

# TensorFlow实践 - AlphaGo 与天弈围棋

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# AlphaGo 取胜之道？



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# 分享内容


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Deep Learning



TensorFlow



AlphaGo



天弈围棋

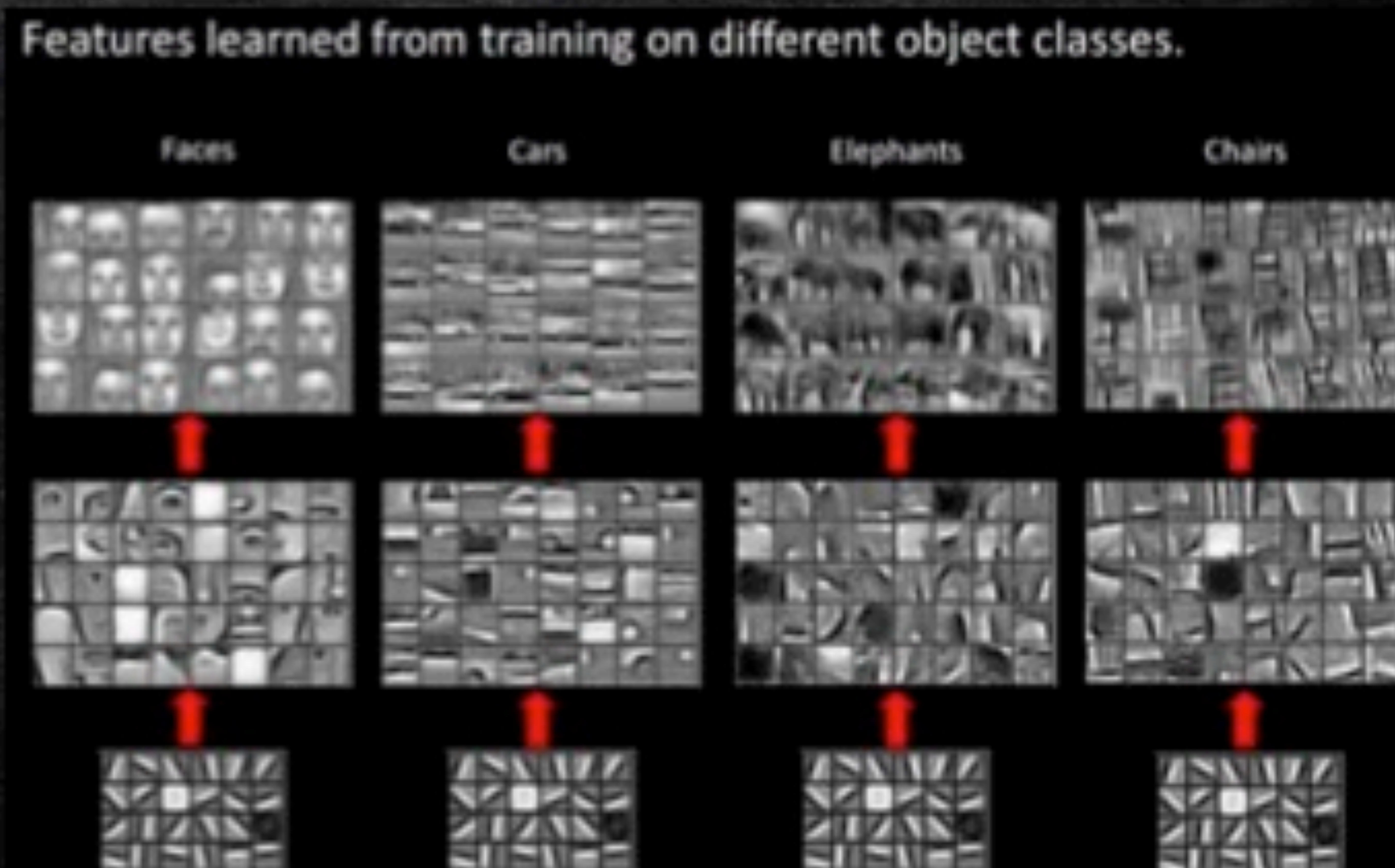


Deep Q-Network



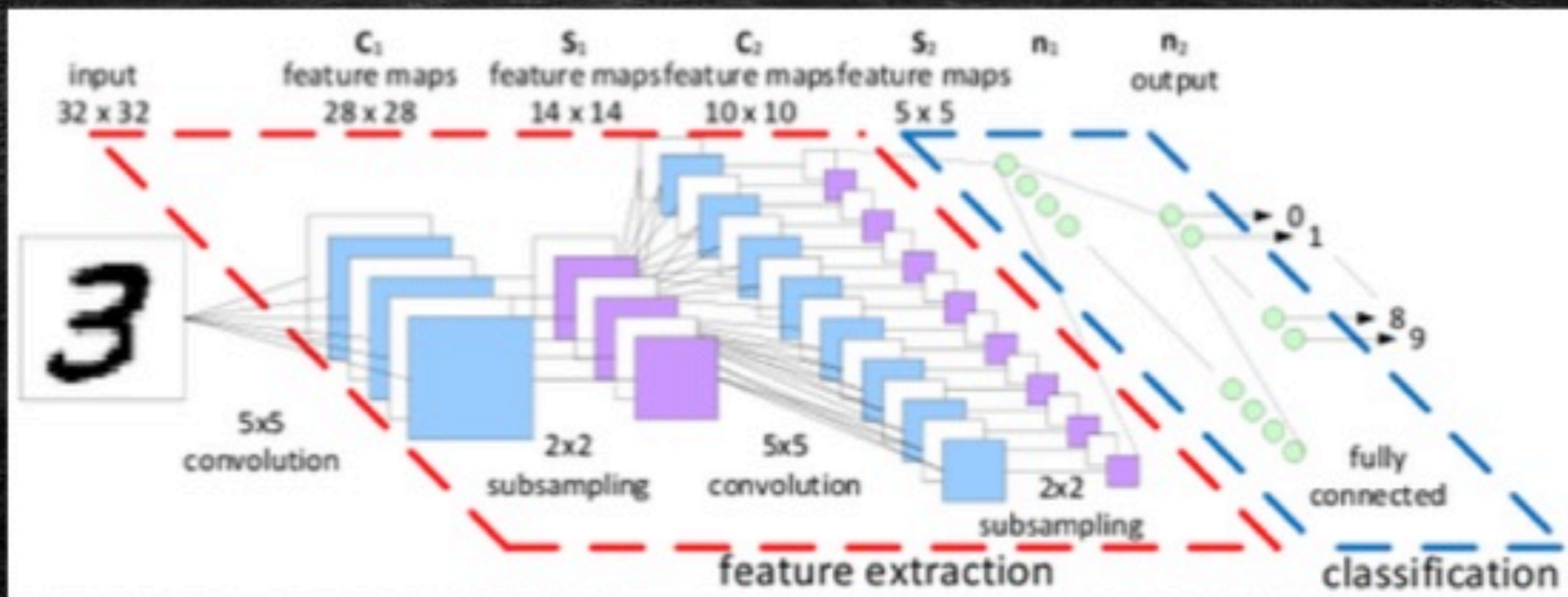
# Deep Learning

- 不需要太多的feature work
- 拟合复杂函数的能力
- 需要强大的计算能力
- 不能简单的迁移知识





# Deep Learning





# Deep Learning Training

- 神经元数量
- 激活函数
- 损失函数
- 正则化参数
- Much parameters .....
- GPU Cluster

	Propagation	Back-propagation
Sigmoid	$y_s = \frac{1}{1+e^{-x_s}}$	$\left[\frac{\partial E}{\partial x}\right]_s = \left[\frac{\partial E}{\partial y}\right]_s \frac{1}{(1+e^{x_s})(1+e^{-x_s})}$
Tanh	$y_s = \tanh(x_s)$	$\left[\frac{\partial E}{\partial x}\right]_s = \left[\frac{\partial E}{\partial y}\right]_s \frac{1}{\cosh^2 x_s}$
ReLu	$y_s = \max(0, x_s)$	$\left[\frac{\partial E}{\partial x}\right]_s = \left[\frac{\partial E}{\partial y}\right]_s \mathbb{I}\{x_s > 0\}$
Ramp	$y_s = \min(-1, \max(1, x_s))$	$\left[\frac{\partial E}{\partial x}\right]_s = \left[\frac{\partial E}{\partial y}\right]_s \mathbb{I}\{-1 < x_s < 1\}$



# TensorFlow

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TensorFlow [1] is an interface for expressing machine learning algorithms, and an implementation for executing such algorithms. A computation expressed using TensorFlow can be executed with little or no change on a wide variety of heterogeneous systems, ranging from mobile devices such as phones and tablets up to large-scale distributed systems of hundreds of machines and thousands of computational devices such as GPU cards. The system is flexible and can be used to express

Tensor（张量）意味着N维数组，Flow（流）意味着基于数据流图的计算，TensorFlow即为张量从图的一端流动到另一端。TensorFlow一大亮点是支持异构设备分布式计算，它能够在各个平台上自动运行模型，从电话、单个CPU / GPU到成百上千GPU卡组成的分布式系统。



# TensorFlow - 架构

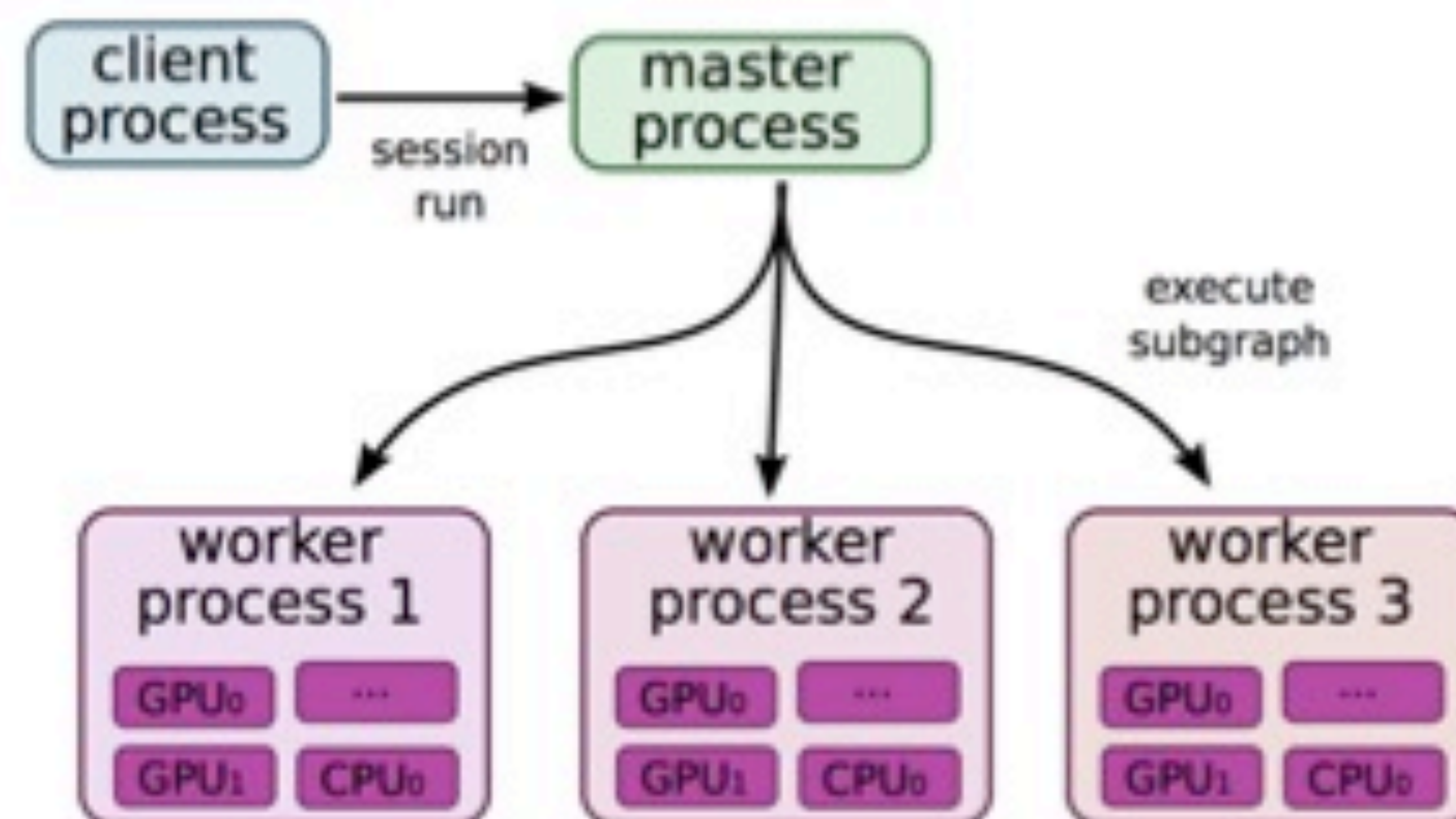
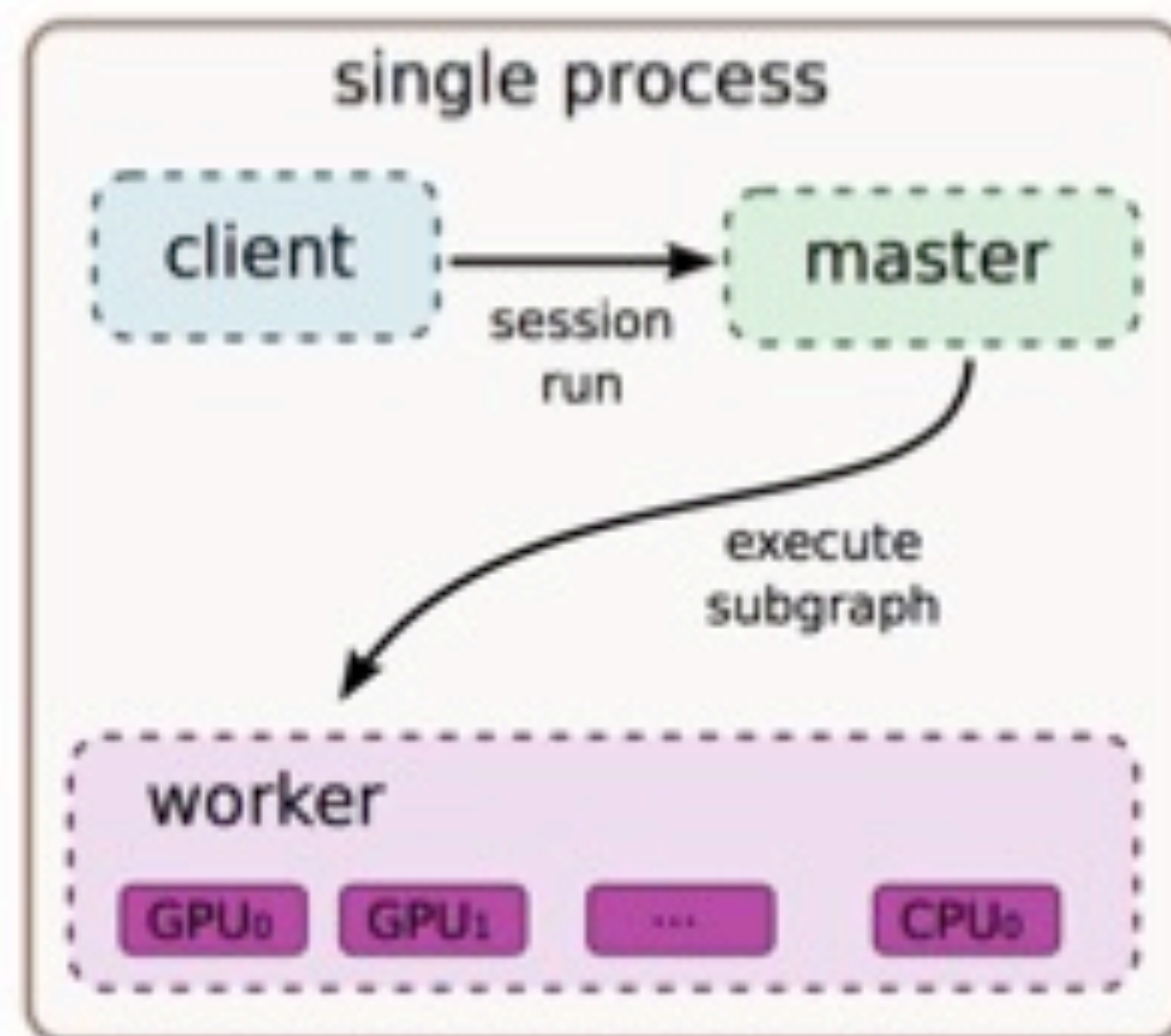


Figure 3: Single machine and distributed system structure



# TensorFlow - 案例

```
import tensorflow as tf

b = tf.Variable(tf.zeros([100])) # 100-d vector, init to zeroes
W = tf.Variable(tf.random_uniform([784,100],-1,1)) # 784x100 matrix w/rnd vals
x = tf.placeholder(name="x") # Placeholder for input
relu = tf.nn.relu(tf.matmul(W, x) + b) # Relu(Wx+b)
C = [...] # Cost computed as a function of Relu

s = tf.Session()
for step in xrange(0, 10):
    input = ...construct 100-D input array ... # Create 100-d vector for input
    result = s.run(C, feed_dict={x: input}) # Fetch cost, feeding x=input
    print step, result
```

Figure 1: Example TensorFlow code fragment



# TensorFlow - 案例

```
# Import the library
import tensorflow as tf

# Define the graph
hello_op = tf.constant('Hello, TensorFlow!')
a = tf.constant(10)
b = tf.constant(32)
compute_op = tf.add(a, b)

# Define the session to run graph
with tf.Session() as sess:
    print(sess.run(hello_op))
    print(sess.run(compute_op))
```

```
import tensorflow as tf
import numpy as np

# Prepare train data
train_X = np.linspace(-1, 1, 100)
train_Y = 2 * train_X + np.random.randn(*train_X.shape) * 0.33 + 10

# Define the model
X = tf.placeholder("float")
Y = tf.placeholder("float")
w = tf.Variable(0.0, name="weight")
b = tf.Variable(0.0, name="bias")
loss = tf.square(Y - tf.mul(X, w) - b)
train_op = tf.train.GradientDescentOptimizer(0.01).minimize(loss)

# Create session to run
with tf.Session() as sess:
    sess.run(tf.initialize_all_variables())
    epoch = 1
    for i in range(10):
        for (x, y) in zip(train_X, train_Y):
            _, w_value, b_value = sess.run([train_op, w, b], feed_dict={X: x, Y: y})
        print("Epoch: {}, w: {}, b: {}".format(epoch, w_value, b_value))
        epoch += 1
```



# TensorFlow - 案例 build network

```
with tf.op_scope([inputs], scope, 'inception_v3'):
    with scopes.arg_scope([ops.conv2d, ops.fc, ops.batch_norm, ops.dropout], is_training=is_training):
        with scopes.arg_scope([ops.conv2d, ops.max_pool, ops.avg_pool], stride=1, padding='VALID'):

            # 299 x 299 x 3
            end_points['conv0'] = ops.conv2d(inputs, 32, [3, 3], stride=2, scope='conv0')

            # 149 x 149 x 32
            end_points['conv1'] = ops.conv2d(end_points['conv0'], 32, [3, 3], scope='conv1')

            # 147 x 147 x 32
            end_points['conv2'] = ops.conv2d(end_points['conv1'], 64, [3, 3], padding='SAME', scope='conv2')

            # 147 x 147 x 64
            end_points['pool1'] = ops.max_pool(end_points['conv2'], [3, 3], stride=2, scope='pool1')

            # 73 x 73 x 64
            end_points['conv3'] = ops.conv2d(end_points['pool1'], 80, [1, 1], scope='conv3')

            # 73 x 73 x 80.
            end_points['conv4'] = ops.conv2d(end_points['conv3'], 192, [3, 3], scope='conv4')

            # 71 x 71 x 192.
            end_points['pool2'] = ops.max_pool(end_points['conv4'], [3, 3], stride=2, scope='pool2')

            # 35 x 35 x 192.
            net = end_points['pool2']
```

典型的CNN卷积  
网络



# TensorFlow - 亮点

```
# Create session to run graph
with tf.Session() as sess:
    summary_op = tf.merge_all_summaries()
    writer = tf.train.SummaryWriter(tensorboard_dir, sess.graph)
    sess.run(init_op)
    sess.run(tf.initialize_local_variables())

    if mode == "train" or mode == "train_from_scratch":
        if mode != "train_from_scratch":
            ckpt = tf.train.get_checkpoint_state(checkpoint_dir)
            if ckpt and ckpt.model_checkpoint_path:
                print("Continue training from the model {}".format(
                    ckpt.model_checkpoint_path))
                saver.restore(sess, ckpt.model_checkpoint_path)
```

Continues Learning



Figure 10: TensorBoard graph visualization of a convolutional neural network model

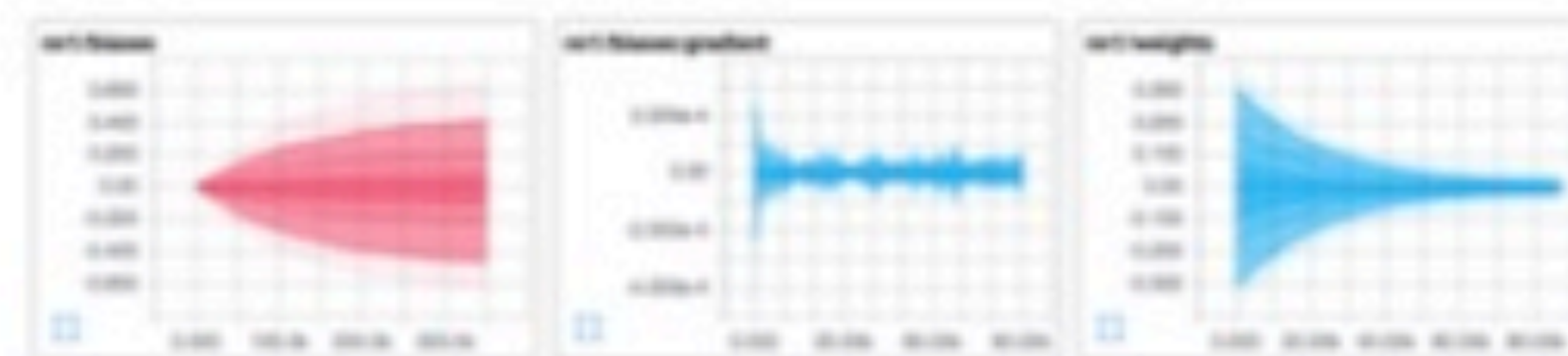


Figure 11: TensorBoard graphical display of model summary statistics time series data

TensorBoard

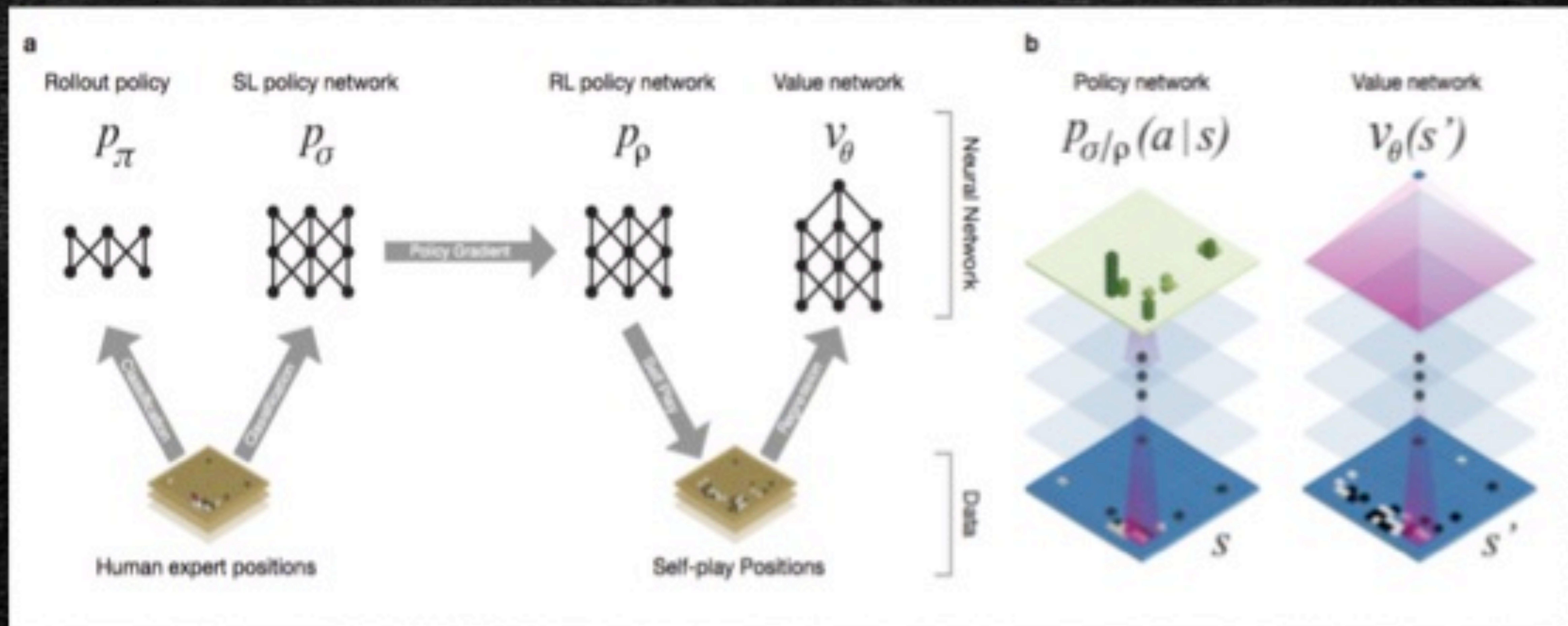


# 深度学习框架对比

	网络与模型能力	接口	模型部署	性能	架构
Caffe	第一个主流的工业级深度学习工具	支持pycaffe接口，使用protobuf定义模型	跨平台	简单快速	平均水准
CNTK	通用的、平台独立	配置文件，没有高级语言接口	跨平台，不支持ARM架构	简单快速	
TensorFlow	工业级深度学习平台	支持python和C++两个接口	跨平台，不支持Windows	非常好	架构清晰，模块化设计
Theano	支持大部分先进网络，引领了符号图在编程网络中使用的趋势	支持python接口	跨平台，但是对工业用户缺少吸引力	启动时间慢	架构比较变态，全要打包为python字符串
Torch	对卷积网络支持非常好	运行在LuaJIT上	需要LuaJIT支持，非常好限制部署		清晰的设计和模块化的接口



# AlphaGo





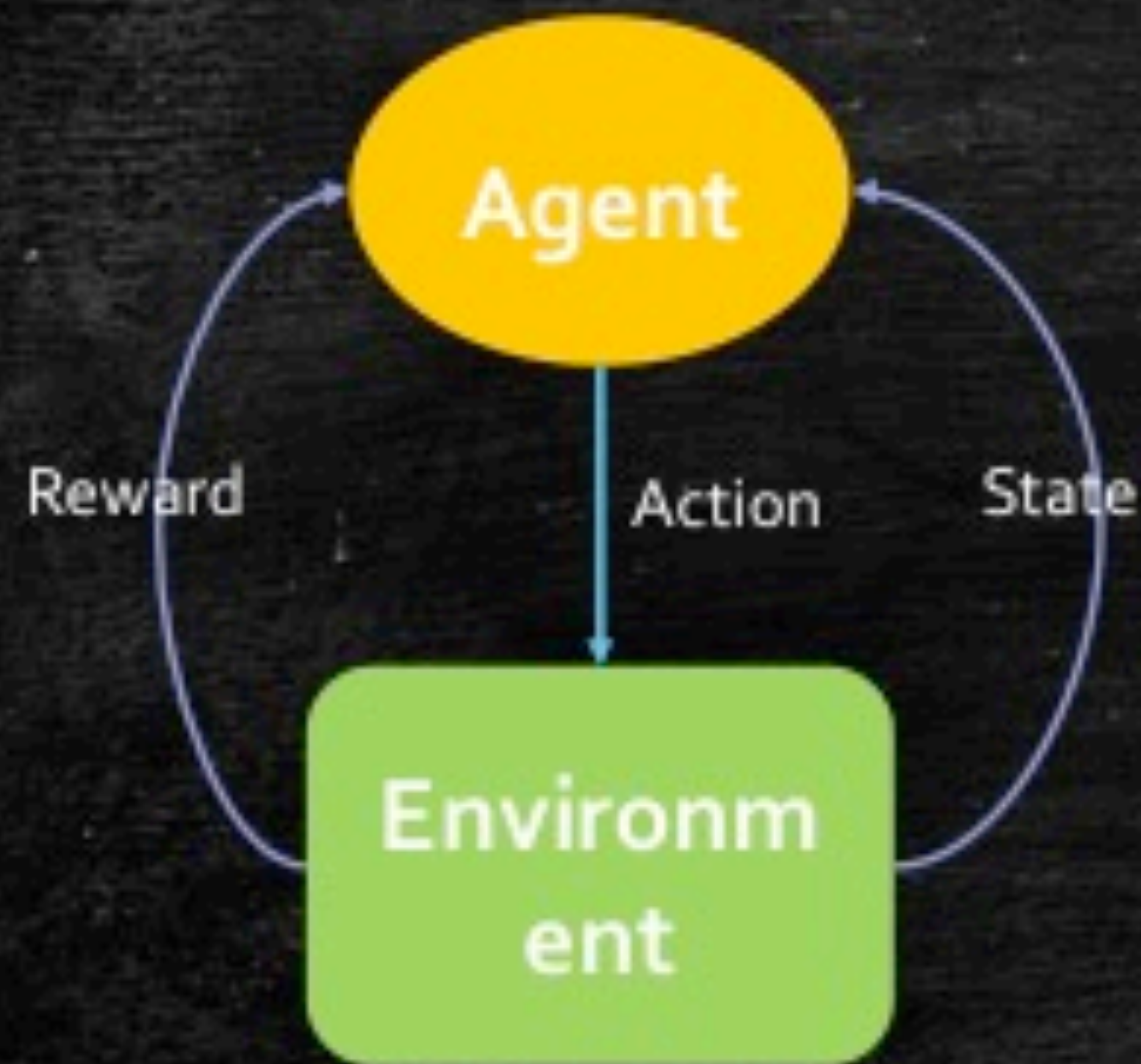
# 天弈围棋

- <http://yi.tianrang.com>
- 基于TensorFlow实现，  
深度神经网络
- 围棋爱好者的训练营





# DQN – Deep Q-Network



## Deep Q-Network Algorithm

The pseudo-code for the Deep Q Learning algorithm, as given in [1], can be found below:

```
Initialize replay memory D to size N
Initialize action-value function Q with random weights
for episode = 1, M do
  Initialize state s_1
  for t = 1, T do
    With probability  $\epsilon$  select random action  $a_t$ 
    otherwise select  $a_t = \arg \max_a Q(s_t, a; \theta_i)$ 
    Execute action  $a_t$  in emulator and observe  $r_t$  and  $s_{t+1}$ 
    Store transition  $(s_t, a_t, r_t, s_{t+1})$  in D
    Sample a minibatch of transitions  $(s_j, a_j, r_j, s_{j+1})$  from D
    Set  $y_j :=$ 
       $r_j$  for terminal  $s_{j+1}$ 
       $r_j + \gamma \max_{a'} Q(s_{j+1}, a'; \theta_i)$  for non-terminal  $s_{j+1}$ 
    Perform a gradient step on  $(y_j - Q(s_j, a_j; \theta_i))^2$  with respect to  $\theta$ 
  end for
end for
```



# DQN - 案例



FlappyBird



BreakOut

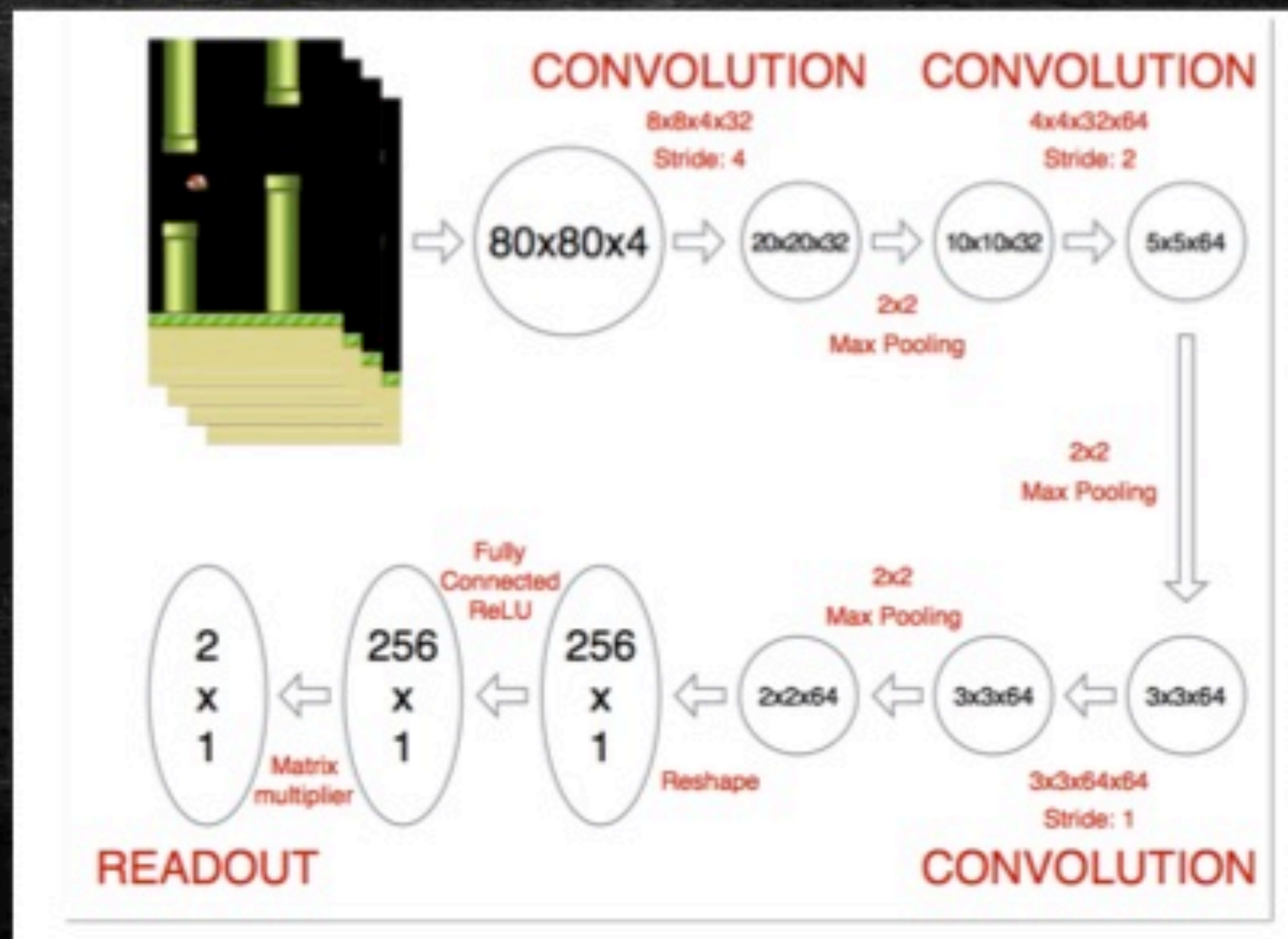


GTA无人驾驶



# DQN – Deep Q-Network

无需领域知识，输入为原始像素，输出为action对应的概率分布





# Reference

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- [1] Mastering the Game of Go with Deep Neural Networks and Tree Search, Nature 2015
- [2] TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems, Google 2015
- [3] Generative Adversarial Nets, Arxiv 2014
- [4] Human-level Control through Deep Reinforcement Learning, Nature 2015
- [5] Playing Atari with Deep Reinforcement Learning, NIPS



# 谢谢！

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天壤网络科技有限公司（上海）有限公司