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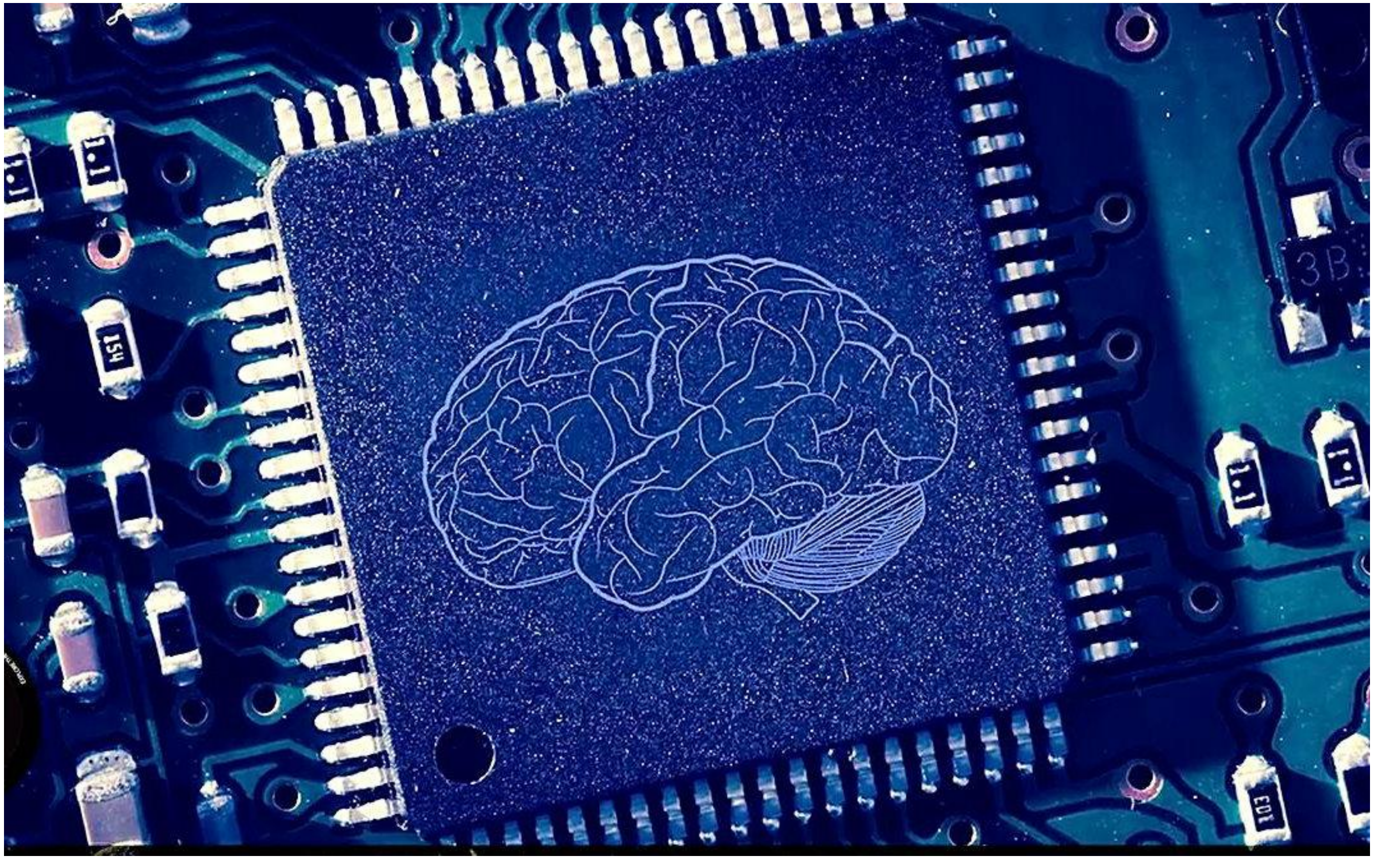

机器读心术之神经网络与深度学习 第11周

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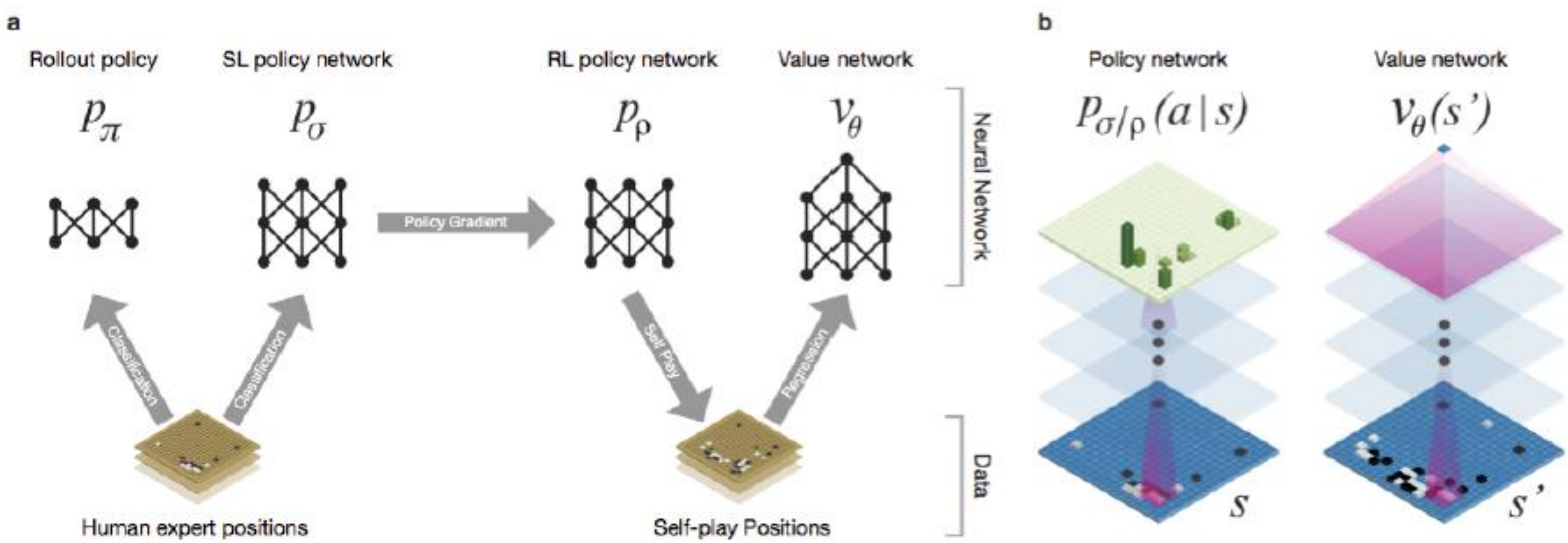
AlphaGo基本组件



走子策略

- Alphago混合策略网络，价值网络，以及MCTS算法进行走子选择
- 详见论文第七页

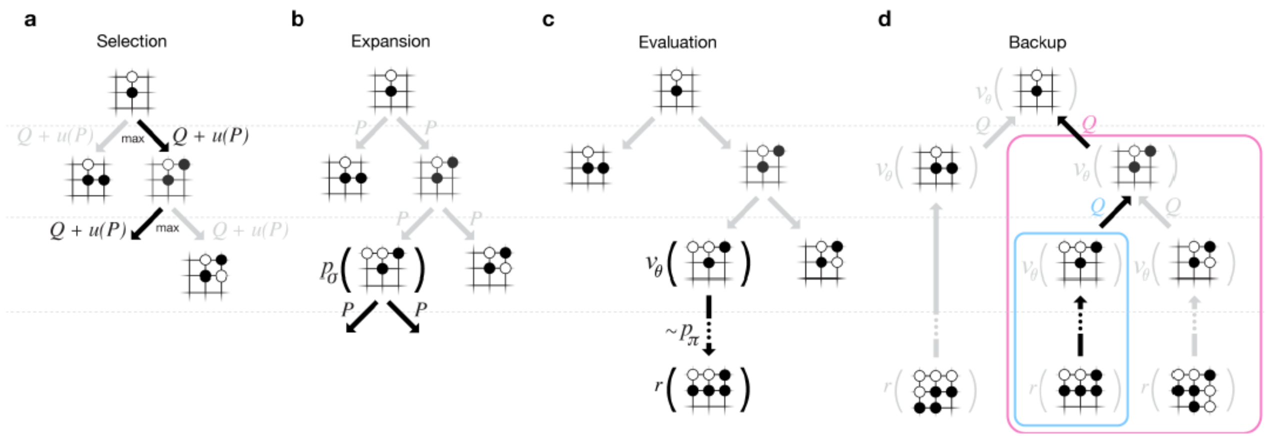
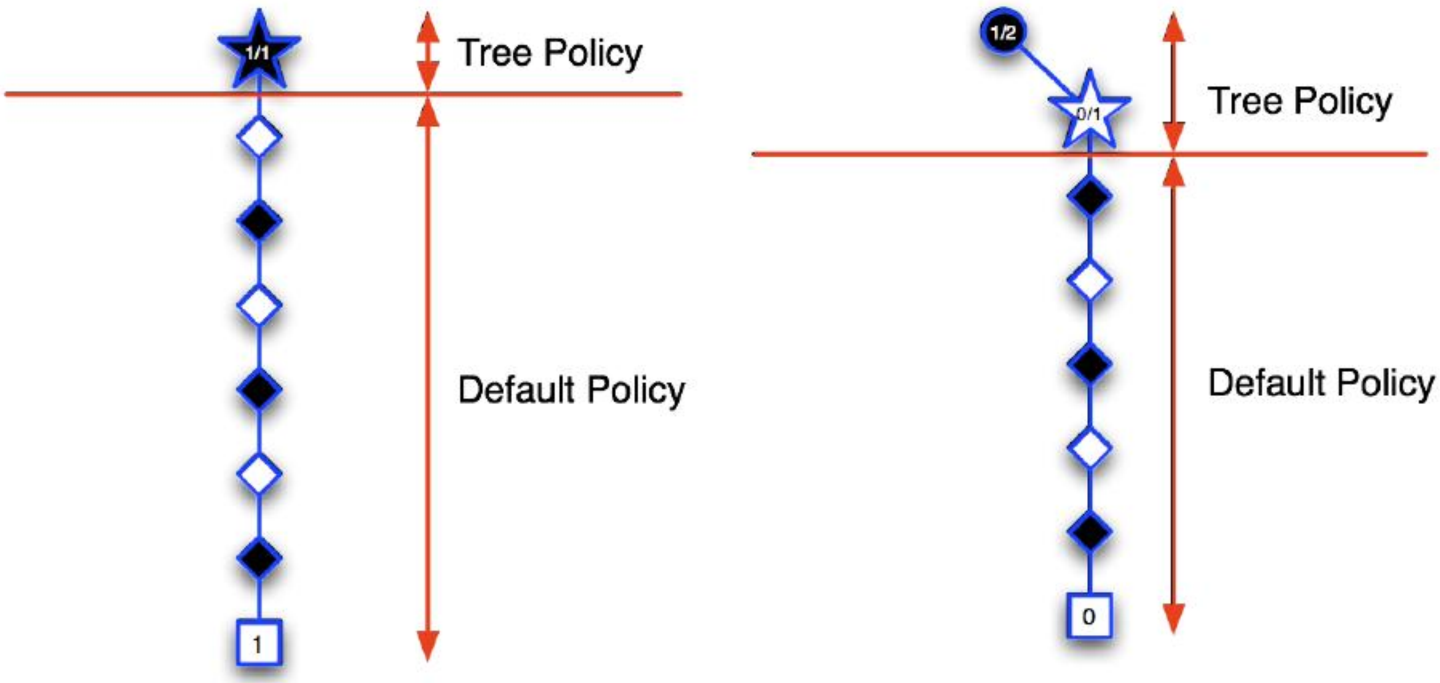
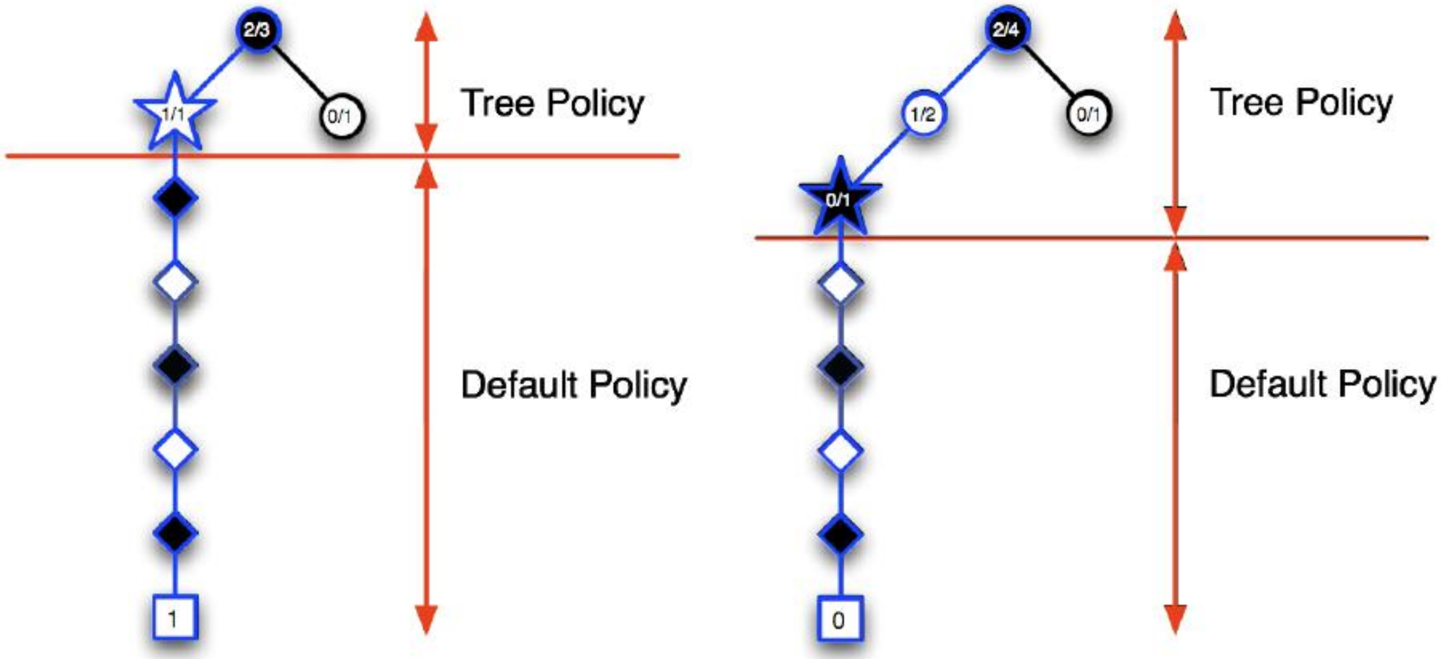


Figure 3: **Monte-Carlo tree search in *AlphaGo*.** **a** Each simulation traverses the tree by selecting the edge with maximum action-value Q, plus a bonus $u(P)$ that depends on a stored prior probability P for that edge. **b** The leaf node may be expanded; the new node is processed once by the policy network p_σ and the output probabilities are stored as prior probabilities P for each action. **c** At the end of a simulation, the leaf node is evaluated in two ways: using the value network v_θ; and by running a rollout to the end of the game with the fast rollout policy p_π, then computing the winner with function r. **d** Action-values Q are updated to track the mean value of all evaluations $r(\cdot)$ and $v_\theta(\cdot)$ in the subtree below that action.

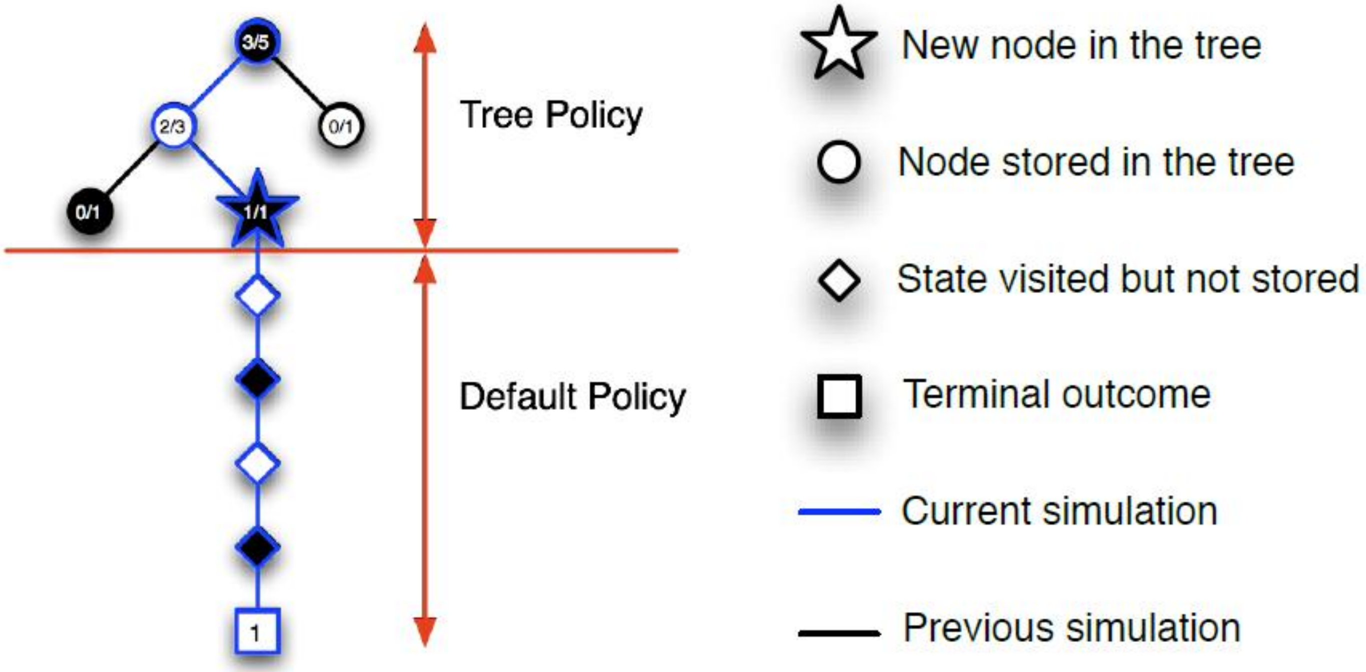
MCTS


1/1
Tree Policy
Default Policy
1
1/2
0/1
Tree Policy
Default Policy
0

MTCS



2/3
1/1
0/1
Tree Policy
Default Policy
1
2/4
1/2
0/1
0/1
Tree Policy
Default Policy
0


3/5
2/3
0/1
0/1
1/1
1
Tree Policy
Default Policy
New node in the tree
Node stored in the tree
State visited but not stored
Terminal outcome
Current simulation
Previous simulation

A Survey of Monte Carlo Tree Search Methods

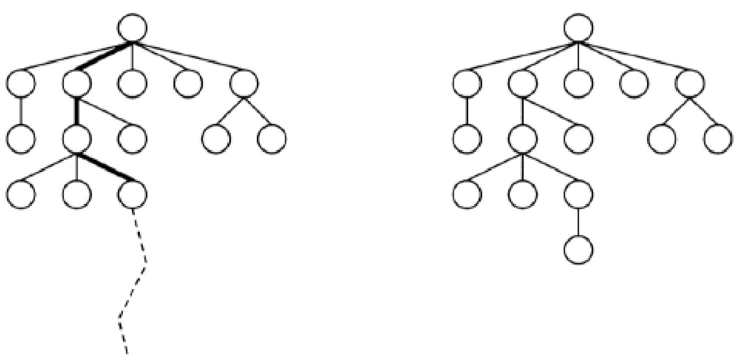
Cameron Browne, *Member, IEEE*, Edward Powley, *Member, IEEE*, Daniel Whitehouse, *Member, IEEE*,
Simon Lucas, *Senior Member, IEEE*, Peter I. Cowling, *Member, IEEE*, Philipp Rohlfshagen,
Stephen Tavener, Diego Perez, Spyridon Samothrakis and Simon Colton

Abstract—Monte Carlo Tree Search (MCTS) is a recently proposed search method that combines the precision of tree search with the generality of random sampling. It has received considerable interest due to its spectacular success in the difficult problem of computer Go, but has also proved beneficial in a range of other domains. This paper is a survey of the literature to date, intended to provide a snapshot of the state of the art after the first five years of MCTS research. We outline the core algorithm's derivation, impart some structure on the many variations and enhancements that have been proposed, and summarise the results from the key game and non-game domains to which MCTS methods have been applied. A number of open research questions indicate that the field is ripe for future work.

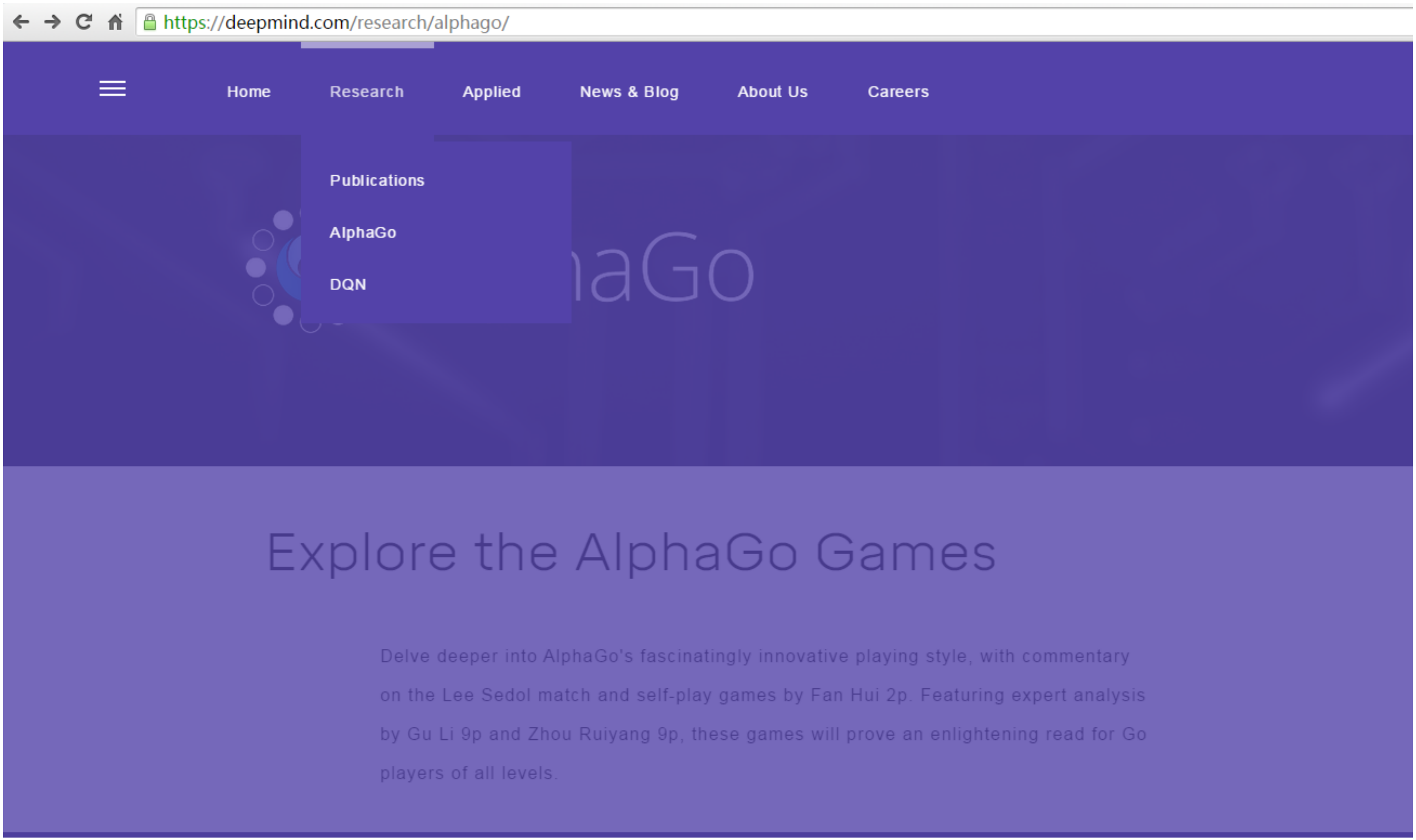
Index Terms—Monte Carlo Tree Search (MCTS), Upper Confidence Bounds (UCB), Upper Confidence Bounds for Trees (UCT), Bandit-based methods, Artificial Intelligence (AI), Game search, Computer Go.

1 INTRODUCTION

MONTE Carlo Tree Search (MCTS) is a method for finding optimal decisions in a given domain by taking random samples in the decision space and building a search tree according to the results. It has already had a profound impact on Artificial Intelligence (AI) approaches for domains that can be represented as trees of sequential decisions, particularly games and planning problems.



Deepmind还在做什么？



DQN

Human-level control through deep reinforcement learning

Volodymyr Mnih[1]*, Koray Kavukcuoglu[1]*, David Silver[1]*, Andrei A. Rusu[1], Joel Veness[1], Marc G. Bellemare[1], Alex Graves[1], Martin Riedmiller[1], Andreas K. Fidjeland[1], Georg Ostrovski[1], Stig Petersen[1], Charles Beattie[1], Amir Sadik[1], Ioannis Antonoglou[1], Helen King[1], Dharshan Kumaran[1], Daan Wierstra[1], Shane Legg[1] & Demis Hassabis[1]

The theory of reinforcement learning provides a normative account[1], deeply rooted in psychological[2] and neuroscientific[3] perspectives on animal behaviour, of how agents may optimize their control of an environment. To use reinforcement learning successfully in situations approaching real-world complexity, however, agents are confronted with a difficult task: they must derive efficient representations of the environment from high-dimensional sensory inputs, and use these to generalize past experience to new situations. Remarkably, humans and other animals seem to solve this problem through a harmonious combination of reinforcement learning and hierarchical sensory processing systems[4,5], the former evidenced by a wealth of neural data revealing notable parallels between the phasic signals emitted by dopaminergic neurons and temporal difference reinforcement learning algorithms[3]. While reinforcement learning agents have achieved some successes in a variety of domains[6–8], their applicability has previously been limited to domains in which useful features can be handcrafted, or to domains with fully observed, low-dimensional state spaces. Here we use recent advances in training deep neural networks[9–11] to develop a novel artificial agent, termed a deep Q-network, that can

agent is to select actions in a fashion that maximizes cumulative future reward. More formally, we use a deep convolutional neural network to approximate the optimal action-value function

$$Q^*(s,a) = \max_{\pi} \mathbb{E}\left[r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \ldots \middle| s_t = s,\ a_t = a,\ \pi\right],$$

which is the maximum sum of rewards r_t discounted by γ at each time-step t, achievable by a behaviour policy $\pi = P(a|s)$, after making an observation (s) and taking an action (a) (see Methods)[19].

Reinforcement learning is known to be unstable or even to diverge when a nonlinear function approximator such as a neural network is used to represent the action-value (also known as Q) function[20]. This instability has several causes: the correlations present in the sequence of observations, the fact that small updates to Q may significantly change the policy and therefore change the data distribution, and the correlations between the action-values (Q) and the target values $r + \gamma \max_{a'} Q(s', a')$. We address these instabilities with a novel variant of Q-learning, which uses two key ideas. First, we used a biologically inspired mechanism termed experience replay[21–23] that randomizes over the data, thereby

Deepmind Health

For Patients

Patients have a unique knowledge of their own health and their preferences for treatment. Outcomes are better when patients and clinicians make decisions together, and we think this should apply to the way in which technology is developed too.

We are incorporating patient and public involvement (PPI) at every stage of our projects. We have already benefited from the use of patient feedback from external groups but are now bringing together a diverse group of patient representatives to meet our specific needs.

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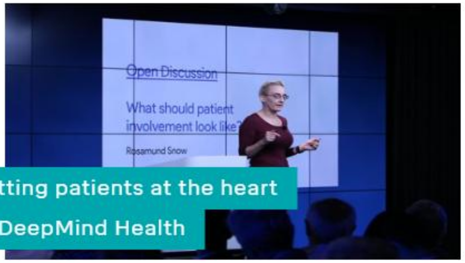

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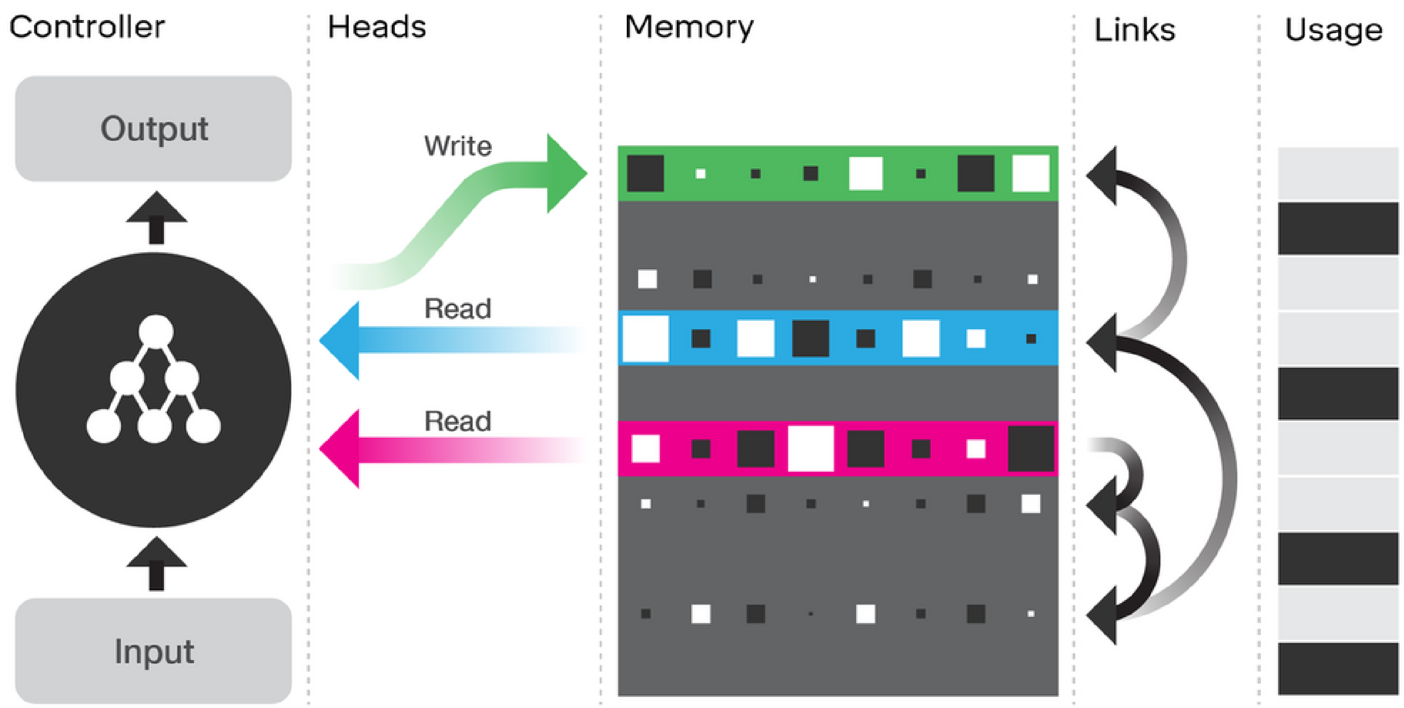
可微神经计算机（DNC）

- http://www.nature.com/nature/journal/v538/n7626/pdf/nature20101.pdf
- http://bi.dataguru.cn/article-10095-1.html

Illustration of the DNC architecture



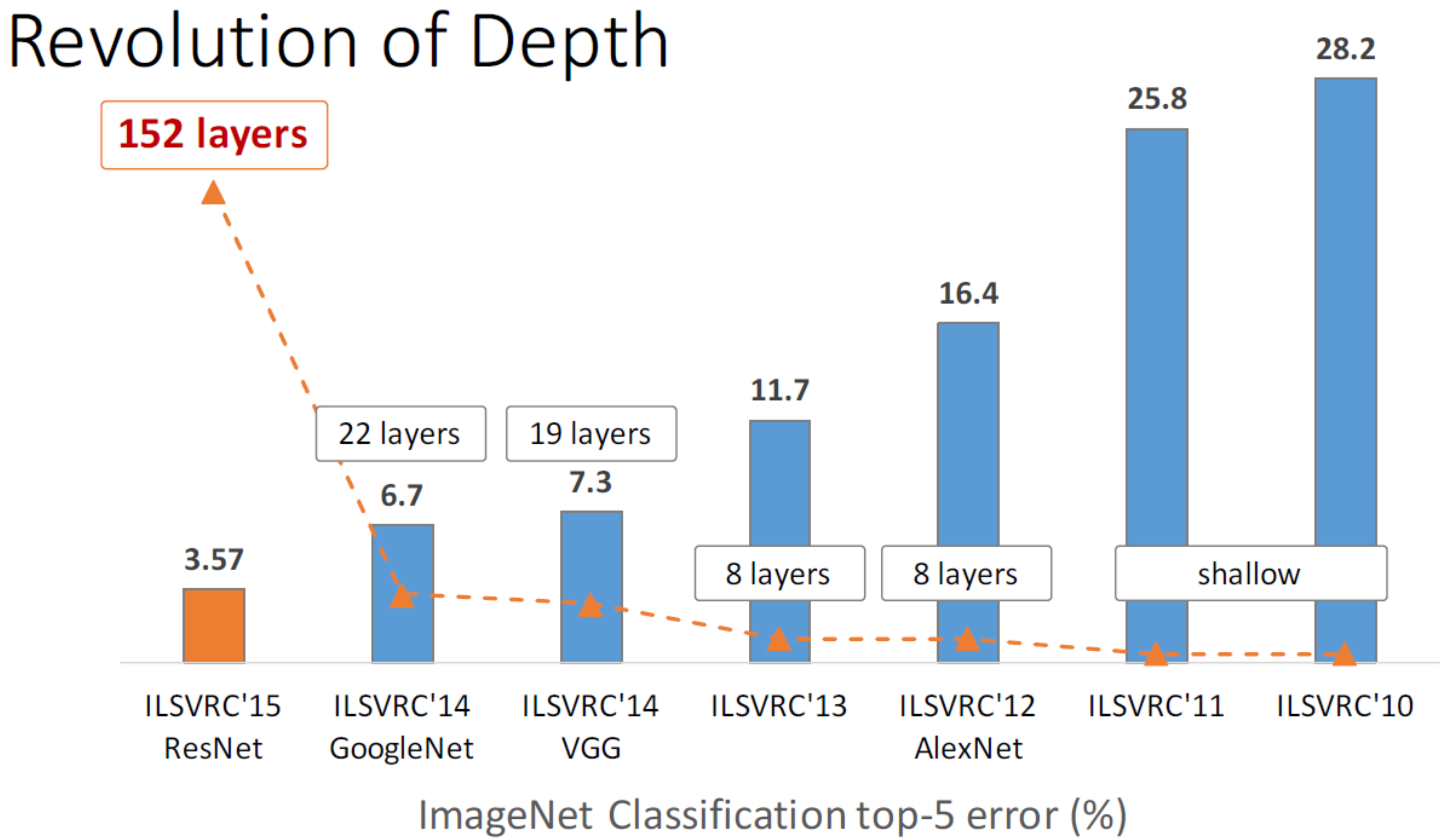
参考论文

Hybrid computing using a neural network with dynamic external memory

Alex Graves[1]*, Greg Wayne[1]*, Malcolm Reynolds[1], Tim Harley[1], Ivo Danihelka[1], Agnieszka Grabska-Barwińska[1], Sergio Gómez Colmenarejo[1], Edward Grefenstette[1], Tiago Ramalho[1], John Agapiou[1], Adrià Puigdomènech Badia[1], Karl Moritz Hermann[1], Yori Zwols[1], Georg Ostrovski[1], Adam Cain[1], Helen King[1], Christopher Summerfield[1], Phil Blunsom[1], Koray Kavukcuoglu[1] & Demis Hassabis[1]

Artificial neural networks are remarkably adept at sensory processing, sequence learning and reinforcement learning, but are limited in their ability to represent variables and data structures and to store data over long timescales, owing to the lack of an external memory. Here we introduce a machine learning model called a differentiable neural computer (DNC), which consists of a neural network that can read from and write to an external memory matrix, analogous to the random-access memory in a conventional computer. Like a conventional computer, it can use its memory to represent and manipulate complex data structures, but, like a neural network, it can learn to do so from data. When trained with supervised learning, we demonstrate that a DNC can successfully answer synthetic questions designed to emulate reasoning and inference problems in natural language. We show that it can learn tasks such as finding the shortest path between specified points and inferring the missing links in randomly generated graphs, and then generalize these tasks to specific graphs such as transport networks and family trees. When trained with reinforcement learning, a DNC can complete a moving blocks puzzle in which changing goals are specified by sequences of symbols. Taken together, our results demonstrate that DNCs have the capacity to solve complex, structured tasks that are inaccessible to neural networks without external read–write memory.

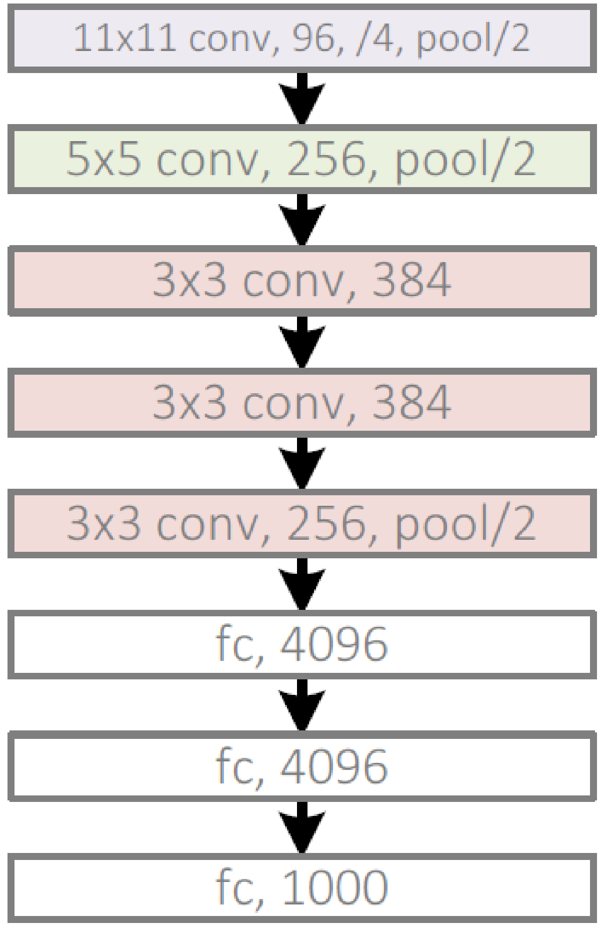
向更多层网络进军



Revolution of Depth
152 layers
22 layers
19 layers
8 layers
8 layers
shallow
3.57
6.7
7.3
11.7
16.4
25.8
28.2
ILSVRC'15 ResNet
ILSVRC'14 GoogleNet
ILSVRC'14 VGG
ILSVRC'13
ILSVRC'12 AlexNet
ILSVRC'11
ILSVRC'10
ImageNet Classification top-5 error (%)

深度革命

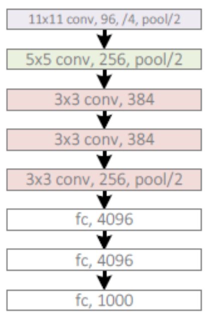
AlexNet, 8 layers
(ILSVRC 2012)



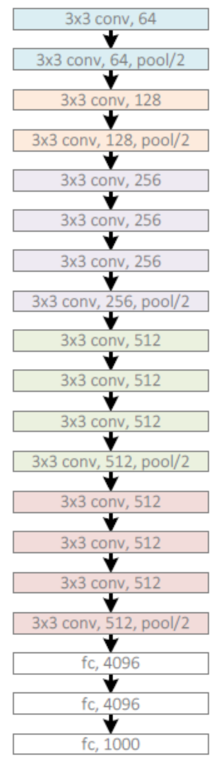
深度革命

Revolution of Depth

AlexNet, 8 layers
(ILSVRC 2012)



VGG, 19 layers
(ILSVRC 2014)



GoogleNet, 22 layers
(ILSVRC 2014)

深度革命

Revolution of Depth

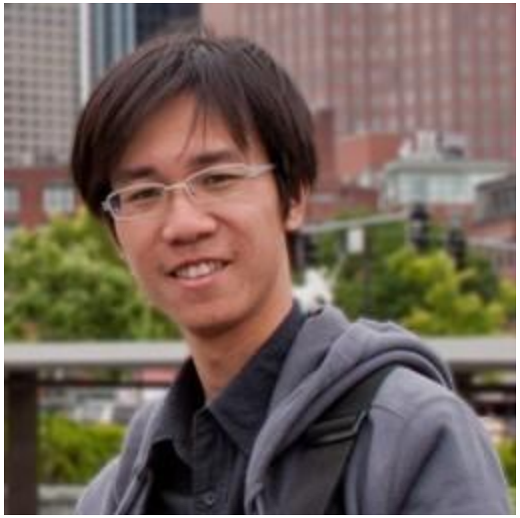
AlexNet, 8 layers
(ILSVRC 2012)

VGG, 19 layers
(ILSVRC 2014)

ResNet, 152 layers
(ILSVRC 2015)

何凯明

- 何凯明博士，广东省高考状元，进入清华。2007年清华大学毕业之后开始在微软亚洲研究院（MSRA）实习
- 2011年香港中文大学博士毕业后正式加入MSRA，目前在Facebook AI Research (FAIR)实验室担任研究科学家。
- 曾以第一作者身份拿过两次CVPR最佳论文奖（2009和2016）——其中2016年CVPR最佳论文为图像识别中的深度残差学习（Deep Residual Learning for Image Recognition）
- 2009年获奖论文是《Single Image Haze Removal Using Dark Channel Prior》（《暗通道图像去雾算法》）



参考论文

Deep Residual Learning for Image Recognition

Kaiming He   Xiangyu Zhang   Shaoqing Ren   Jian Sun
Microsoft Research
{kahe, v-xiangz, v-shren, jiansun}@microsoft.com

Abstract

Deeper neural networks are more difficult to train. We present a residual learning framework to ease the training of networks that are substantially deeper than those used previously. We explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. We provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset we evaluate residual nets with a depth of up to 152 layers—8× deeper than VGG nets [41] but still having lower complexity. An ensemble of these residual nets achieves 3.57% error on the ImageNet test *set. This result won the 1st place on the ILSVRC 2015 classification task. We also present analysis on CIFAR-10 with 100 and 1000 layers.*

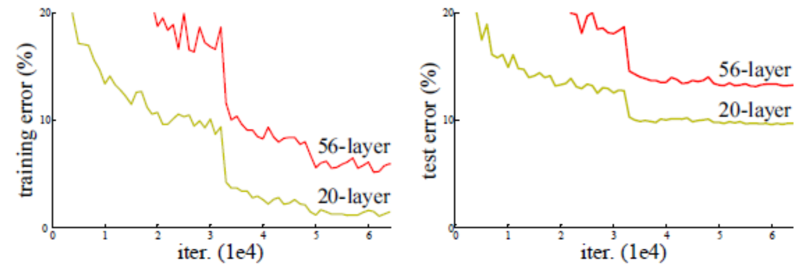


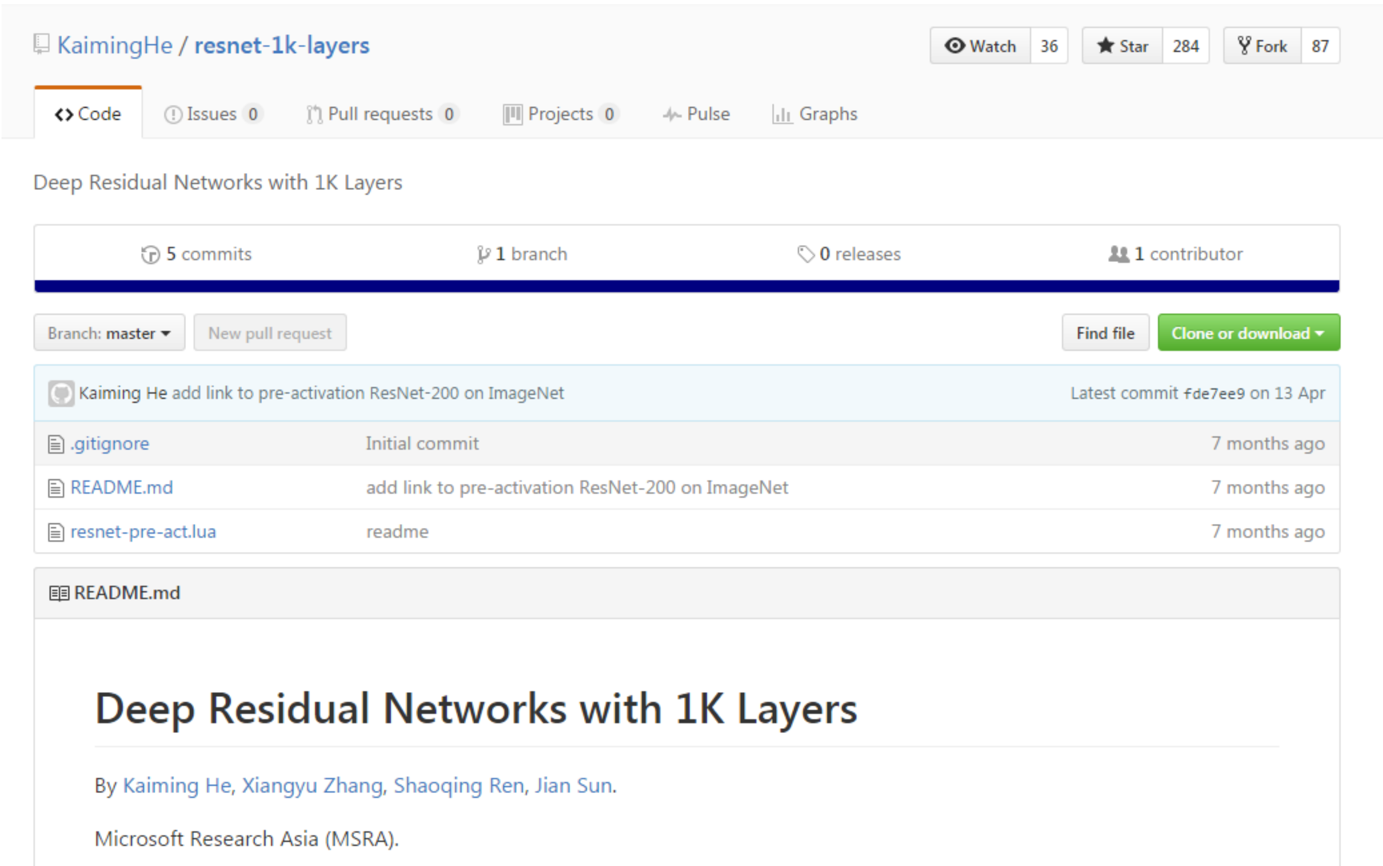
Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

greatly benefited from very deep models.

Driven by the significance of depth, a question arises: *Is learning better networks as easy as stacking more layers?* An obstacle to answering this question was the notorious problem of vanishing/exploding gradients [1, 9], which

有关代码

- https://github.com/KaimingHe/resnet-1k-layers



“传统”深度学习的困难

- 深度学习目前进展取决于技巧：初始权值选择，局部感受野，权值共享等等，但使用更深层的网络时（例如>100），依然要面对反向传播时梯度消失这类传统困难
- 退化问题：层数越多，训练错误率与测试错误率反而升高

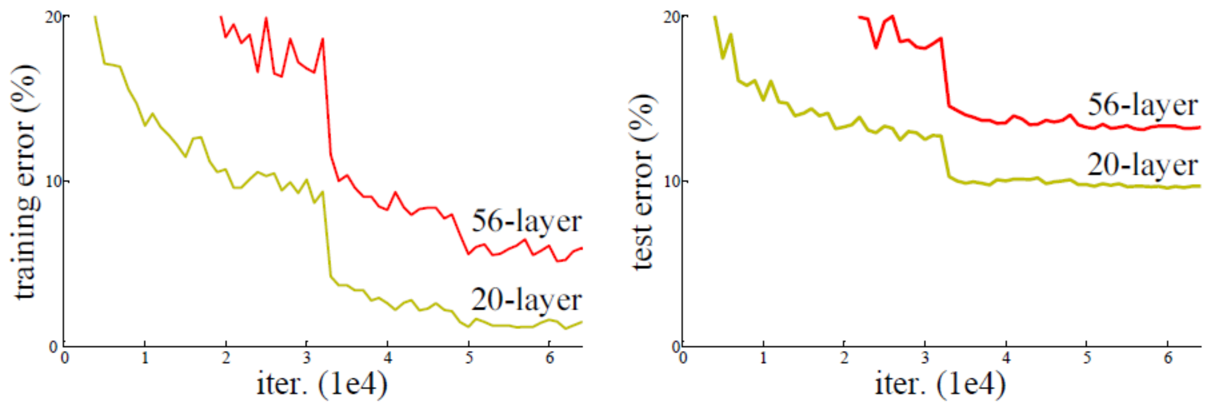


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer “plain” networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

CIFAR-10和CIFAR-100

- http://www.cs.toronto.edu/~kriz/cifar.html

The CIFAR-10 and CIFAR-100 are labeled subsets of the 80 million tiny images dataset. They were collected by Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton.

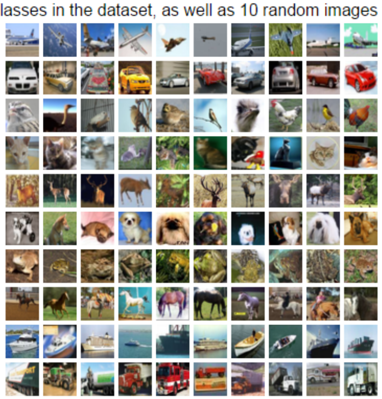
The CIFAR-10 dataset

The CIFAR-10 dataset consists of 60000 32x32 colour images in 10 classes, with 6000 images per class. There are 50000 training images and 10000 test images.

The dataset is divided into five training batches and one test batch, each with 10000 images. The test batch contains exactly 1000 randomly-selected images from each class. The training batches contain the remaining images in random order, but some training batches may contain more images from one class than another. Between them, the training batches contain exactly 5000 images from each class.

Here are the classes in the dataset, as well as 10 random images from each:

airplane
automobile
bird
cat
deer
dog
frog
horse
ship
truck



The classes are completely mutually exclusive. There is no overlap between automobiles and trucks. "Automobile" includes sedans, SUVs, things of that sort. "Truck" includes only big trucks. Neither includes pickup trucks.

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If you're going to use this dataset, please cite the tech report at the bottom of this page.

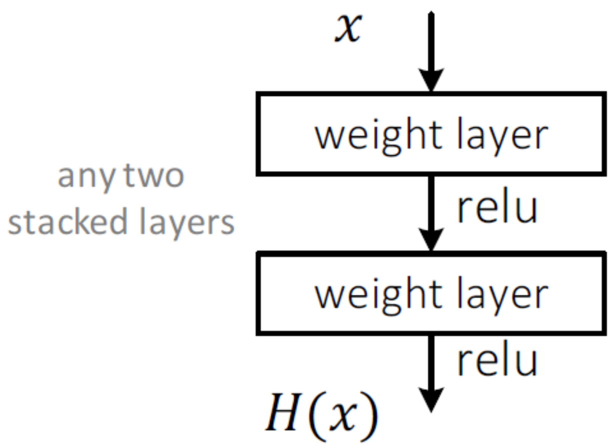
Version	Size	md5sum
CIFAR-10 python version	163 MB	c58f30108f718f92721af3b95e74349a
CIFAR-10 Matlab version	175 MB	70270af85842c9e89bb428ec9976c926
CIFAR-10 binary version (suitable for C programs)	162 MB	c32a1d4ab5d03f1284b67883e8d87530

深度残差网络的思路

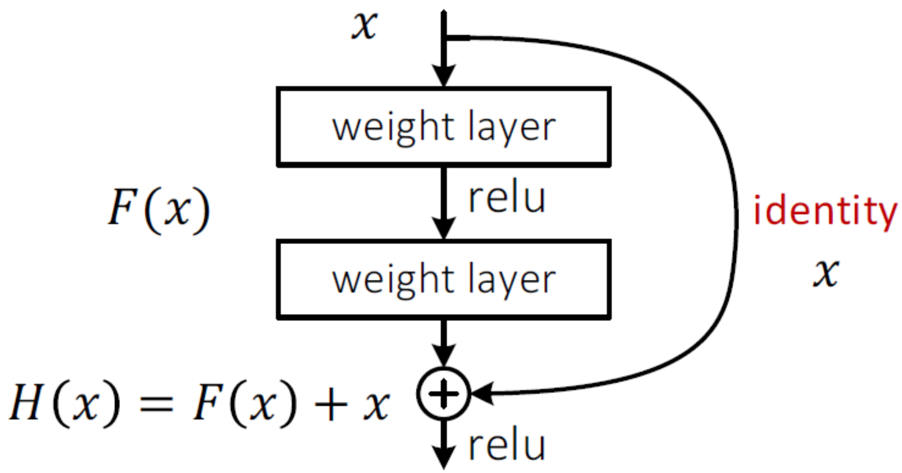
- 引入“捷径”，可以防止梯度消失问题
- 直觉认为可以混合利用不同层级的特征进一步抽取深层特征（对比Alphago中将输入局面数据人为加工成48张输入平面——人为干预特征抽取）
- 其它类似的工作在进行中： Srivastava等人的《 Highway Networks 》，《 Training Very Deep Networks 》
- 目标：更深层的网络应该也是易于优化的，层数越多准确率越高，训练方法与“传统”深度网络相比不会有很大变化

基本构件

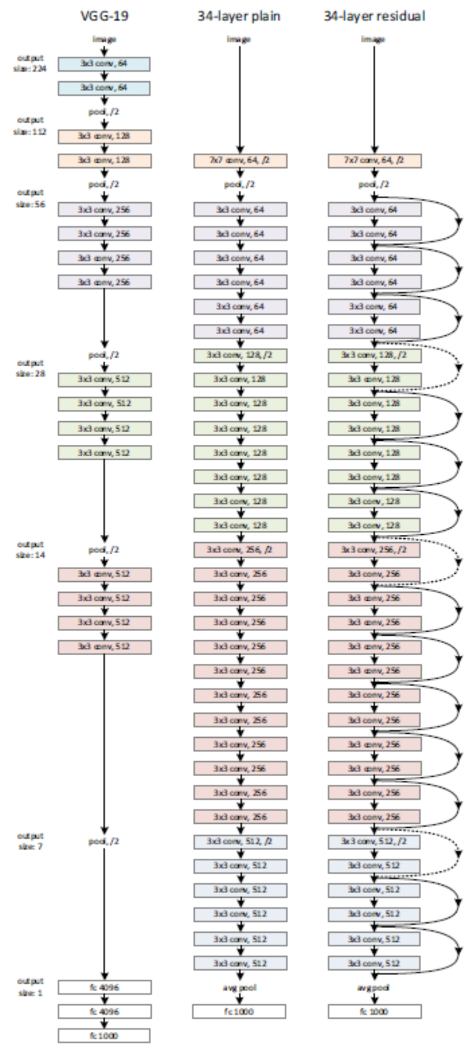
- Plaint net



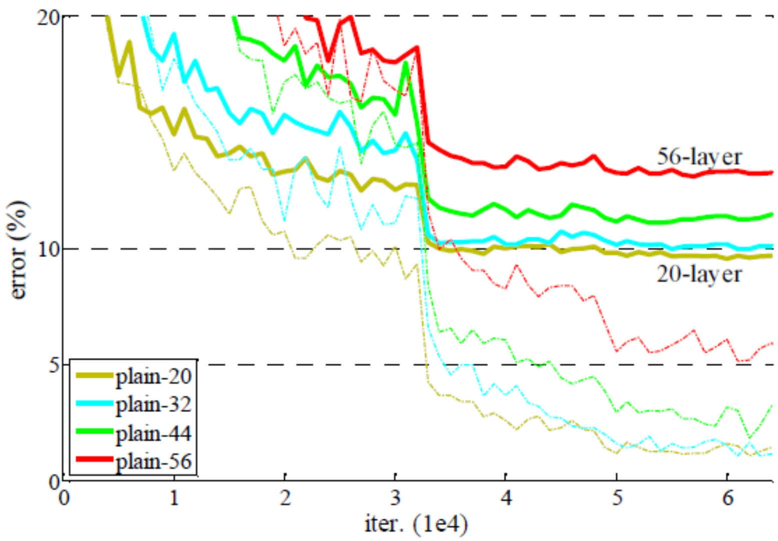
- Residual net

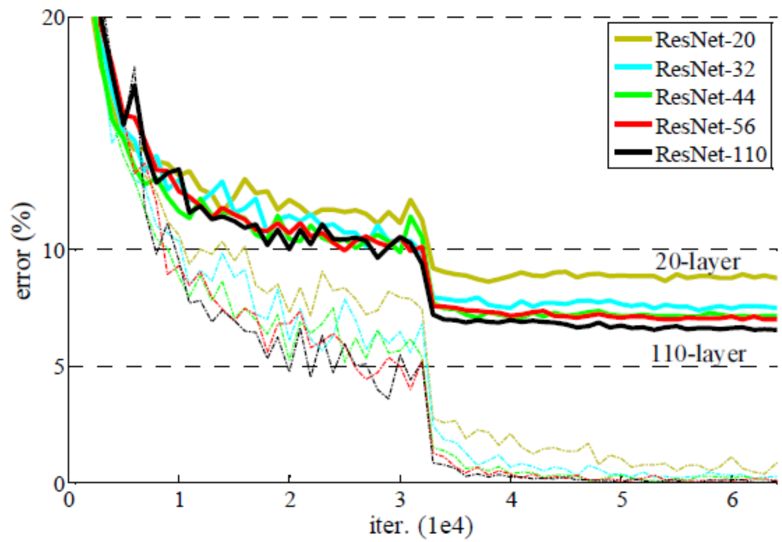


网络结构

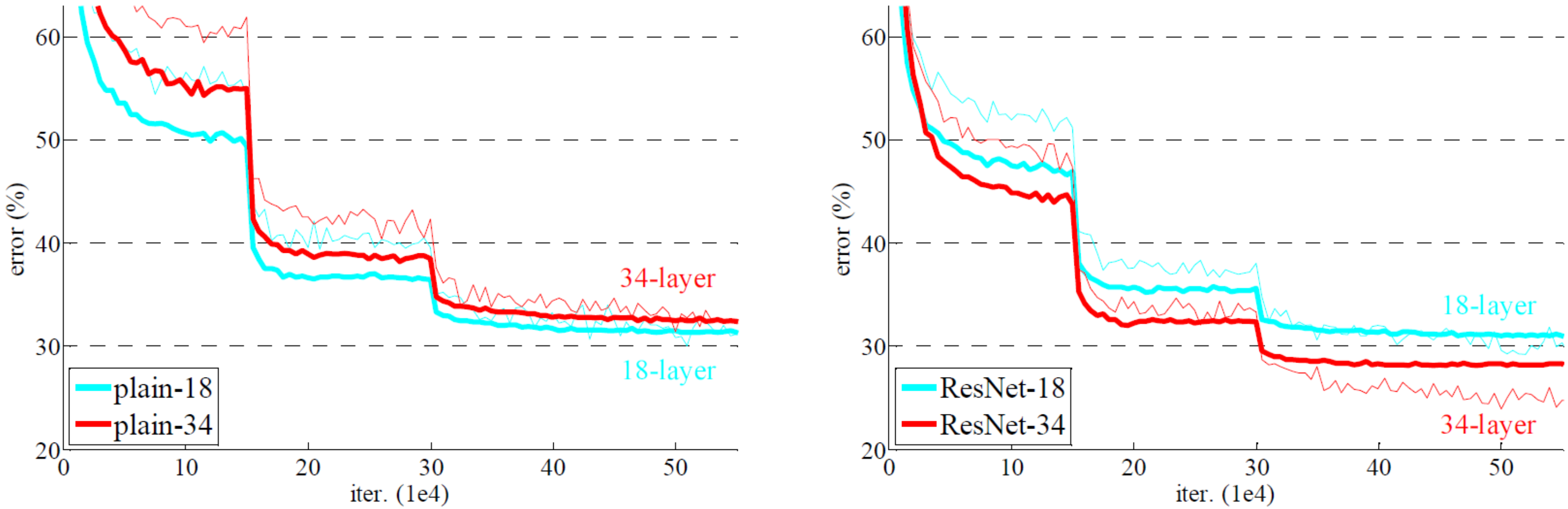


CIFAR-10上的测试对比





ImageNet上的测试结果



另一种构件

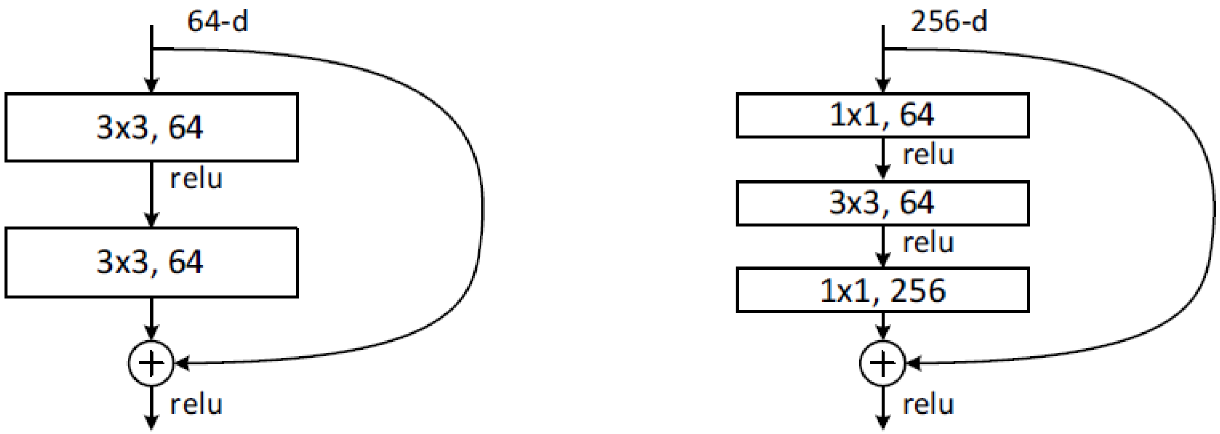
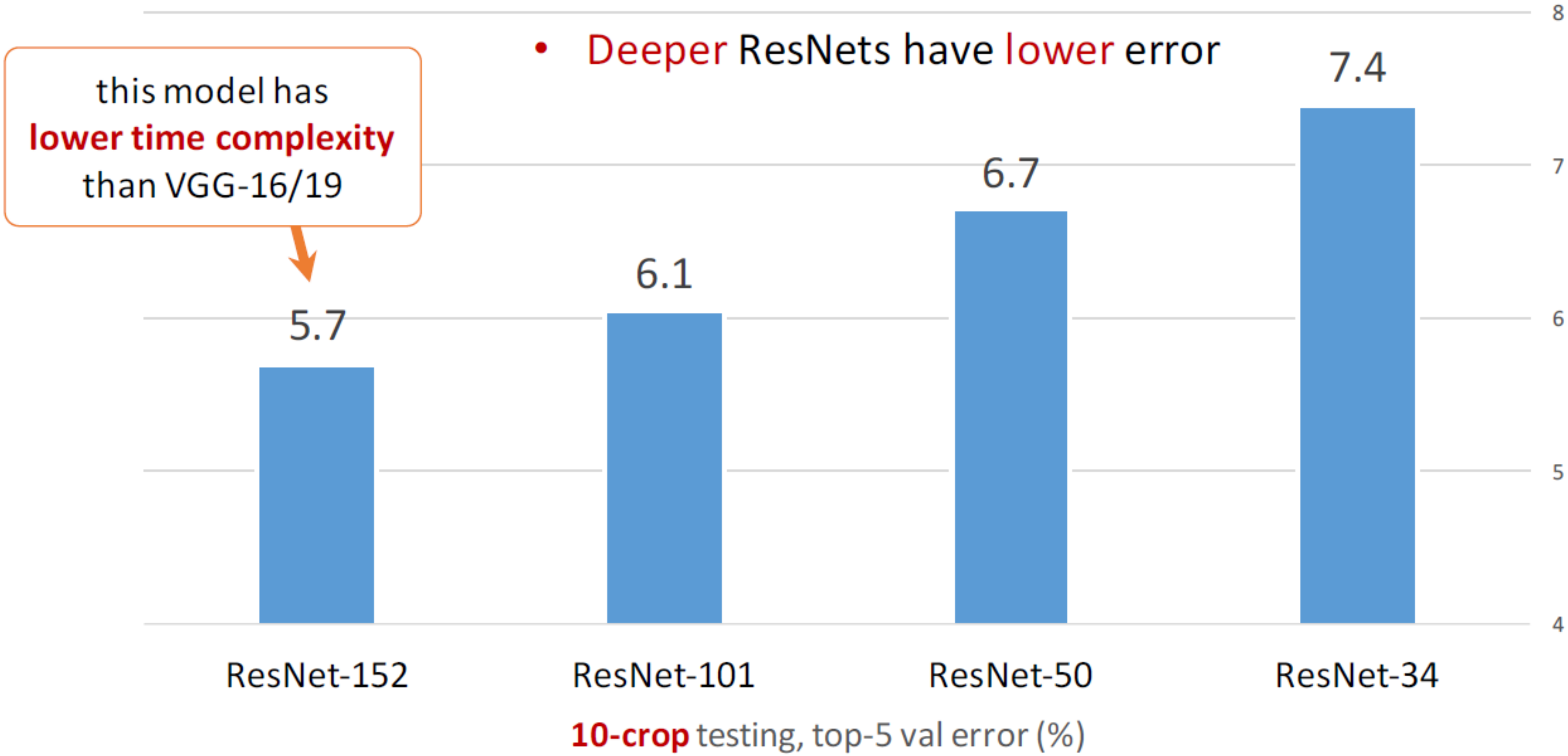


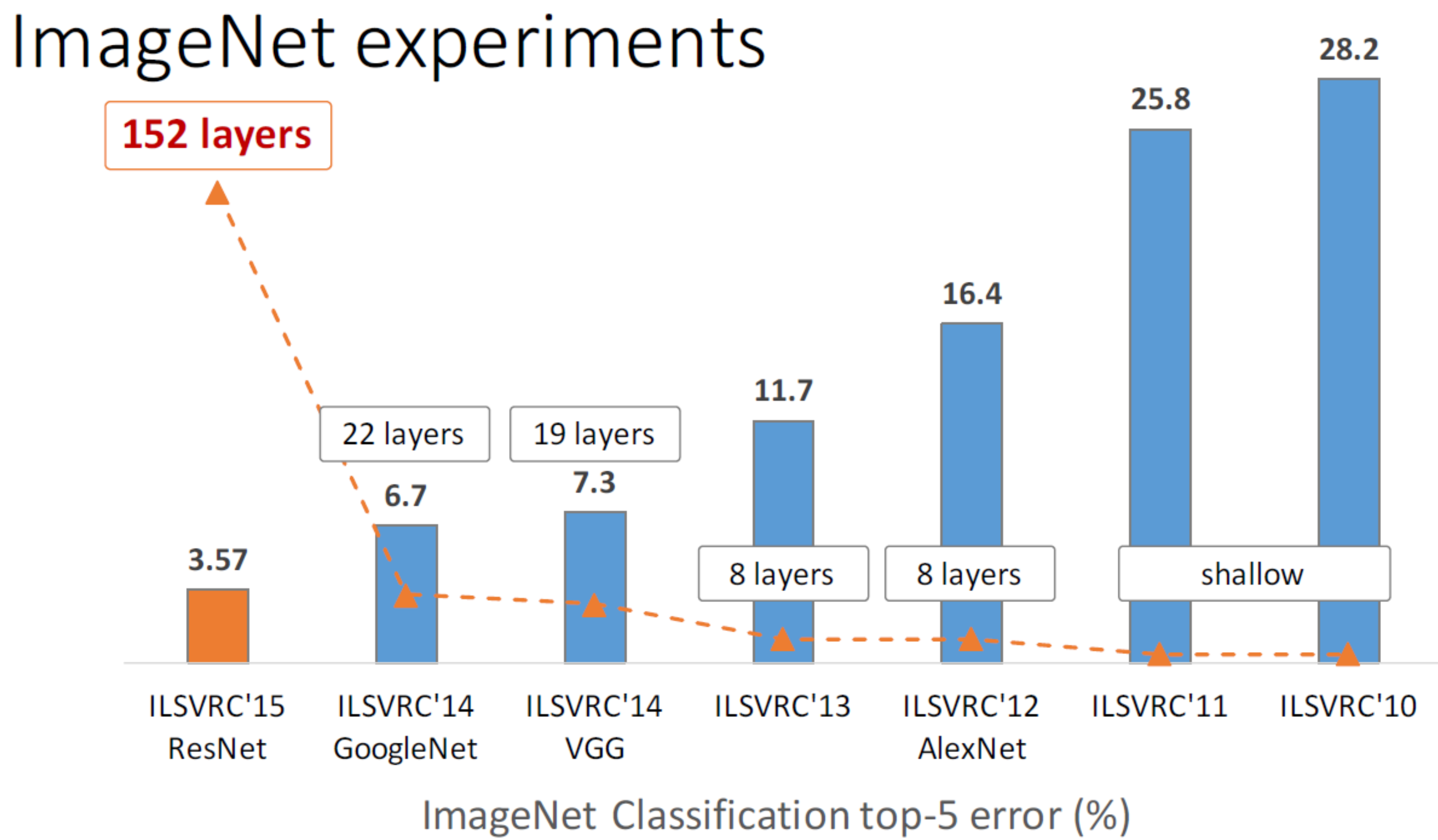
Figure 5. A deeper residual function $\mathcal{F}$ for ImageNet. Left: a building block (on 56×56 feature maps) as in Fig. 3 for ResNet-34. Right: a "bottleneck" building block for ResNet-50/101/152.

Image实验

ImageNet experiments



ImageNet实验



ImageNet experiments
152 layers
22 layers
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28.2
ILSVRC'15 ResNet
ILSVRC'14 GoogleNet
ILSVRC'14 VGG
ILSVRC'13
ILSVRC'12 AlexNet
ILSVRC'11
ILSVRC'10
ImageNet Classification top-5 error (%)

Identity Mappings in Deep Residual Networks

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun

Microsoft Research

Abstract Deep residual networks [1] have emerged as a family of extremely deep architectures showing compelling accuracy and nice convergence behaviors. In this paper, we analyze the propagation formulations behind the residual building blocks, which suggest that the forward and backward signals can be directly propagated from one block to any other block, when using identity mappings as the skip connections and after-addition activation. A series of ablation experiments support the importance of these identity mappings. This motivates us to propose a new residual unit, which further makes training easy and improves generalization. We report improved results using a 1001-layer ResNet on CIFAR-10 (4.62% error) and CIFAR-100, and a 200-layer ResNet on ImageNet. Code is available at: https://github.com/KaimingHe/resnet-1k-layers.

恒等映射有更好效果

* ResNet-110 on CIFAR-10

$h(x) = x$
error: 6.6%

$h(x) = 0.5x$
error: 12.4%

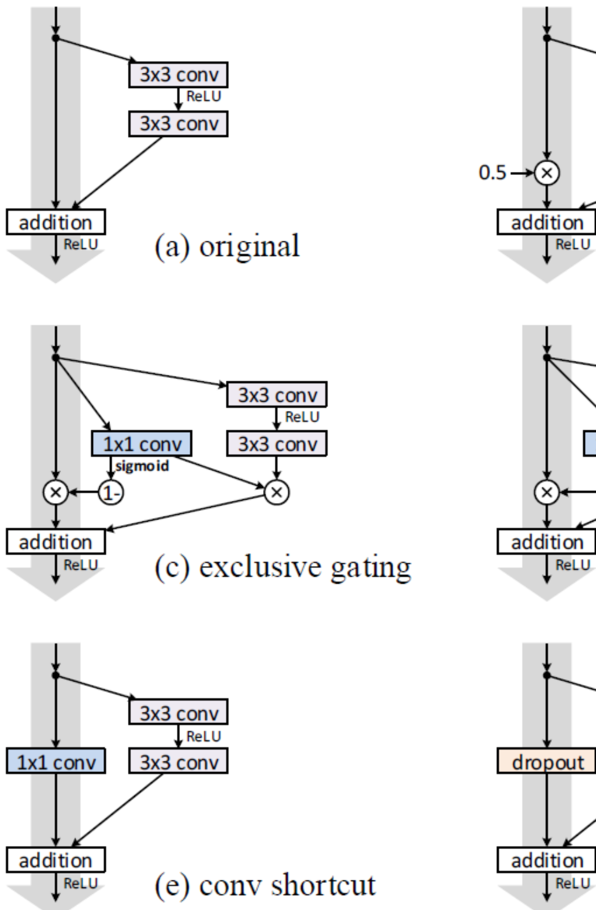
$h(x) = \text{gate} \cdot x$
error: 8.7%

*similar to "Highway Network"

$h(x) = \text{gate} \cdot x$
error: 12.9%

$h(x) = \text{conv}(x)$
error: 12.2%

$h(x) = \text{dropout}(x)$
error: > 20%



(a) original

(b) constant scaling

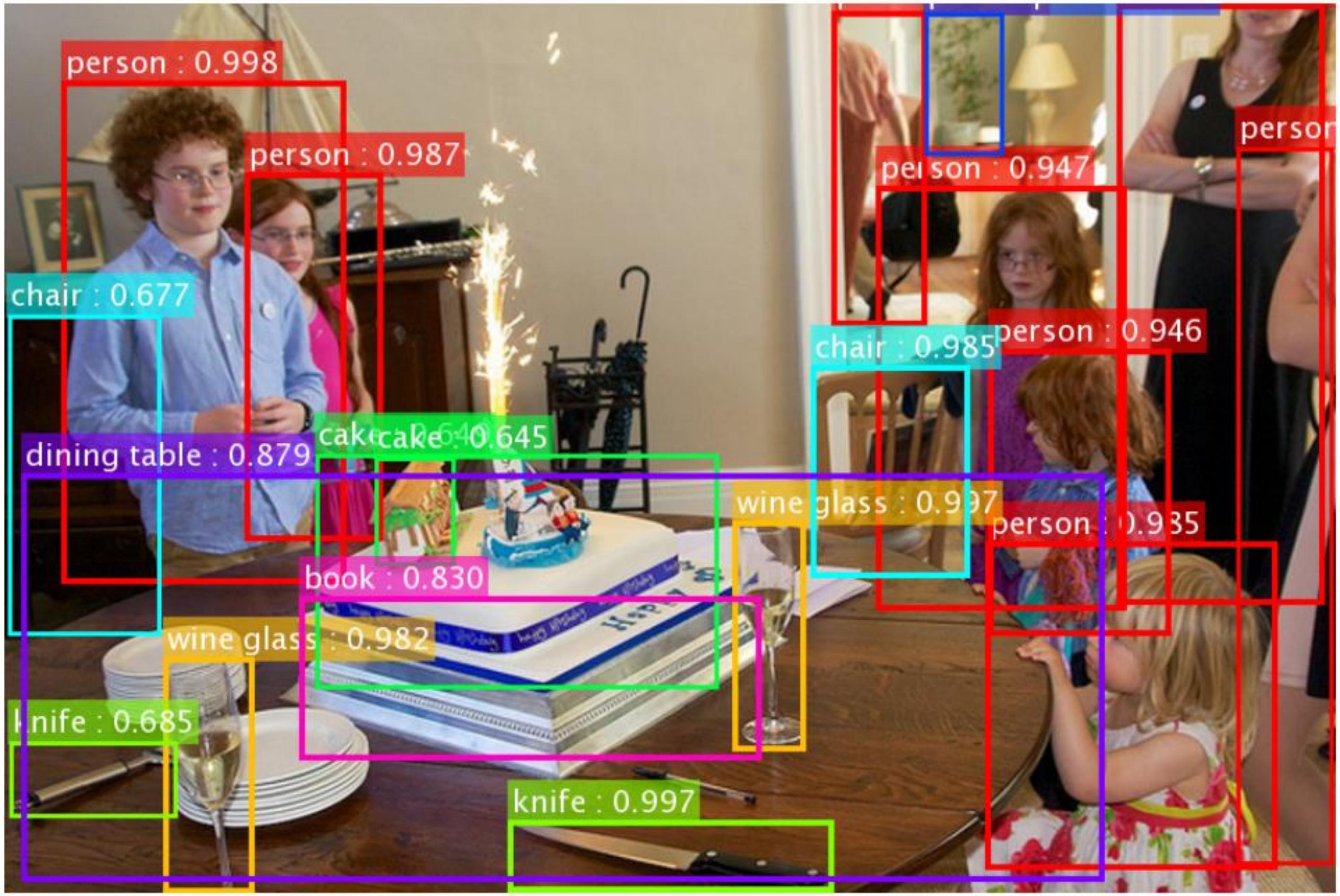
(c) exclusive gating

(d) shortcut-only gating

(e) conv shortcut

(f) dropout shortcut

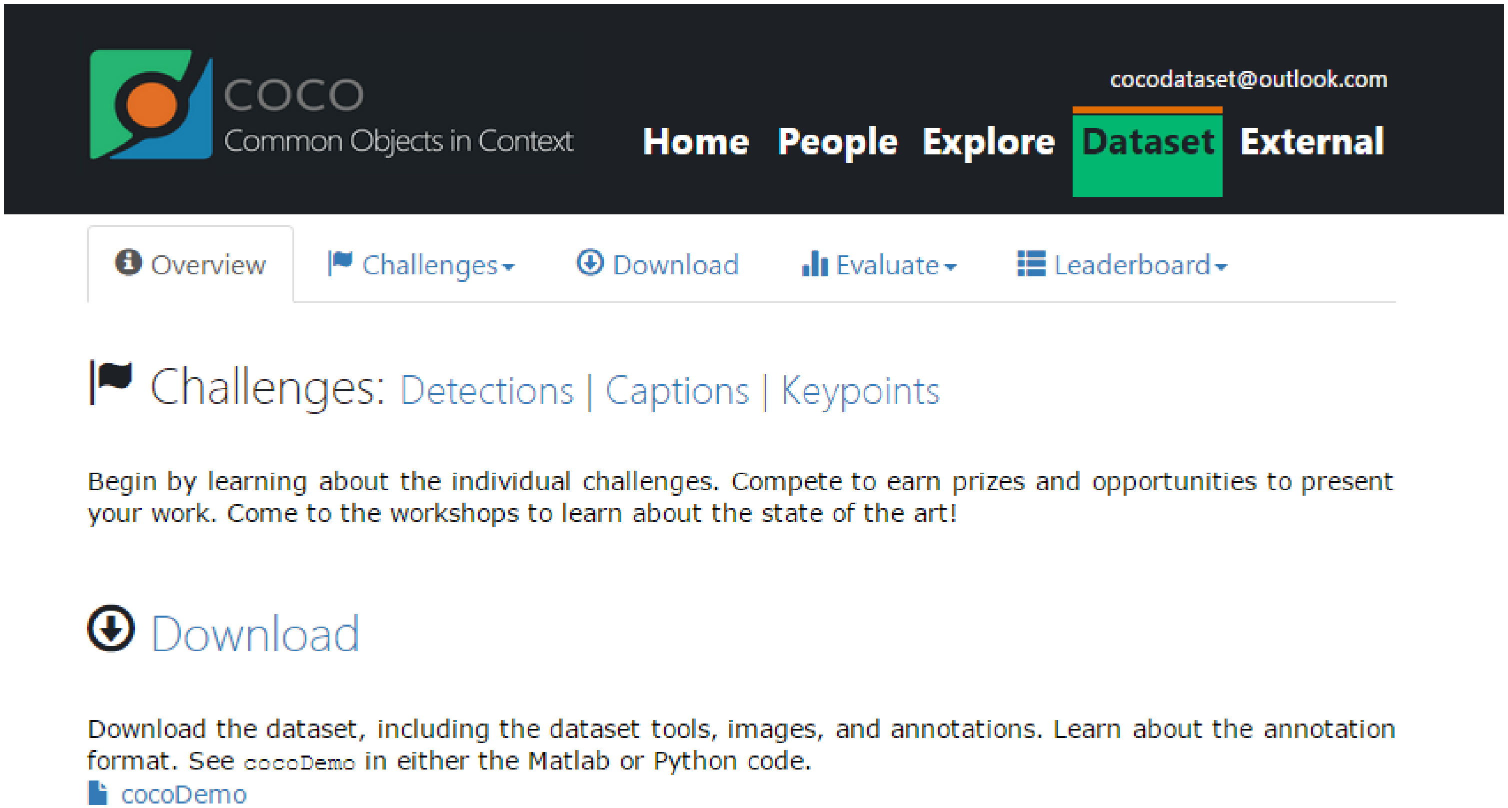
应用



ResNet's object detection result on COCO

微软COCO图像识别大赛

- http://mscoco.org/dataset/#overview



炼数成金逆向收费式网络课程

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Thanks

FAQ时间