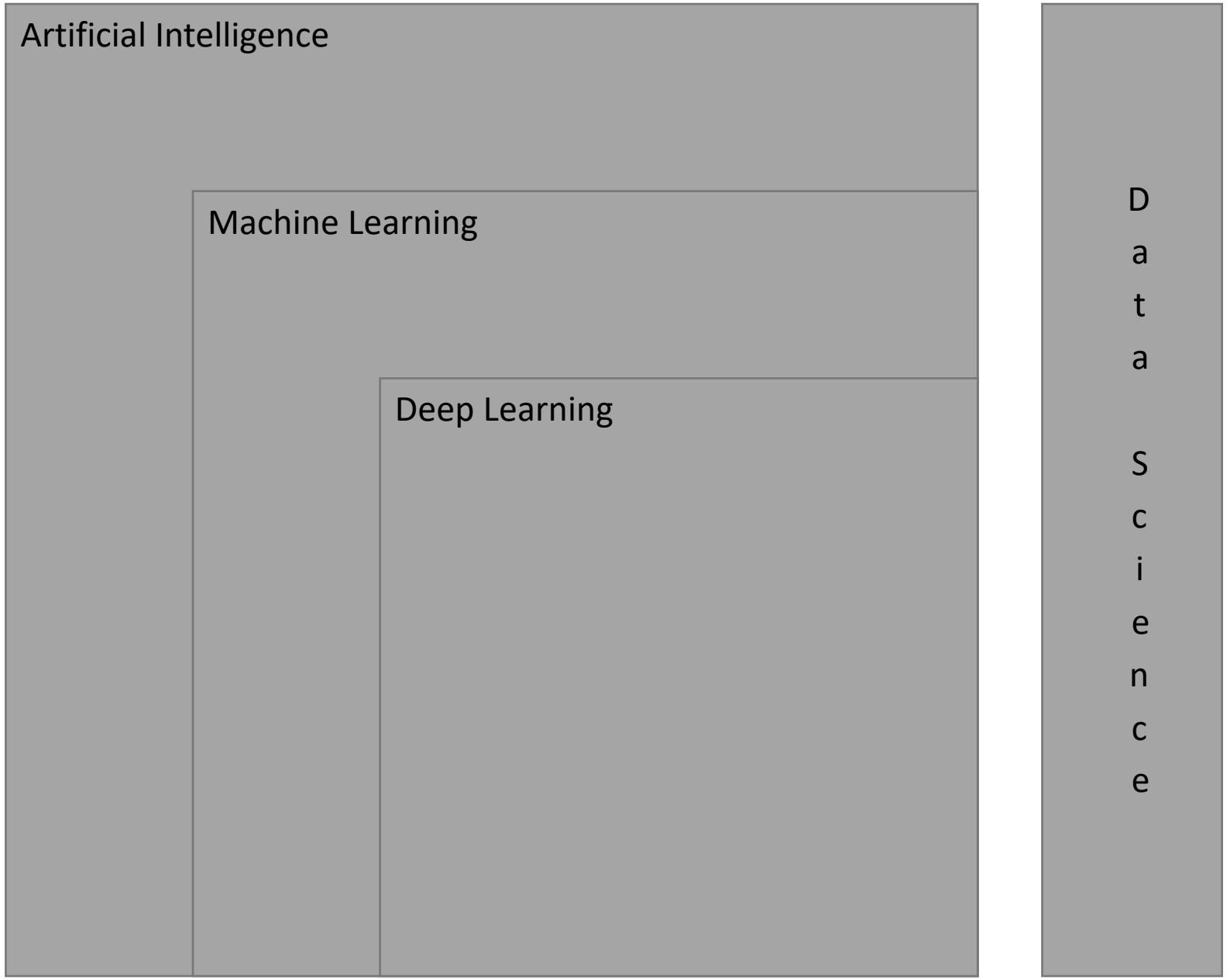

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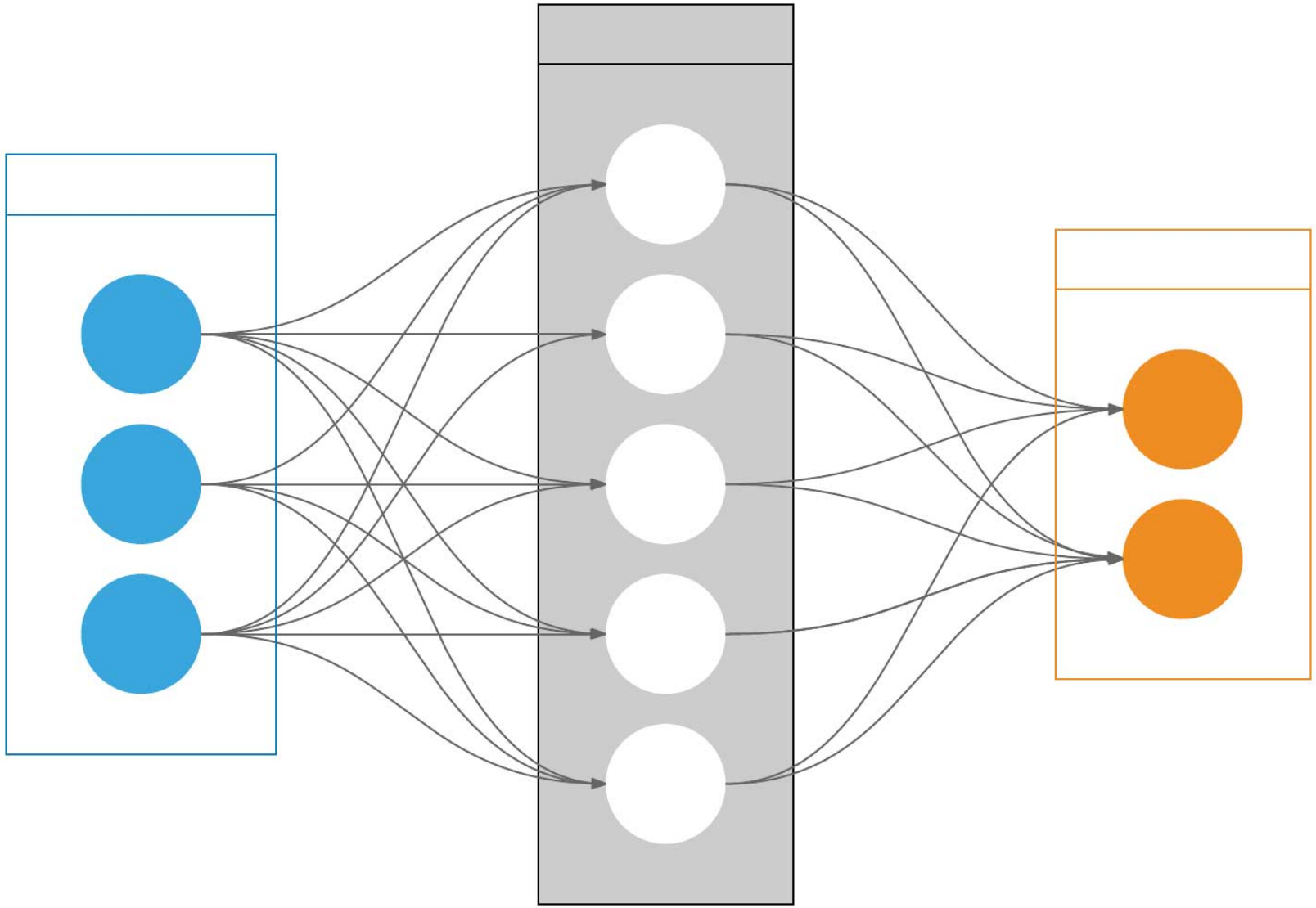

Neural networks are loosely inspired by how neuroscientists today think the brain might possibly work.

(assuming they are on the right track)

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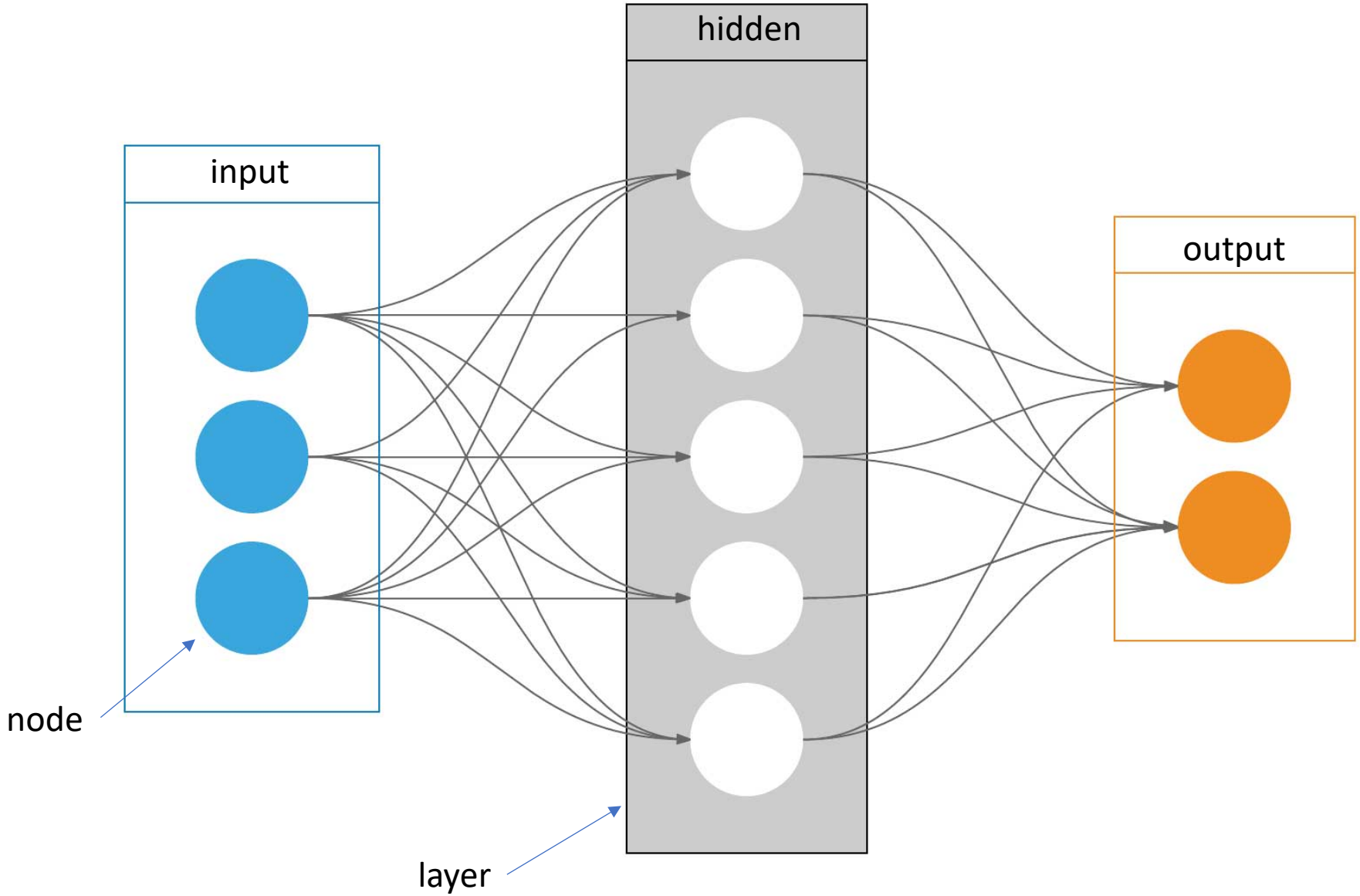
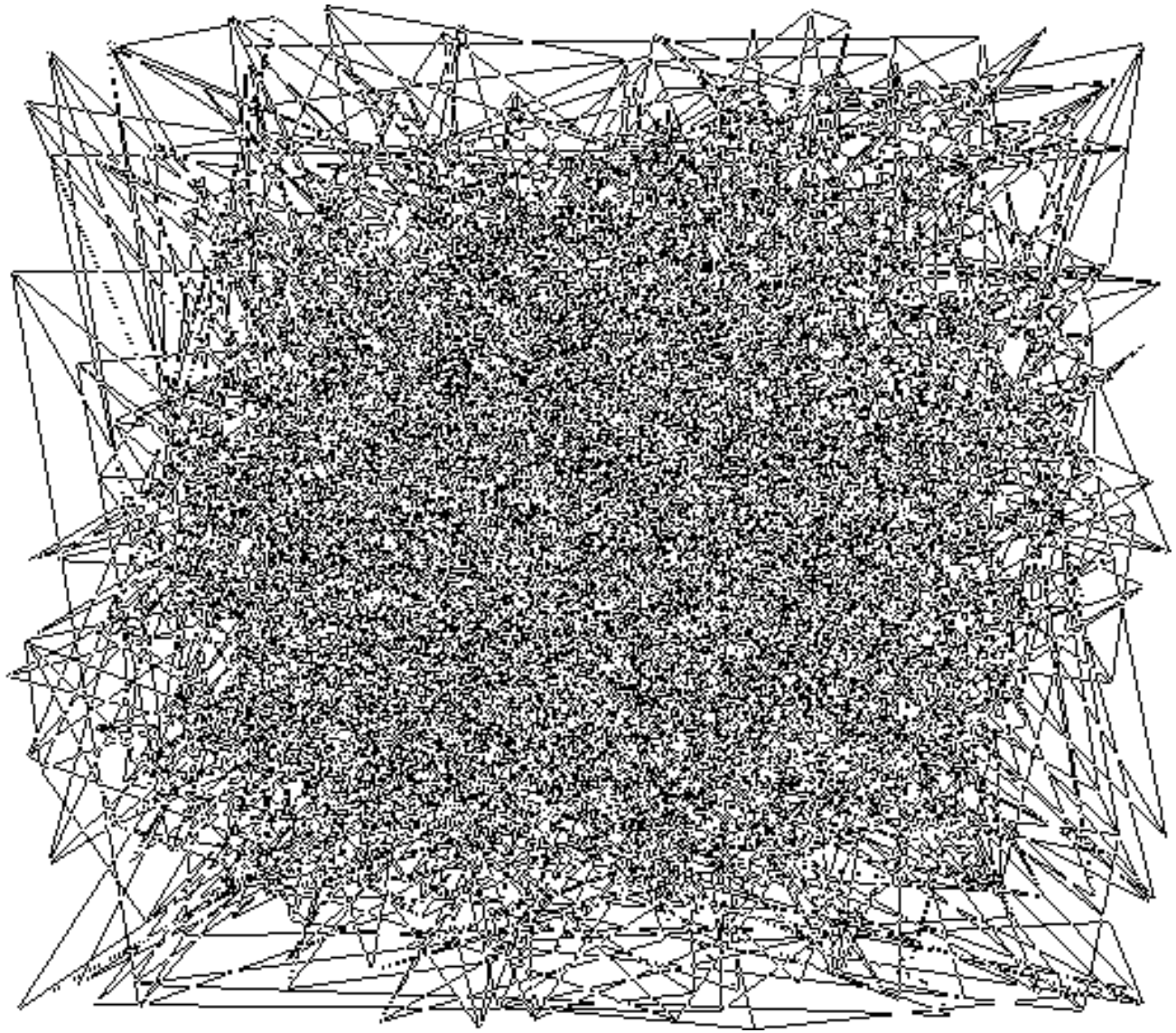

hidden
input
output
node
layer

A neural network with more than two hidden layers is called a **deep** neural network.



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feature vector | target

Sepal Length	Sepal Width	Petal Length	Petal Width	Species
5.1	3.5	1.4	0.2	setosa
…	…	…	…	…
7.0	3.2	4.7	1.4	versicolor
…	…	…	…	…
5.7	2.8	4.1	1.3	virginica

rows -> observations

columns -> features

feature vector / independent variables -> observed values

target / dependent variable(s) -> what we want to predict

train a **model** that, given a **feature vector**, will (hopefully accurately) assign a **target**

train a **model** that, given values for *Sepal Length, Sepal Width, Petal Length, Petal Width*, will assign one value from the set of *setosa, versicolor*, or *virginica*


input
hidden
output
Sepal Length
Sepal Width
Petal Length
Petal Width
Species
5.1
3.5
1.4
0.2
setosa
5.1
3.5
1.4
0.2
.55
55%
setosa
.30
30%
versicolor
.15
15%
virginica
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Is this prediction correct?

There is only one trick question in the entire talk. This is it.

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During training, we are not concerned with making a correct prediction, but rather making a prediction that is as close to correct as possible.


WTF?
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Prediction	Actual
.55	1.0
.30	0
.15	0


I think we can do better!
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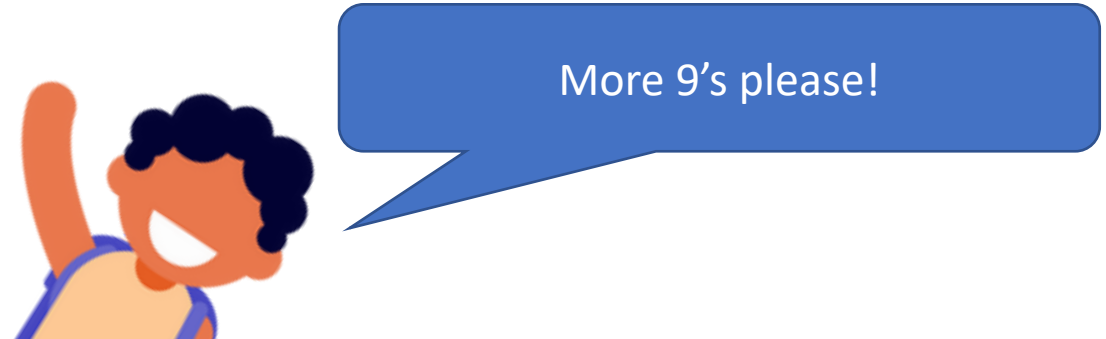
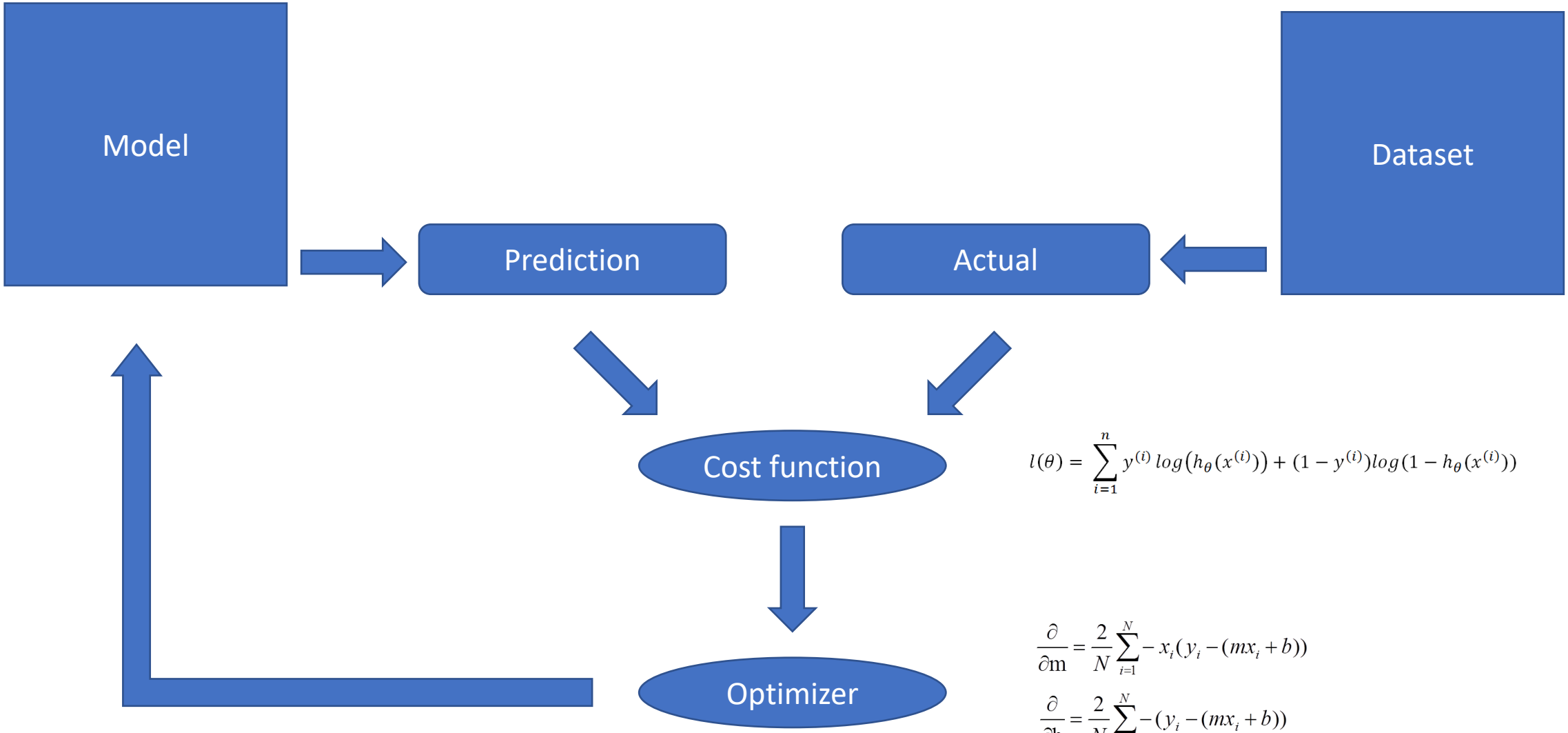
Prediction	Actual
.9999999	1.0
.0000001	0
.0000001	0





$$l(\theta) = \sum_{i=1}^{n} y^{(i)} log\left(h_\theta(x^{(i)})\right) + (1 - y^{(i)}) log(1 - h_\theta(x^{(i)}))$$

$$\frac{\partial}{\partial \mathrm{m}} = \frac{2}{N} \sum_{i=1}^{N} - x_i (y_i - (mx_i + b))$$

$$\frac{\partial}{\partial \mathrm{b}} = \frac{2}{N} \sum_{i=1}^{N} - (y_i - (mx_i + b))$$

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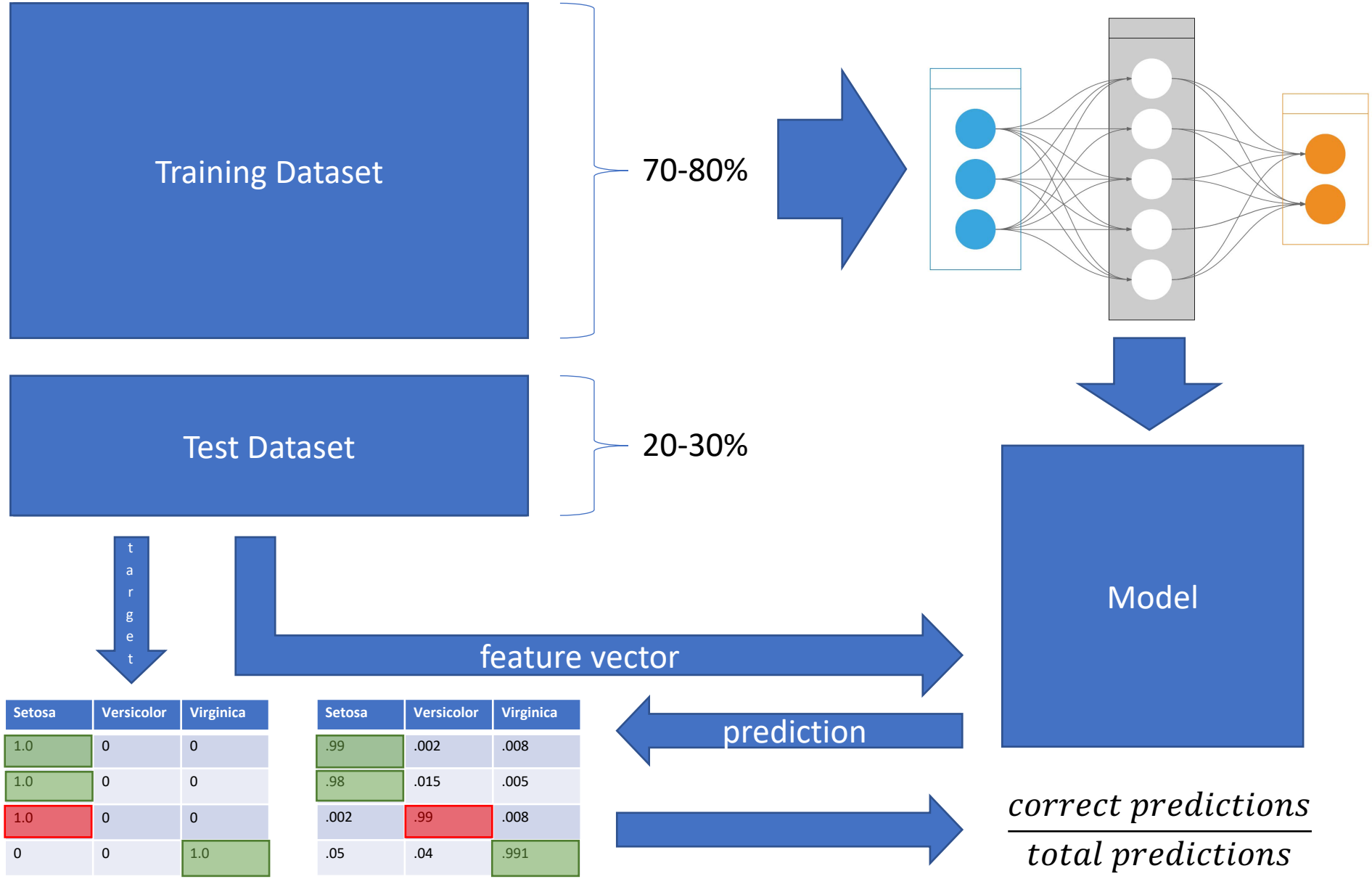
The model is trained

Now what?



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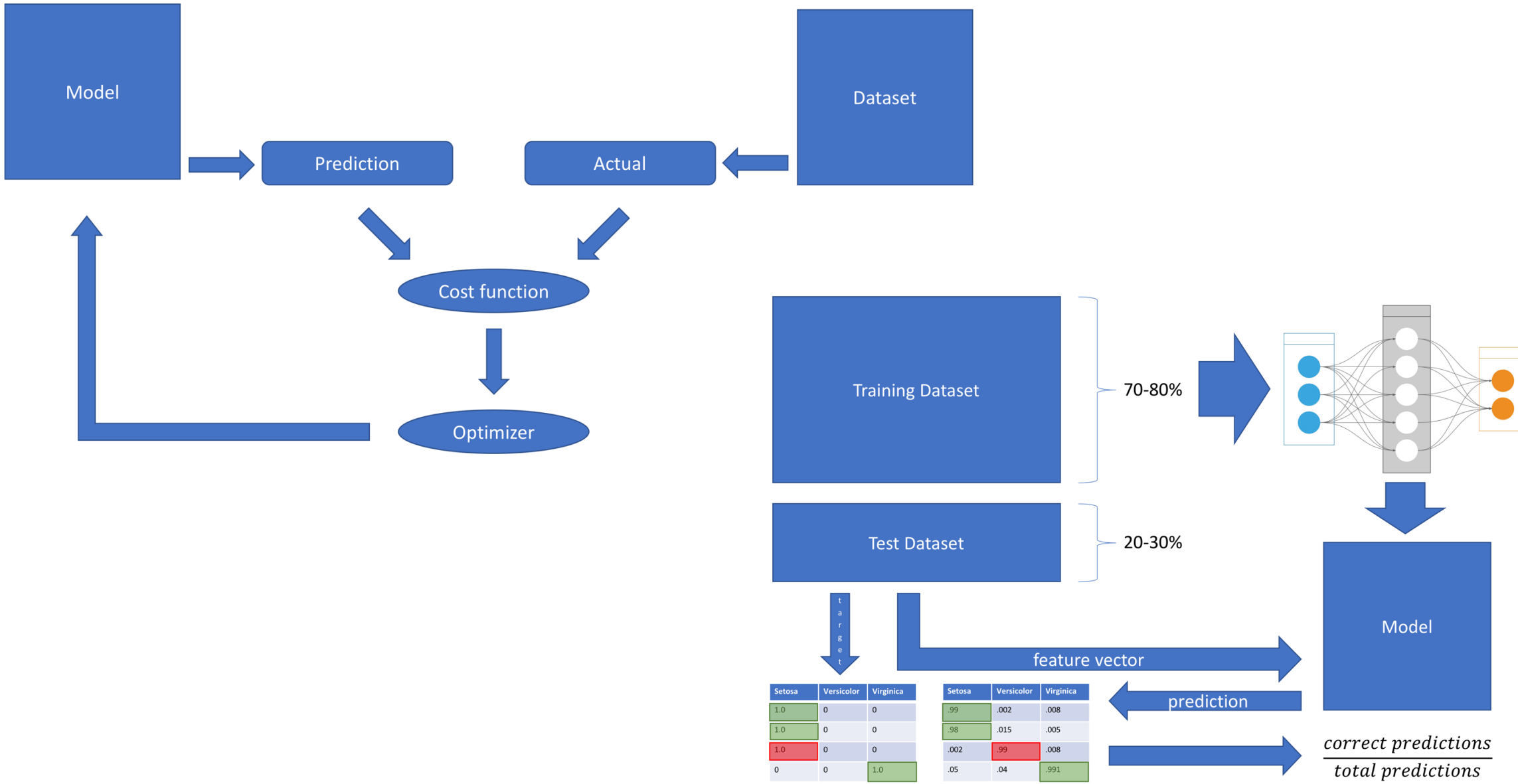
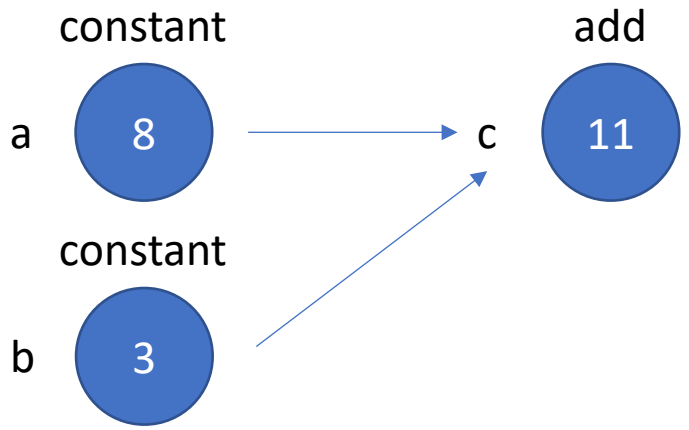


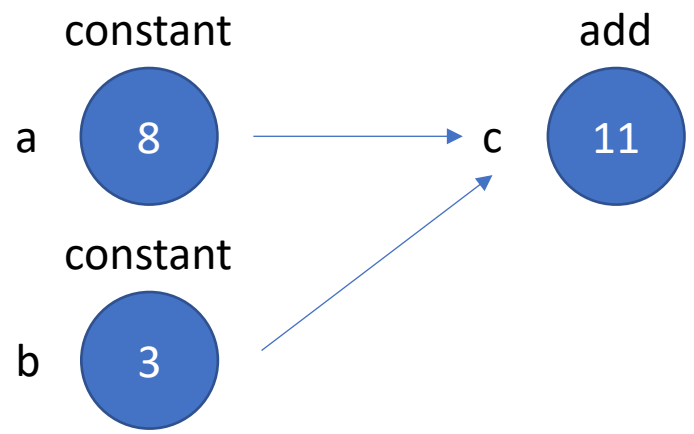
TensorFlow

```
import tensorflow as tf
a = tf.constant(8)
b = tf.constant(3)
c = tf.add(a, b) # or a + b, operator is overloaded
```

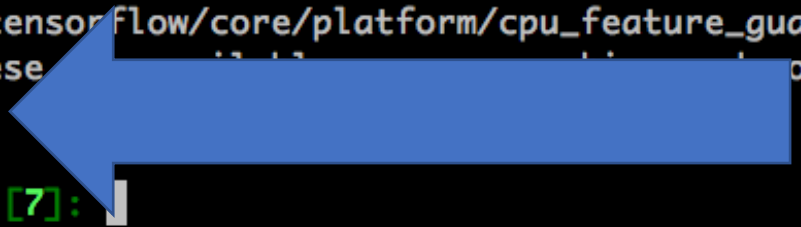


```
Last login: Tue Apr 10 09:40:34 on ttys001
douglasmbpr:~ douglasstarnes$ ipython
Python 3.6.3 |Anaconda custom (64-bit)| (default, Oct  6 2017, 12:04:38)
Type 'copyright', 'credits' or 'license' for more information
IPython 6.1.0 -- An enhanced Interactive Python. Type '?' for help.

In [1]: import tensorflow as tf

In [2]: a = tf.constant(8)

In [3]: b = tf.constant(3)

In [4]: c = tf.add(a, b)

In [5]: print(c)
Tensor("Add:0", shape=(), dtype=int32)

In [6]:
```

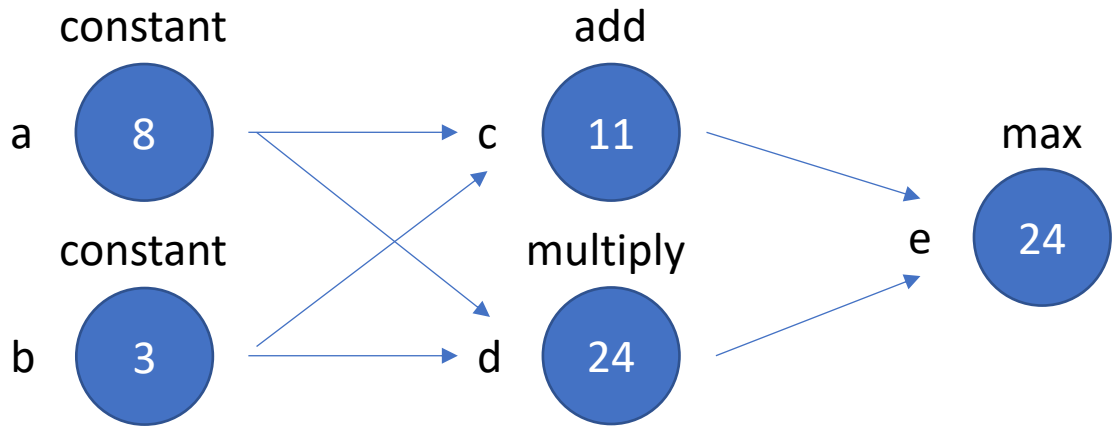
```
import tensorflow as tf
a = tf.constant(8)
b = tf.constant(3)
c = tf.add(a, b) # or a + b
with tf.Session() as s:
    print(s.run(c))
```

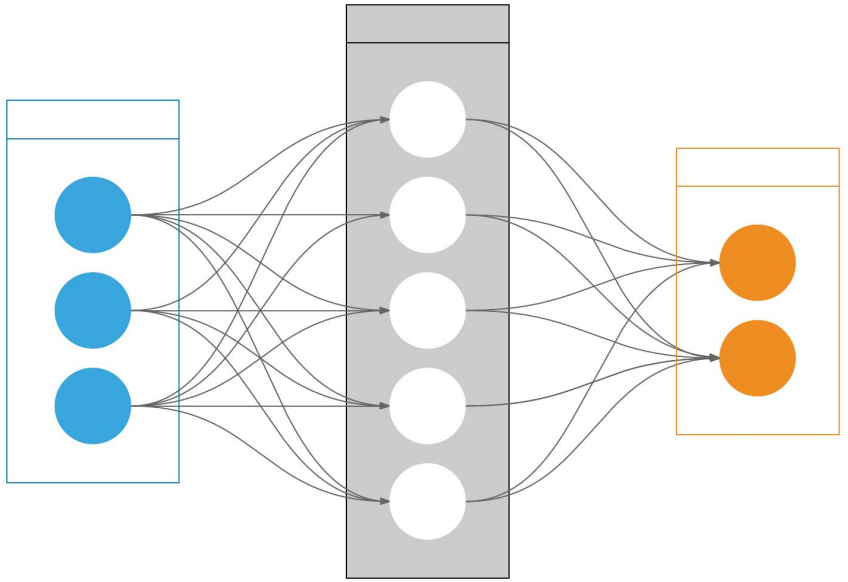


```
In [5]: print(c)
Tensor("Add:0", shape=(), dtype=int32)

In [6]: with tf.Session() as s:
   ...:     print(s.run(c))
   ...:
W tensorflow/core/platform/cpu_feature_guard.cc:45] The TensorFlow library wasn't compiled to use SSE4.1 instructions, b
ut these are available on your machine and could speed up CPU computations.
W tensorflow/core/platform/cpu_feature_guard.cc:45] The TensorFlow library wasn't compiled to use SSE4.2 instructions, b
ut these are available on your machine and could speed up CPU computations.
W tensorflow/core/platform/cpu_feature_guard.cc:45] The TensorFlow library wasn't compiled to use AVX instructions, but
these are available on your machine and could speed up CPU computations.
W tensorflow/core/platform/cpu_feature_guard.cc:45] The TensorFlow library wasn't compiled to use AVX2 instructions, but
 these are available on your machine and could speed up CPU computations.
W tensorflow/core/platform/cpu_feature_guard.cc:45] The TensorFlow library wasn't compiled to use FMA instructions, but
these                                                ould speed up CPU computations.
11

In [7]:
```



```
import tensorflow as tf
a = tf.constant(8)
b = tf.constant(3)
c = tf.add(a, b) # or a + b
with tf.Session() as s:
    print(s.run(c))
d = tf.multiply(a, b) # or a * b
e = tf.max(c, d)
with tf.Session() as s:
    print(s.run(e))
```





Meet MNIST

Scans of handwritten digits

Each image is 28x28 pixels

Each pixel value is 0 (black) to 255 (white)

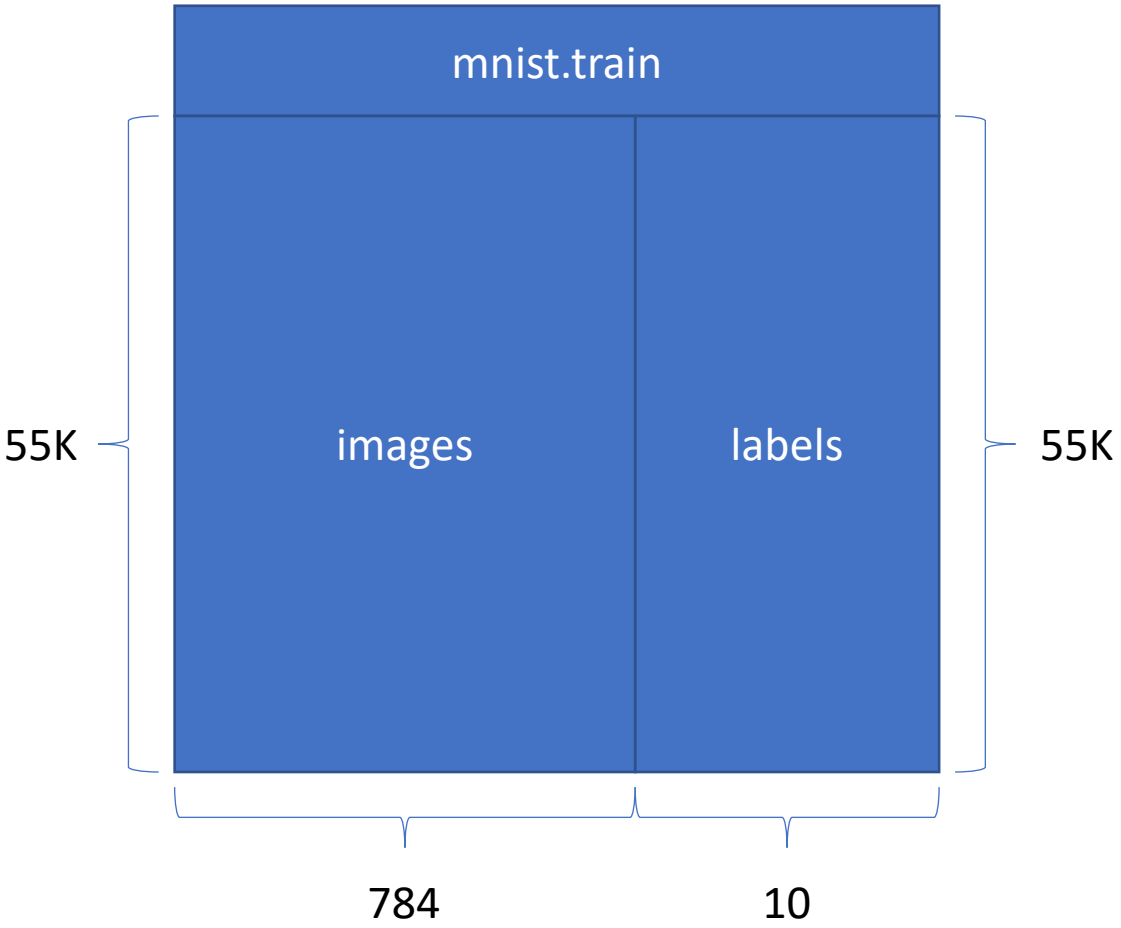
Feature vector is the entire image (784 pixels)

The target is the digit represented (0-9)

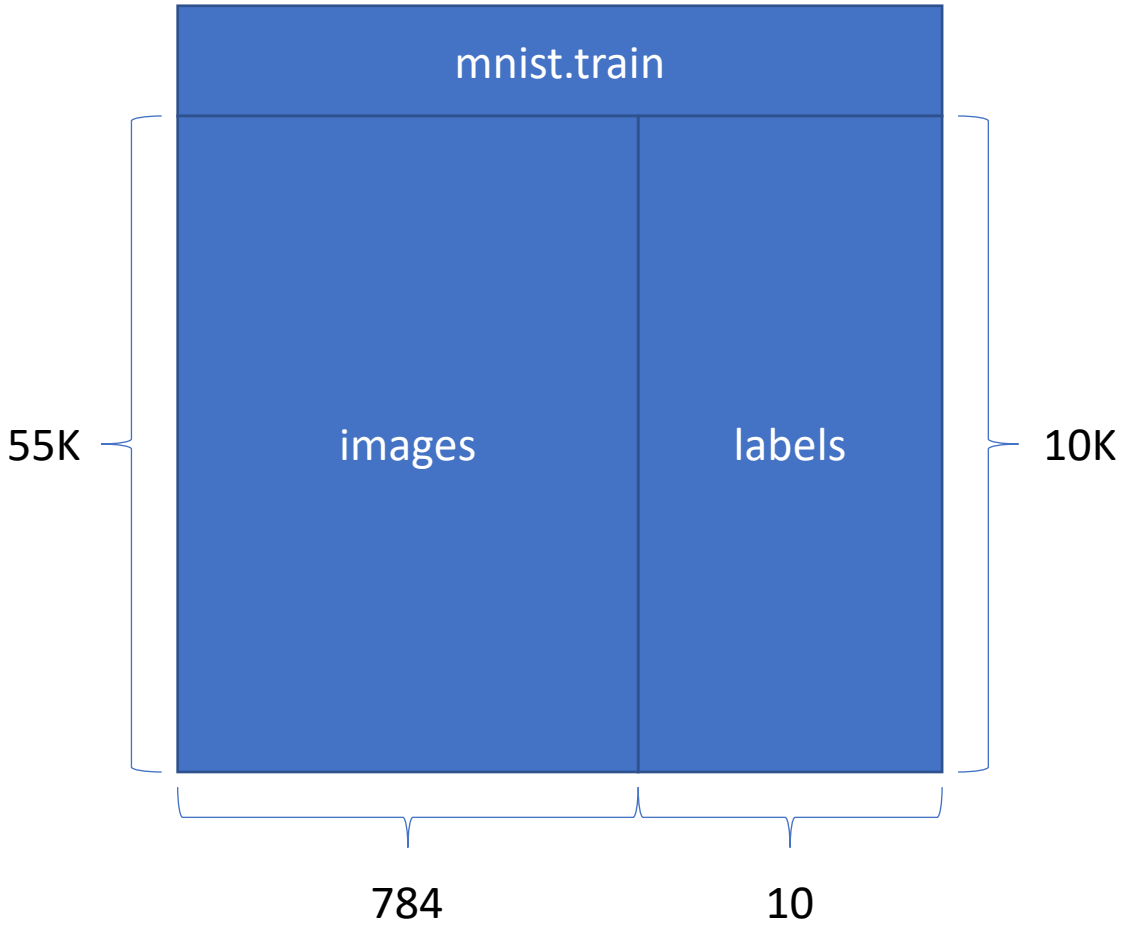
Interesting variations (ie. fashion MNIST)

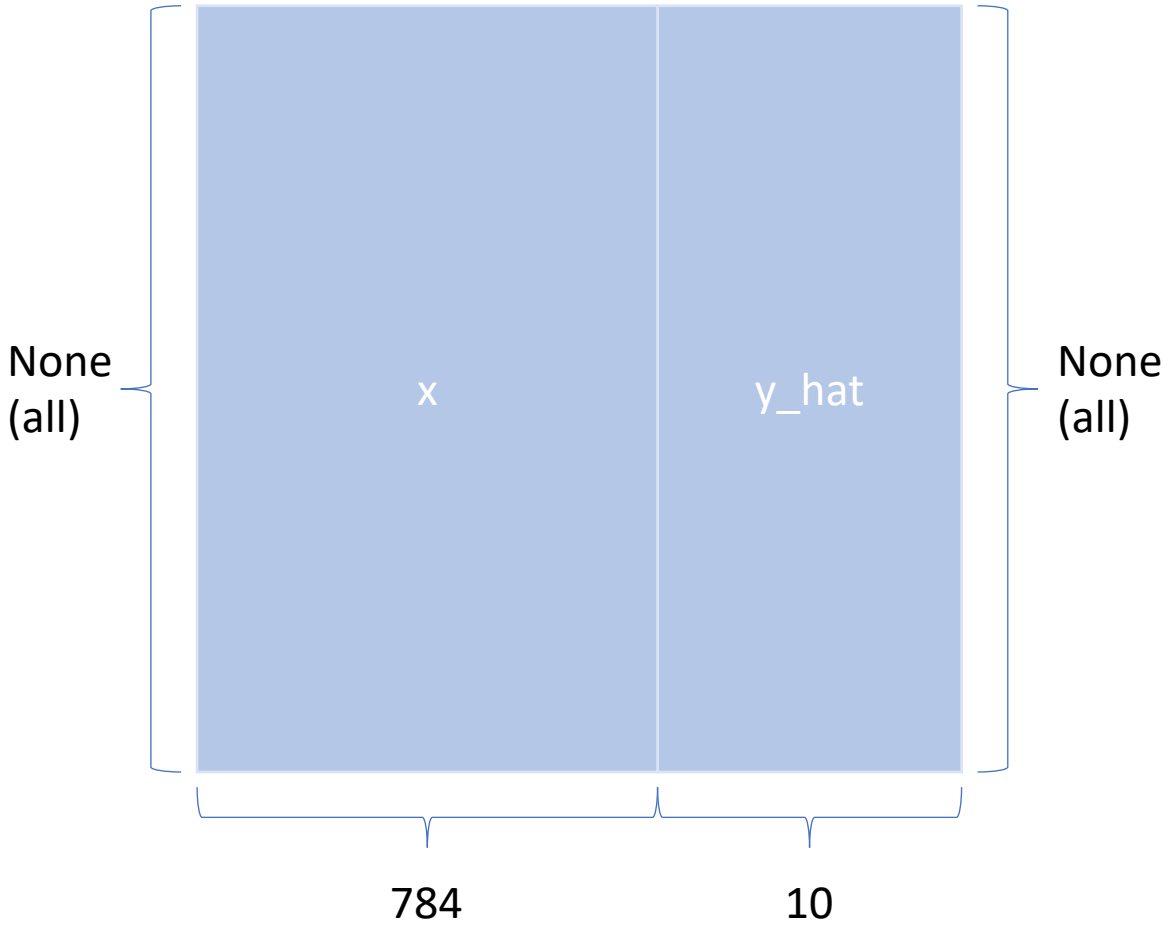
```
# Step 1: Acquire
from tensorflow.examples.tutorials.mnist import input_data
mnist = input_data.read_data_sets('MNIST_data', one_hot=True)
# Step 2: Clean (data is already clean)
# Step 3: Split (data is already split)
print(mnist.train.num_examples) # 55000
print(mnist.test.num_examples) # 10000
# Step 4: Train
x = tf.placeholder(tf.float32, shape=[None, 784]) # input for feature vectors
y_hat = tf.placeholder(tf.float32, shape=[None, 10]) # input for targets
weights = tf.Variable(tf.truncated_normal([784,10]) # initialize model with random values
bias = tf.Variable(tf.truncated_normal([10]) # initialize model with random values
classifier = tf.matmul(x, W) + b # prediction
y = tf.nn.softmax(classifier) # activation function
cost_function =
  tf.reduce_mean(-tf.reduce_sum(y_hat * tf.log(y))) # measure of similiarity
```

```
optimizer = tf.train.GradientDescentOptimizer(0.5).minimize(cost_function) # optimizer
with tf.Session() as sess:
    sess.run(tf.global_variables_initializer()) # assign random values
    for _ in mnist.train.num_examples / 100: # run one epoch
        batch = mnist.train.next_batch(100)
        sess.run(optimizer, feed_dict={x: batch[0], y_hat: batch[1]})
# Step 5: Test
correct_predictions = tf.equal(tf.argmax(y, 1), tf.argmax(y_hat, 1)) # total no. correct
# Step 6: Score
average_correct = tf.reduce_mean(tf.cast(correct_predictions, tf.float32)) # avg. no. correct
with tf.Session() as sess:
    print(
        sess.run(average_correct,
            feed_dict={x: mnist.test.images, y_hat: mnist.test.labels})
# Step 7: Evaluate – make some pretty pictures
```



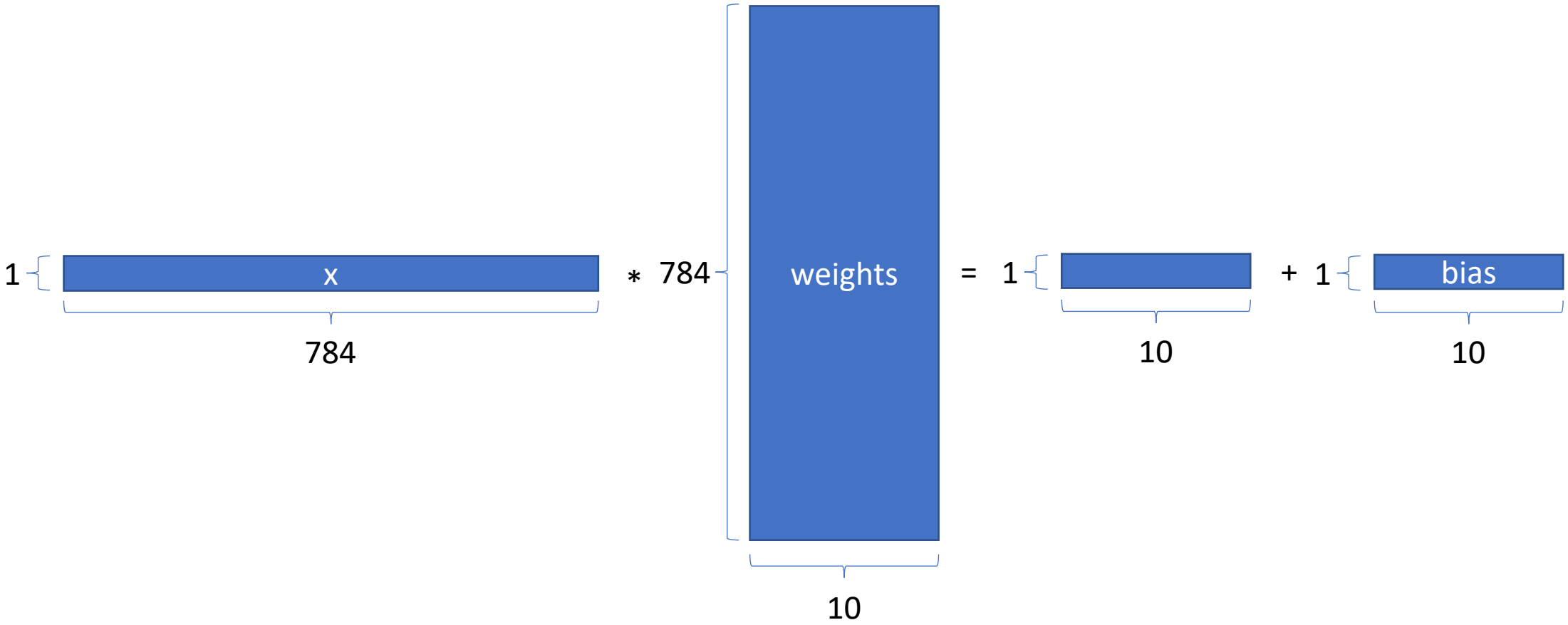

```
# Step 1: Acquire
from tensorflow.examples.tutorials.mnist import input_data
mnist = input_data.read_data_sets('MNIST_data', one_hot=True)
# Step 2: Clean (data is already clean)
# Step 3: Split (data is already split)
print(mnist.train.num_examples)
print(mnist.test.num_examples)
```

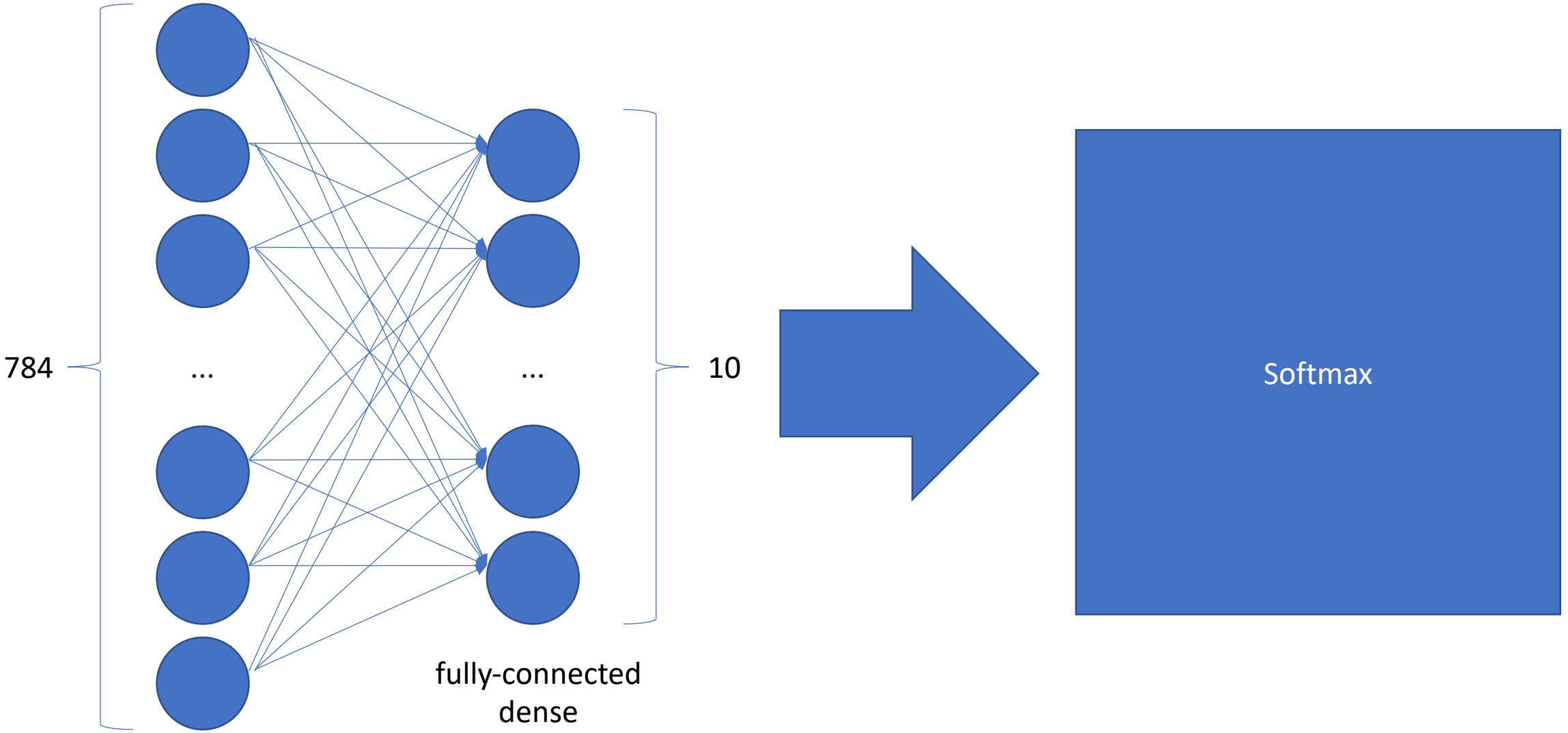





```
# Step 4: Train
x = tf.placeholder(tf.float32, shape=[None, 784])
y_hat = tf.placeholder(tf.float32, shape=[None, 10])
```

```
weights = tf.Variable(tf.truncated_normal([784,10])
bias = tf.Variable(tf.truncated_normal([10])
classifier = tf.matmul(x, weights) + bias
```




784
...
...
10
fully-connected
dense
Softmax

```
y = tf.nn.softmax(classifier)
```

$$softmax(i_x) = \frac{e^{i_x}}{\sum_{j=1}^{k} e^{i_j}}$$

```
from math import exp
i = [100, 101, 102]
def softmax(x):
    return exp(i[x]) / sum([exp(j) for j in i])
print([softmax(a) for a in range(len(i))])
```

```
[0.09003057317038046, 0.24472847105479764, 0.665240955774821 9]
```

9% 24% 67%

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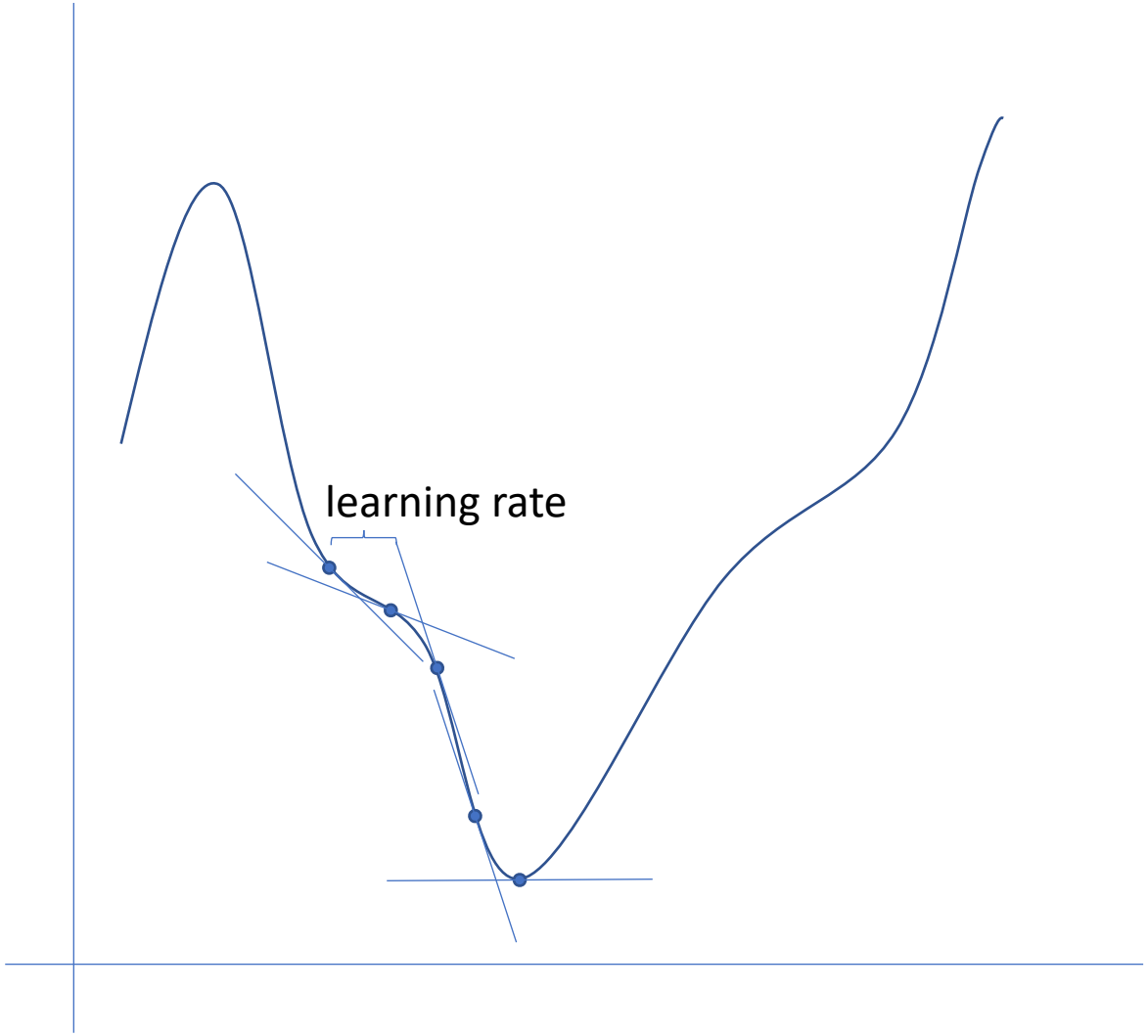
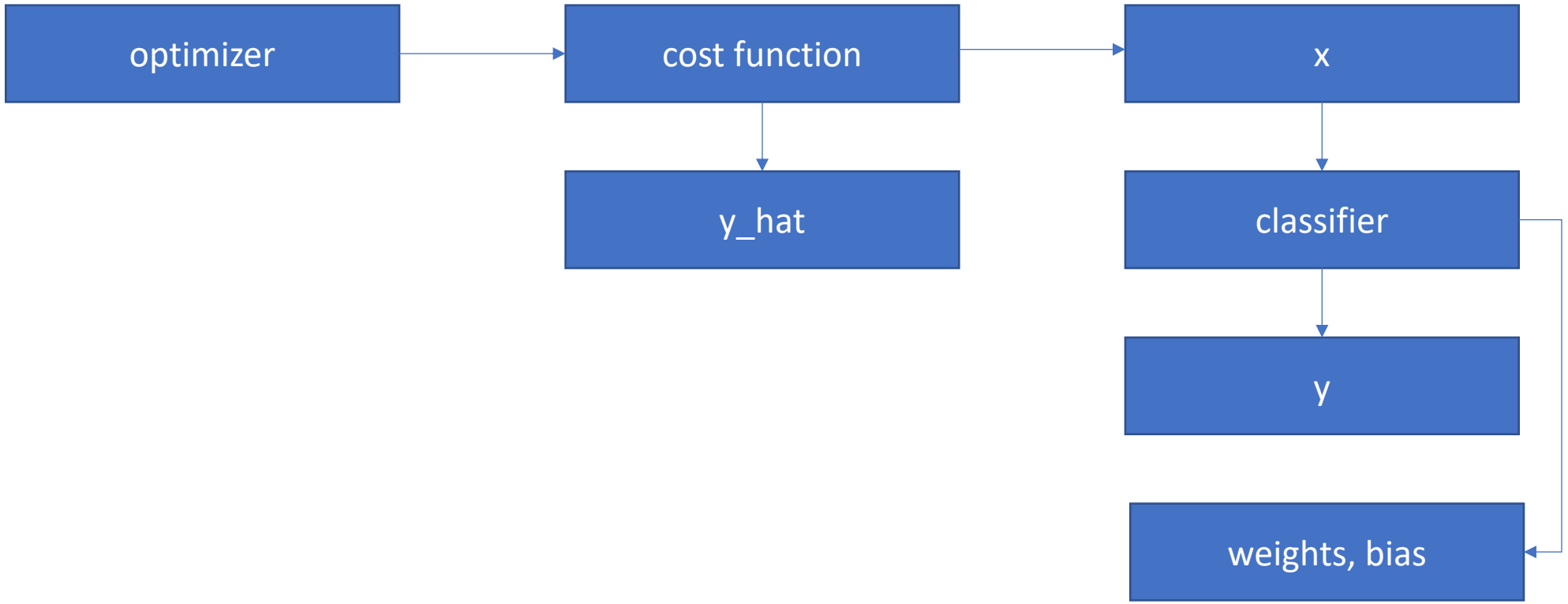
```
optimizer = tf.train.GradientDescentOptimizer(0.5).minimize(cost_function)
```



If the learning rate is too large, we will skip over the minimum.

If the learning rate is too small, we will waste time.

```
with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    for _ in mnist.train.num_examples / 100:
        batch = mnist.train.next_batch(100)
        sess.run(optimizer, feed_dict={x: batch[0], y_hat: batch[1]})
```



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```
correct_predictions = tf.equal(tf.argmax(y, 1), tf.argmax(y_hat, 1))
```

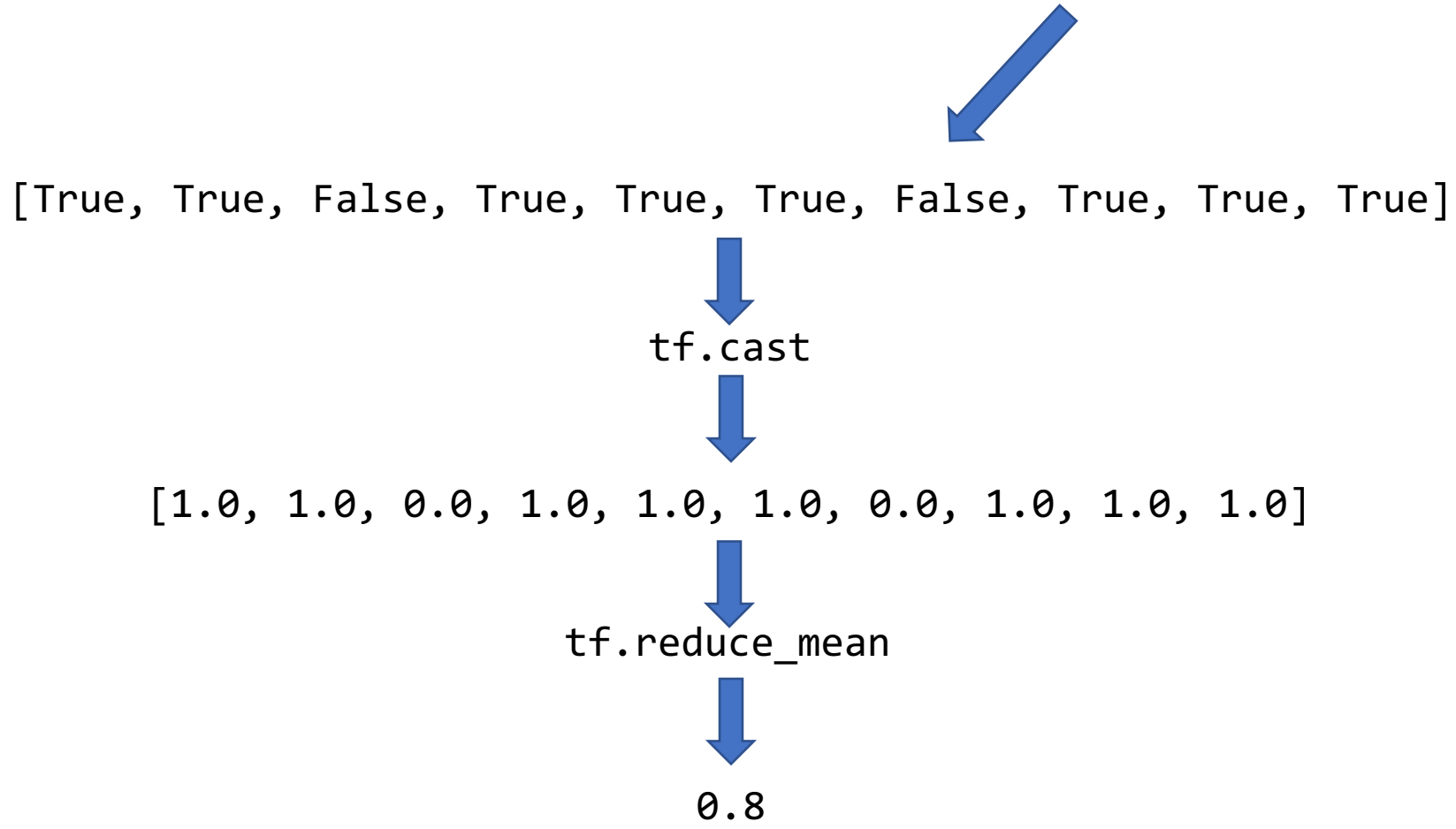
0	1	2	3	4	5	6	7	8	9
.003	.24	.9	.012	.004	0	.031	.001	.013	.008
.01	.019	.012	.003	.9	.02	.012	.014	.005	0

y

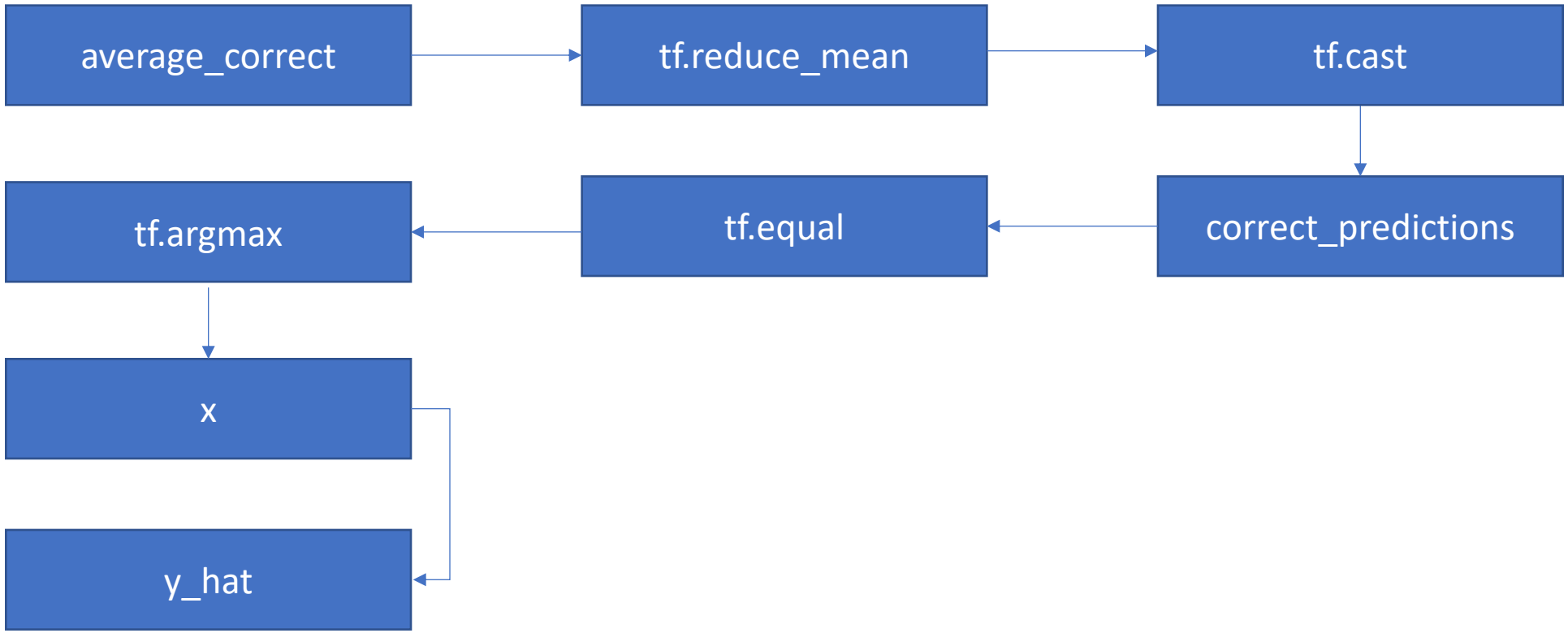
0	1	2	3	4	5	6	7	8	9
0	0	1	0	0	0	0	0	0	0
0	0	0	0	0	0	0	1	0	0

y_hat

```
average_correct = tf.reduce_mean(tf.cast(correct_predictions, tf.float32))
```



```
with tf.Session() as sess:
        sess.run(average_correct, feed_dict={x: mnist.test.images,
          y_hat: mnist.test.labels})
```



(time permitting)


That works but surely there is an easier method?
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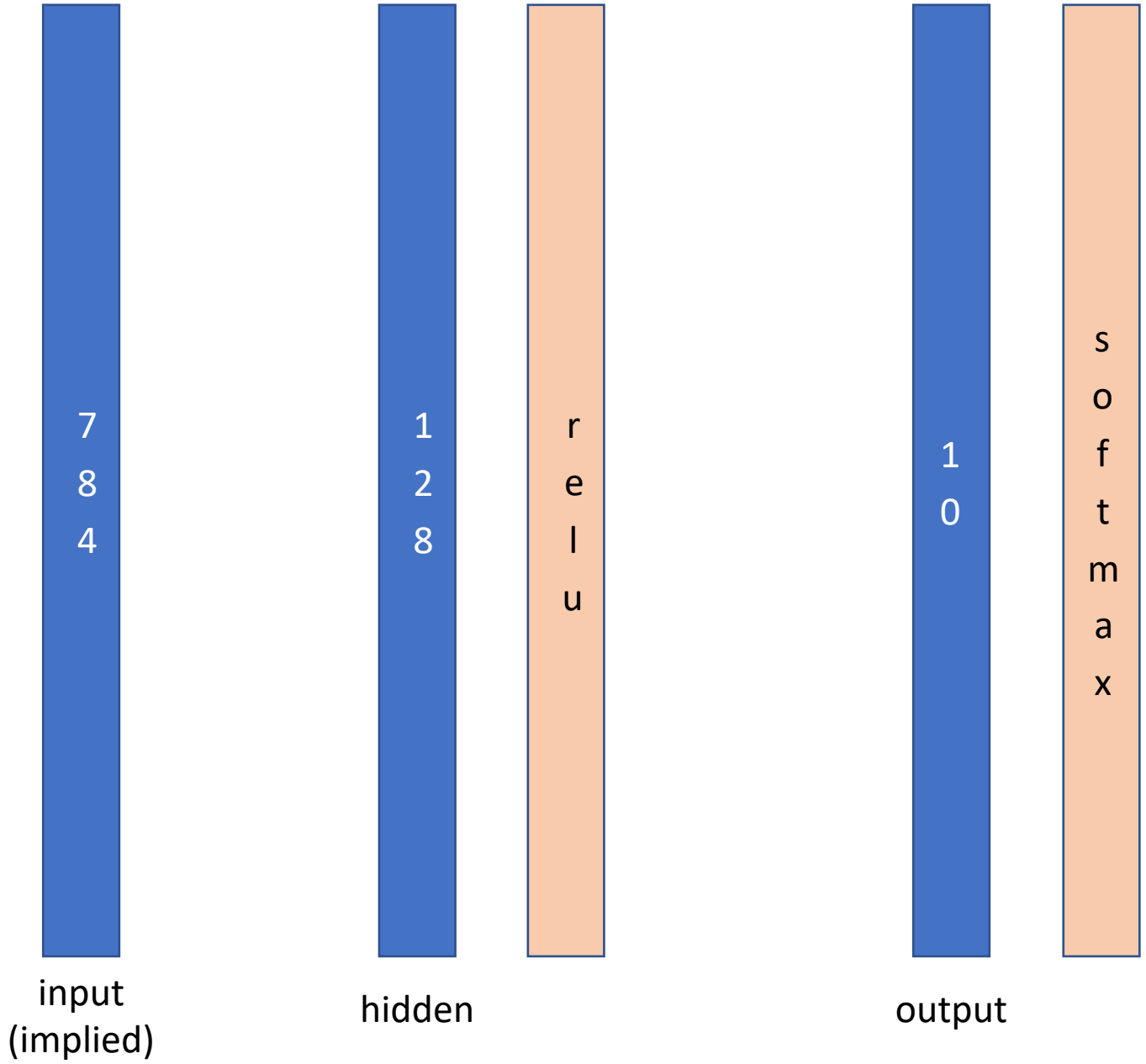
K
Keras

(time permitting)

```
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers.core import Dense, Activation
from keras.optimizers import SGD
from keras.utils import np_utils

(X_train, y_train), (X_test, y_test) = mnist.load_data()

X_train = X_train.reshape(60000, 784).astype('float32') / 255 # apply to X_test

Y_train = np_utils.to_categorical(y_train, 10) # apply to y_test

model = Sequential()

model.add(Dense(128, input_shape=(784,)))

model.add(Activation('relu'))

model.add(Dense(10))

model.add(Activation('softmax'))

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

model.fit(X_train, Y_train, batch_size=128, epochs=20) # around 94%

score = model.evaluate(X_test, Y_test)
```



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That’s all there is to it?

Surely there is a catch.

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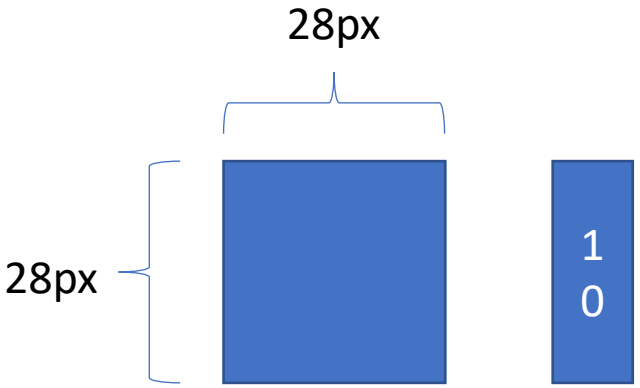
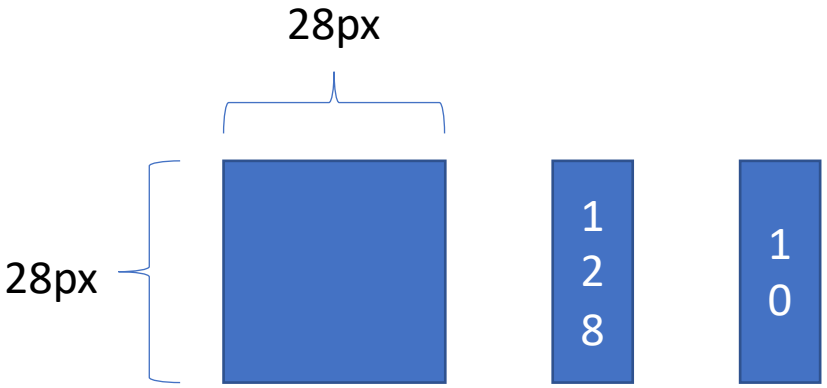
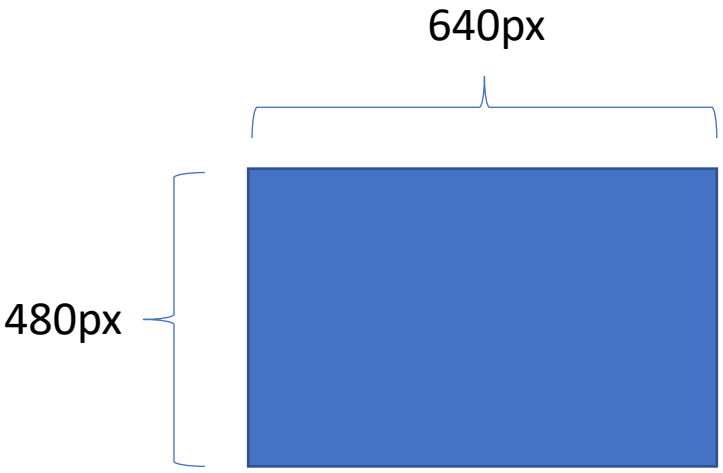


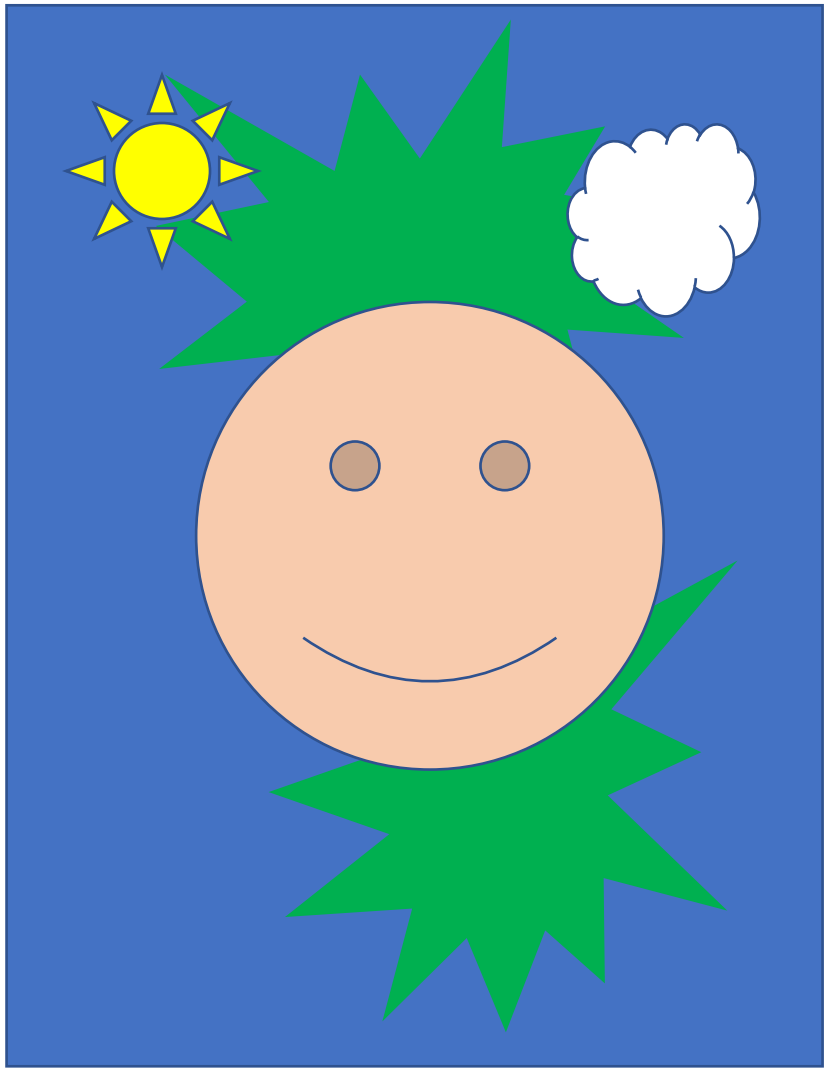
7,840



101,770



>300,000



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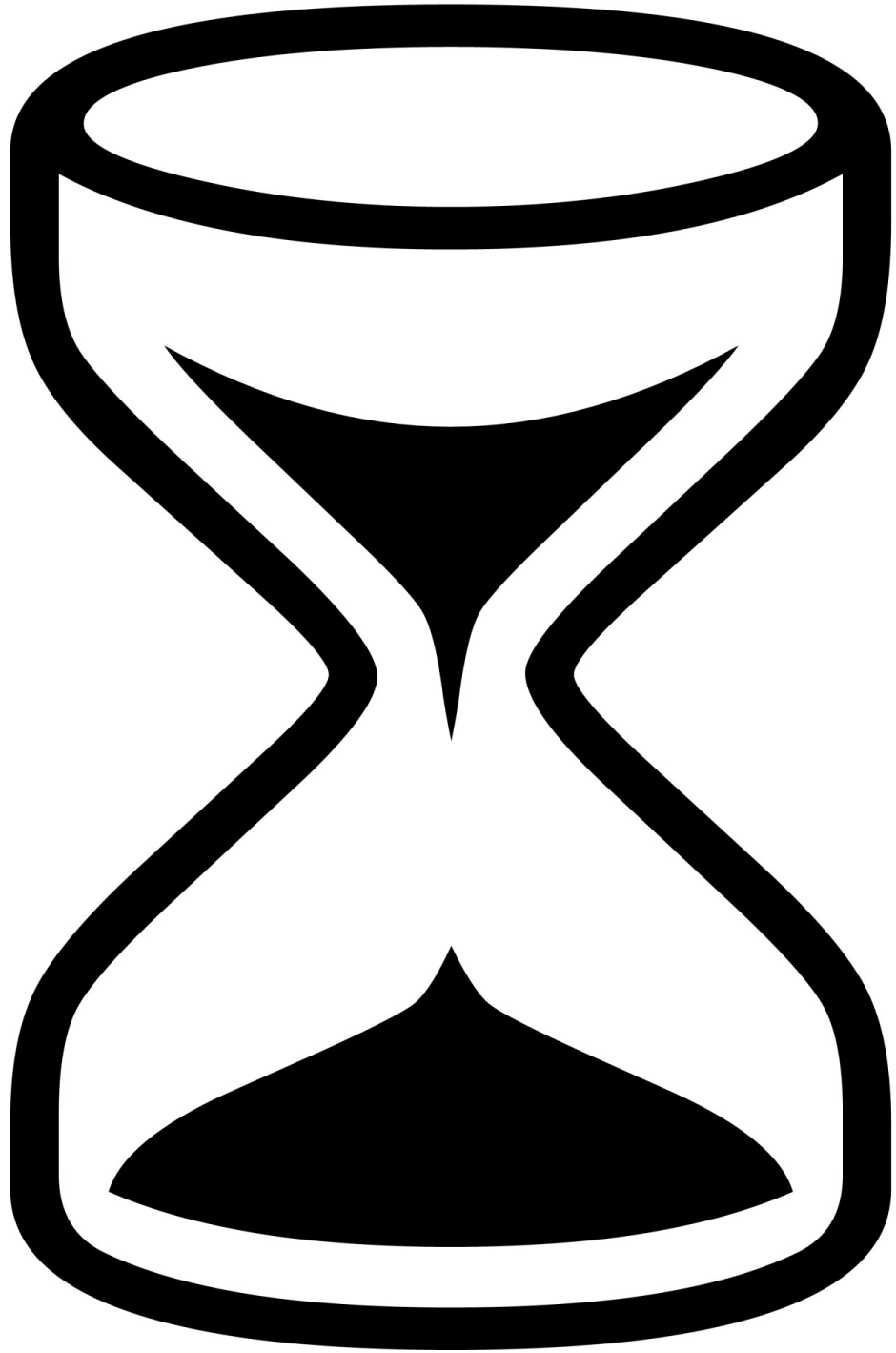

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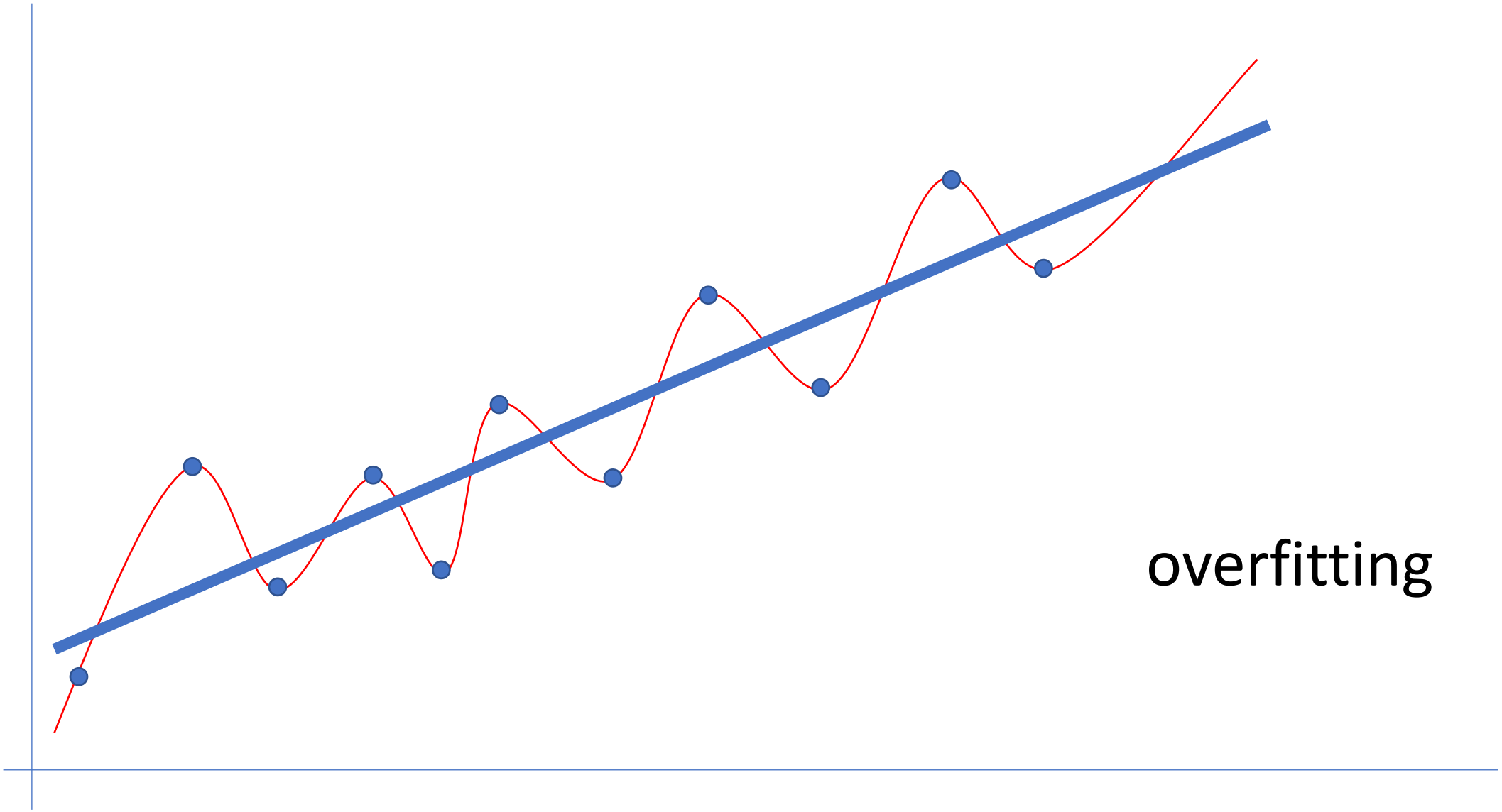

overfitting


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Goal: consider fewer, more relevant, features

How to determine which features are relevant?

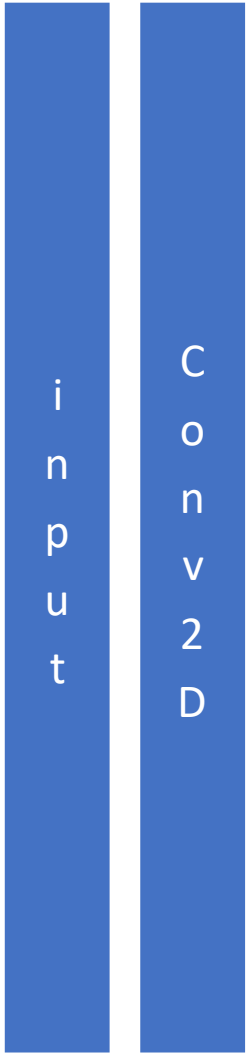
Let the network decide!

Convolutional Neural Network (CNN)

Three new layers

- Convolutional layers – detect features
- Pooling layers – summarize features
- Dropout – prevent overfitting

Features are then used in dense layers


input

Conv2D

1	0	0	1	1	0
1	1	1	0	1	1
0	1	1	1	0	1
1	1	1	0	1	1
0	0	1	1	0	1
0	1	1	0	0	0

1	0	0
1	1	1
0	1	1

filter/kernel

1 1	0 0	0 0	1	1	0
1 1	1 1	1 1	0	1	1
0 0	1 1	1 1	1	0	1
1	1	1	0	1	1
0	0	1	1	0	1
0	1	1	0	0	0

6

1	0 1	0 0	1 0	1	0
1	1 1	1 1	0 1	1	1
0	1 0	1 1	1 1	0	1
1	1	1	0	1	1
0	0	1	1	0	1
0	1	1	0	0	0

6	4

1	0	0 1	1 0	1 0	0
1	1	1 1	0 1	1 1	1
0	1	1 0	1 1	0 1	1
1	1	1	0	1	1
0	0	1	1	0	1
0	1	1	0	0	0

6	4	3

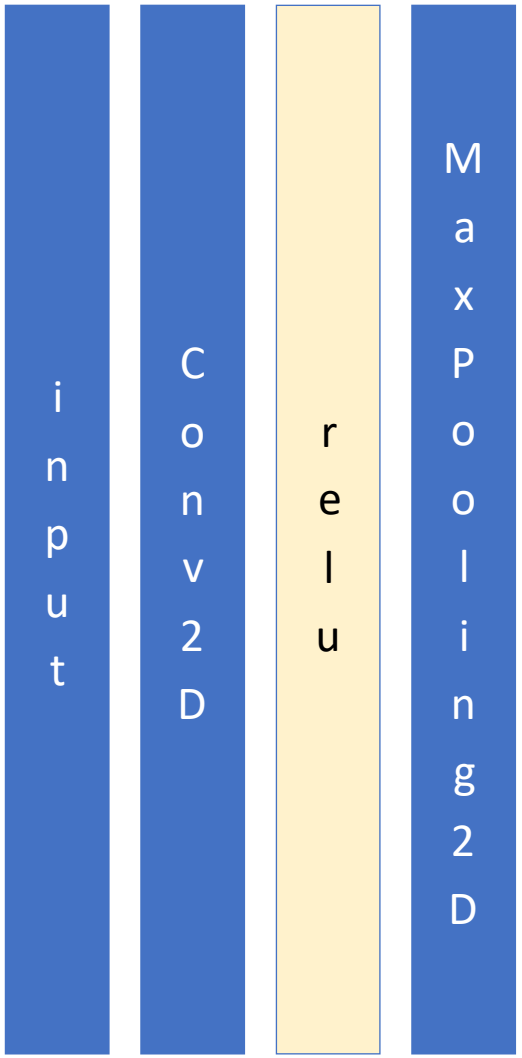
1	0	0	1 1	1 0	0 0
1	1	1	0 1	1 1	1 1
0	1	1	1 0	0 1	1 1
1	1	1	0	1	1
0	0	1	1	0	1
0	1	1	0	0	0

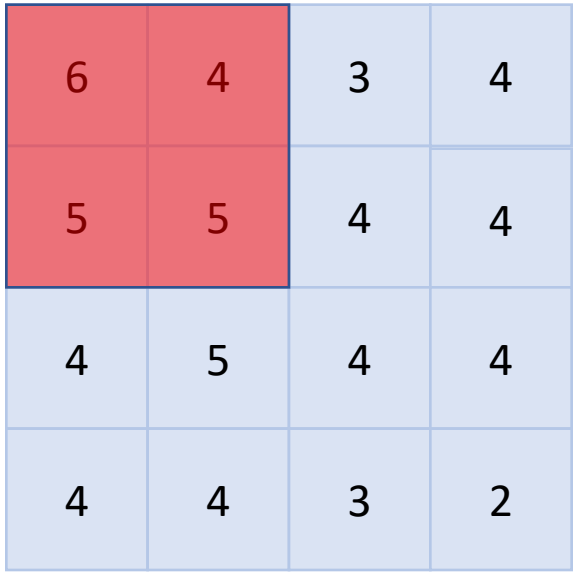
6	4	3	4

1	0	0	1	1	0
1	1	1	0	1	1
0	1	1	1	0	1
1	1	1	0 1	1 0	1 0
0	0	1	1 1	0 1	1 1
0	1	1	0 0	0 1	0 1

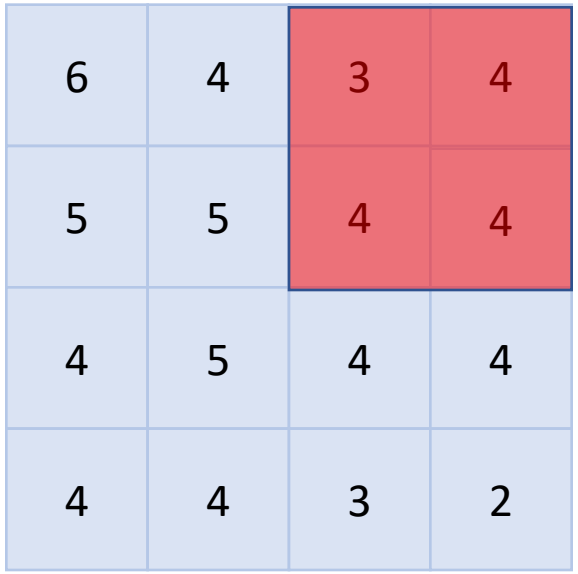
6	4	3	4
5	5	4	4
4	5	4	4
4	4	3	2

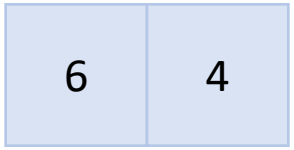
convolution

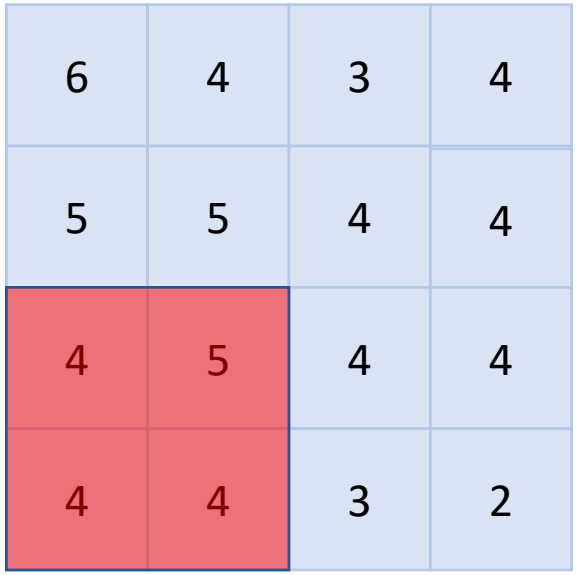

input
Conv2D
relu
MaxPooling2D

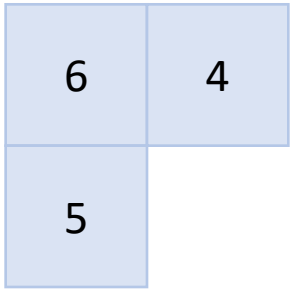

6 4 3 4
5 5 4 4
4 5 4 4
4 4 3 2


6



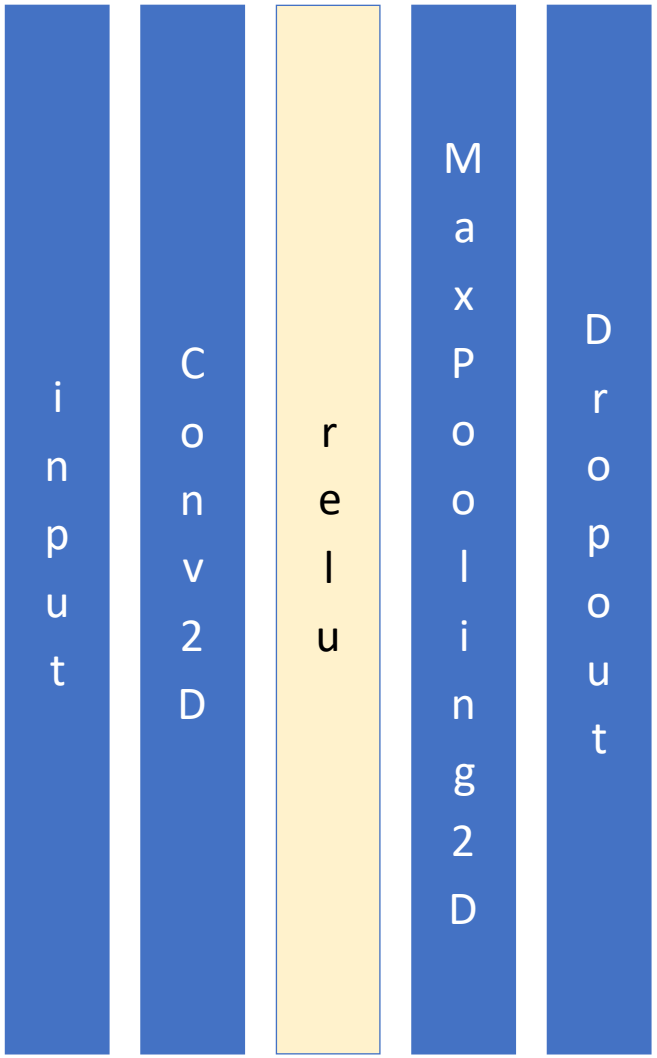


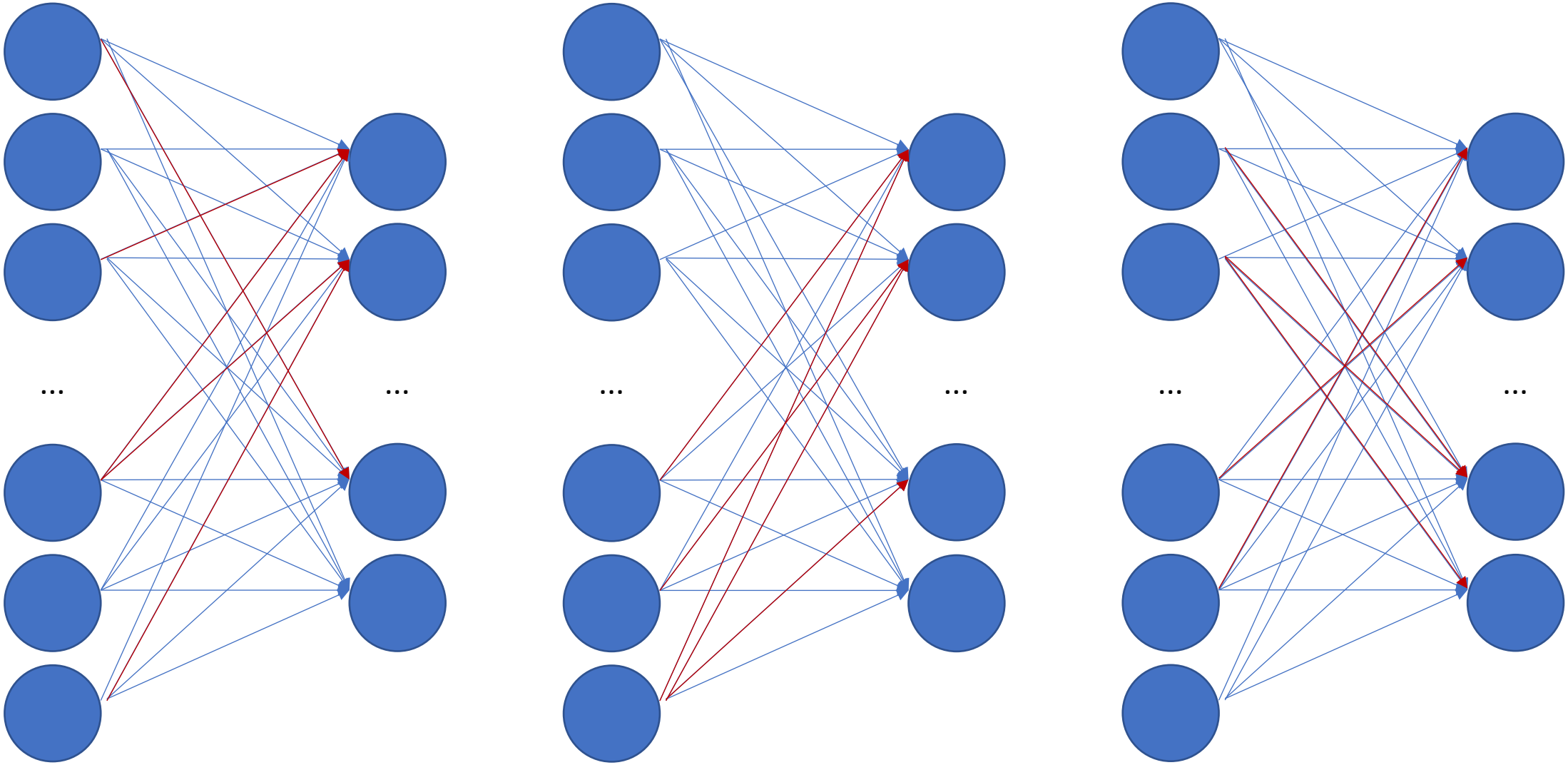




6	4	3	4
5	5	4	4
4	5	4	4
4	4	3	2

6	4
5	4


input
Conv2D
relu
MaxPooling2D
Dropout



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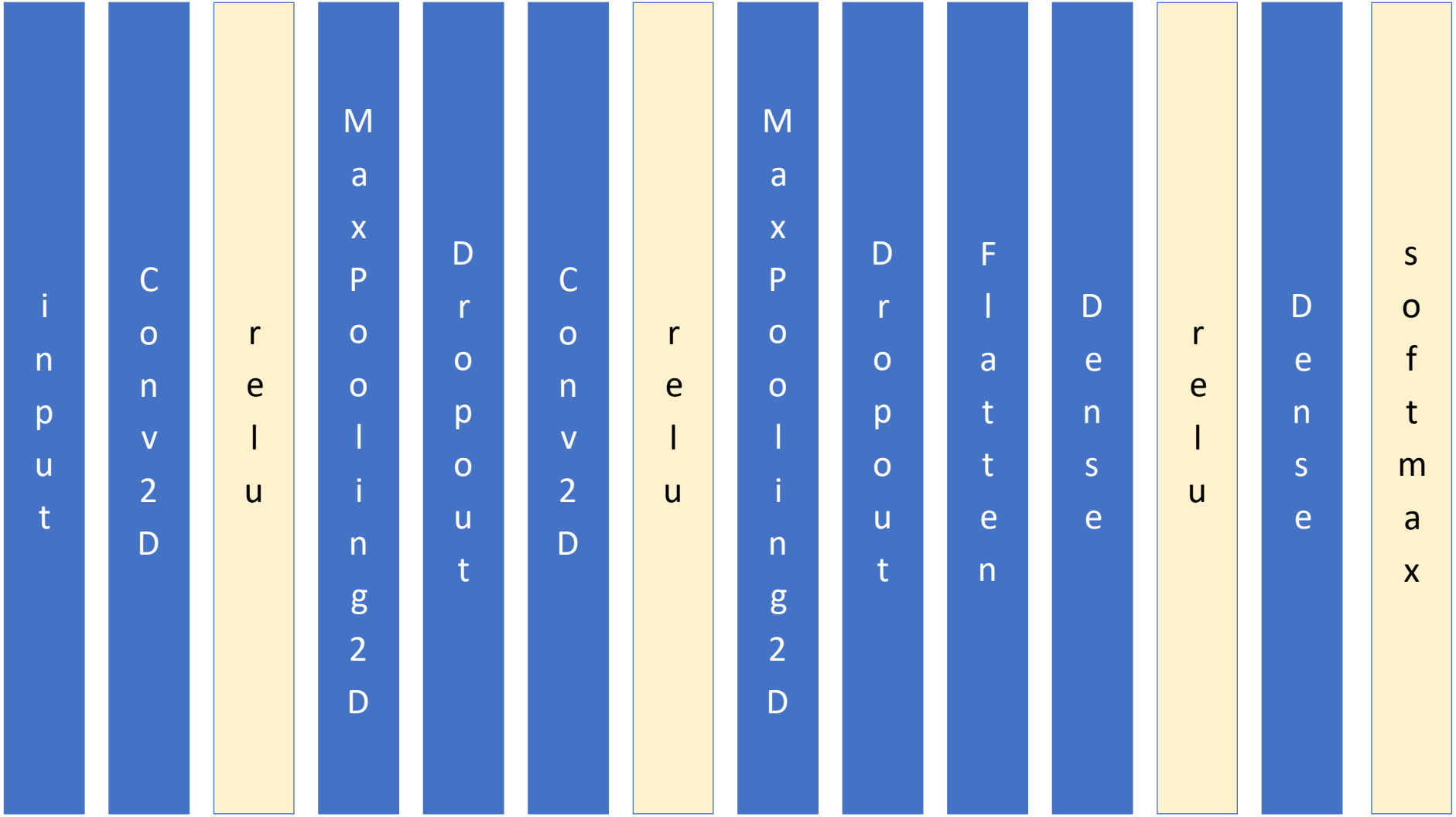

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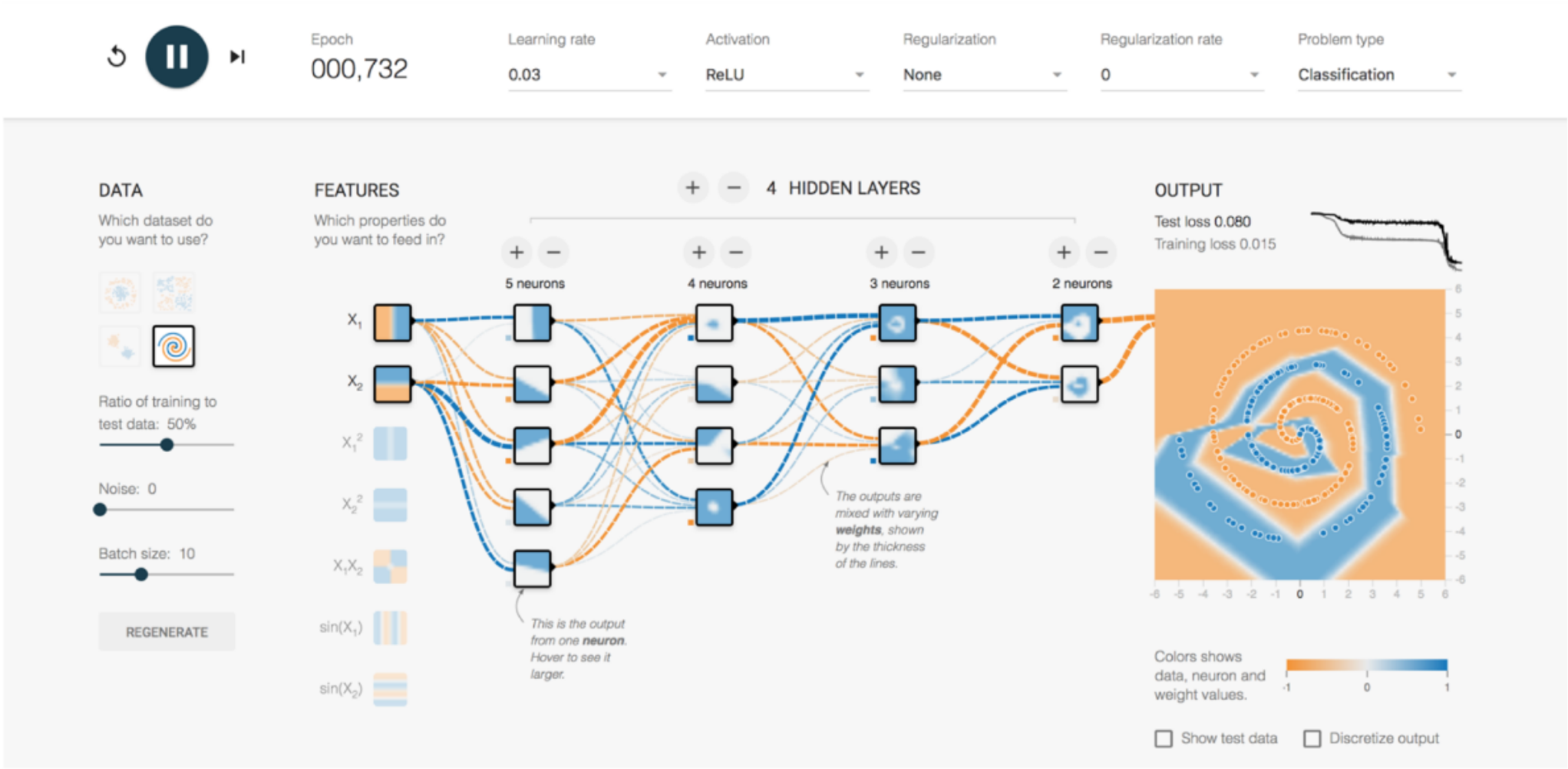
```
from keras.datasets import cifar10

from keras.models import Sequential
from keras.layers import Dense, Dropout, Activation, Flatten,
     Conv2D, MaxPooling2D


(x_train, y_train), (x_test, y_test) = cifar10.load_data()

model = Sequential()

model.add(Conv2D(32, (3, 3), padding='same', input_shape=(32, 32, 3)))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Conv2D(64, (3, 3), padding='same'))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(512))
model.add(Activation('relu')) model.add(Dense(10))
model.add(Activation('softmax'))
```



playground.tensorflow.org

Thank You!

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http://douglasstarnes.com

https://github.com/douglasstarnes/indycodedeeplearing