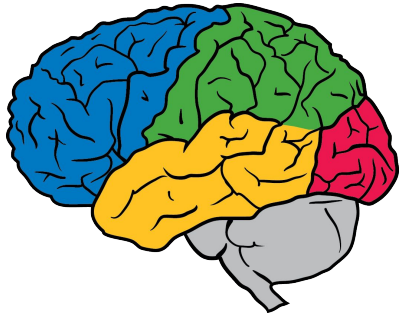


Recent Advances in Artificial Intelligence and the Implications for Computer System Design

人工智能的最新进展及其对计算机系统设计的启示

Jeff Dean

Google Brain team

Google大脑团队

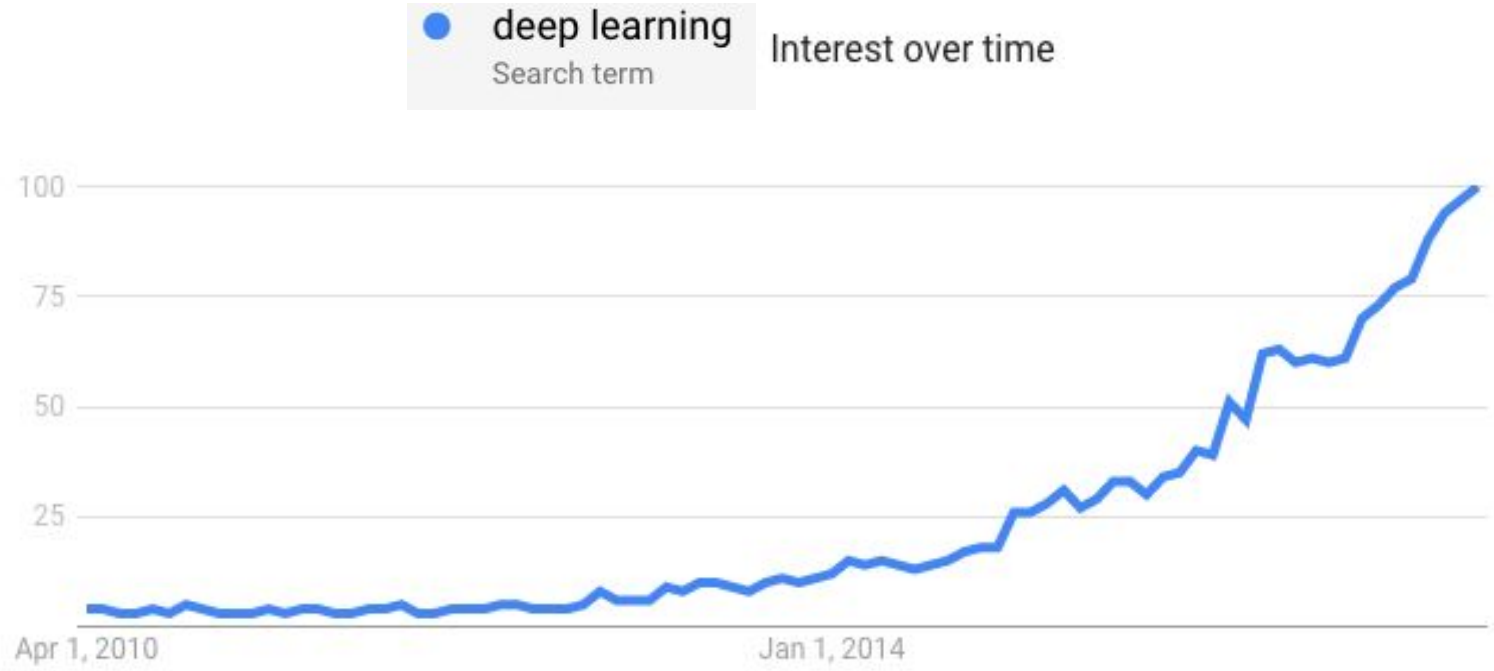
g.co/brain

翻译：Karl Lok @ https://github.com/whitelok

Presenting the work of **many** people at Google

Deep learning is causing a machine learning revolution

深度学习引领机器学习革命



Deep Learning

Modern Reincarnation of Artificial Neural Networks
现代人工神经网络的升级换代

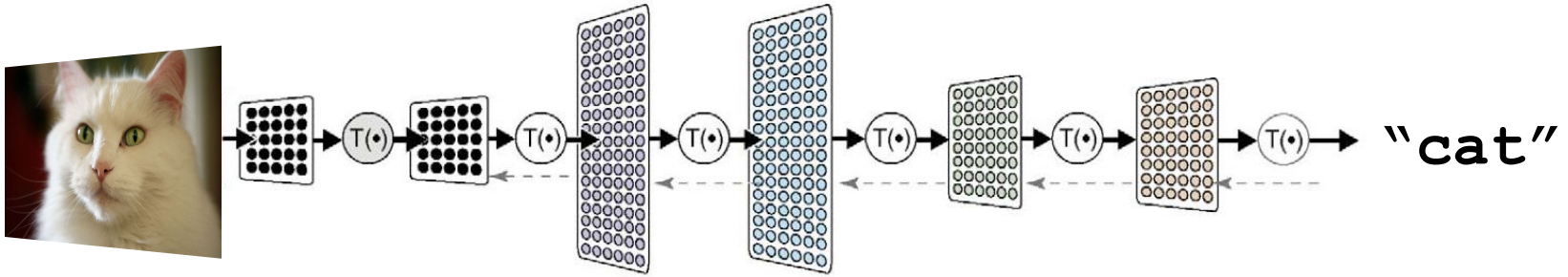
Collection of simple trainable mathematical units, organized in layers, that work together to solve complicated tasks
现代人工神经网络通过简单可训练的数学单元组织成层级结构解决复杂的任务。

What's New

new network architectures,
new training math, ***scale***
新的网络结构，新的训练方法，*灵活可扩展*

Key Benefit

Learns features from raw, heterogeneous, noisy data
No explicit feature engineering required
在未使用特征工程处理的情况下，从未经处理的，异构的，有噪数据中提取出特征



IS THIS A

CAT or DOG?

CAT DOG

OUTPUT LAYER

ACTIVATED NEURONS

INPUT LAYER

DEEP *neural* NETWORK

Functions a Deep Neural Network Can Learn

深度神经网络的功能

input **output**

Pixels: 

“lion”

无论是图片还是声音还是文本，都能作为深度神经网络的输入~~~

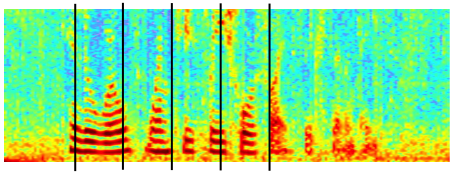
Functions a Deep Neural Network Can Learn

深度神经网络的功能

input **output**

Pixels: 

“lion”

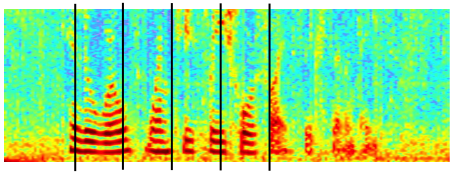
Audio: 

“How cold is it outside?”

无论是图片还是声音还是文本，都能作为深度神经网络的输入~~~

Functions a Deep Neural Network Can Learn

深度神经网络的功能

	input	output
Pixels:		“lion”
Audio:		“How cold is it outside?”
“Hello, how are you?”		“Bonjour, comment allez-vous?”

无论是图片还是声音还是文本，都能作为深度神经网络的输入~~~

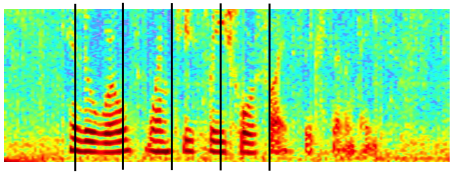
Functions a Deep Neural Network Can Learn

深度神经网络的功能

input **output**

Pixels: 

“lion”

Audio: 

“How cold is it outside?”

“Hello, how are you?”

“Bonjour, comment allez-vous?”

Pixels: 

“A blue and yellow train travelling down the tracks”

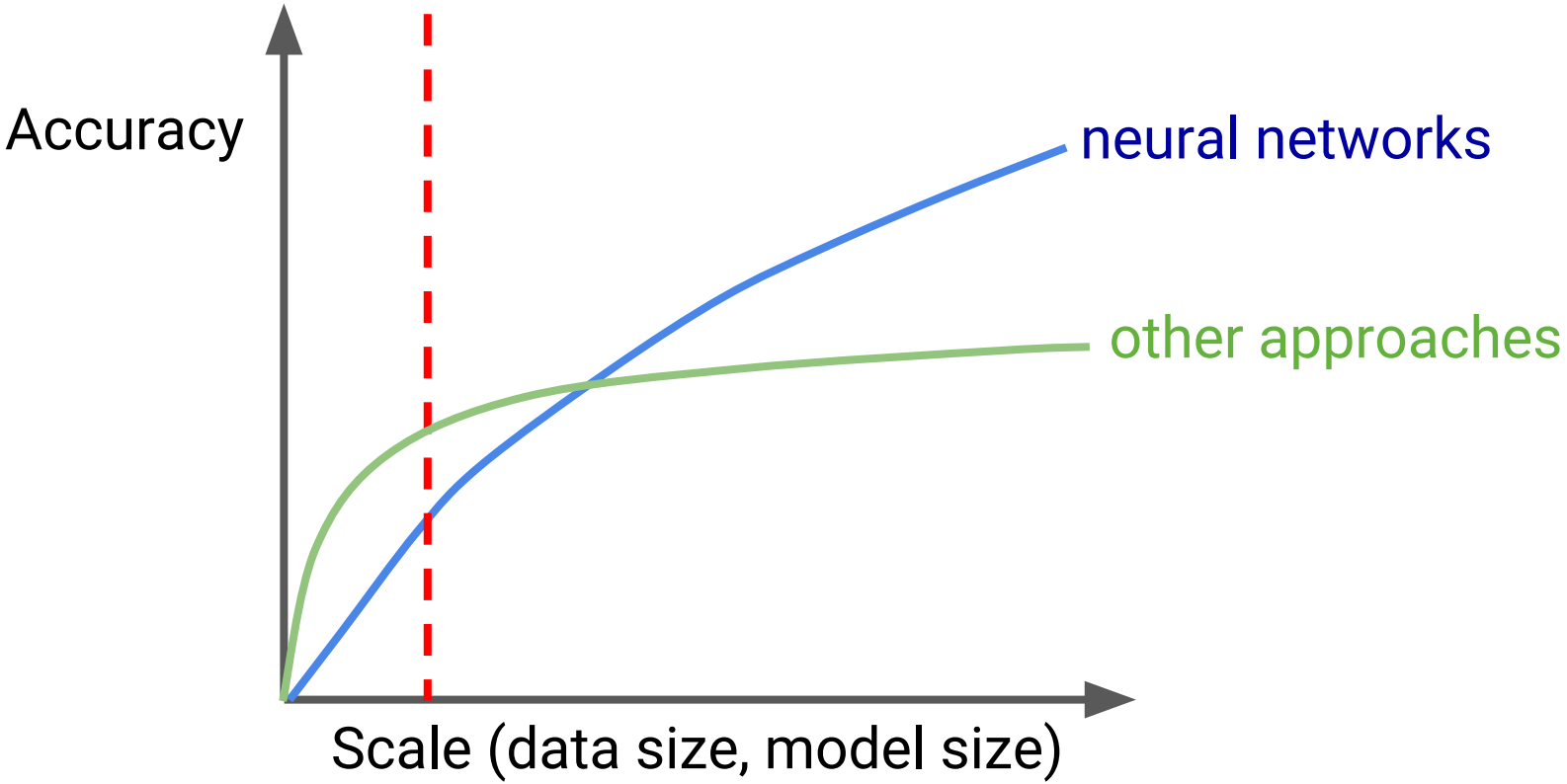
无论是图片还是声音还是文本，都能作为深度神经网络的输入~~~

But why now?
这么好的东西为啥现在才出现

（以前计算能力不够啊~~~）

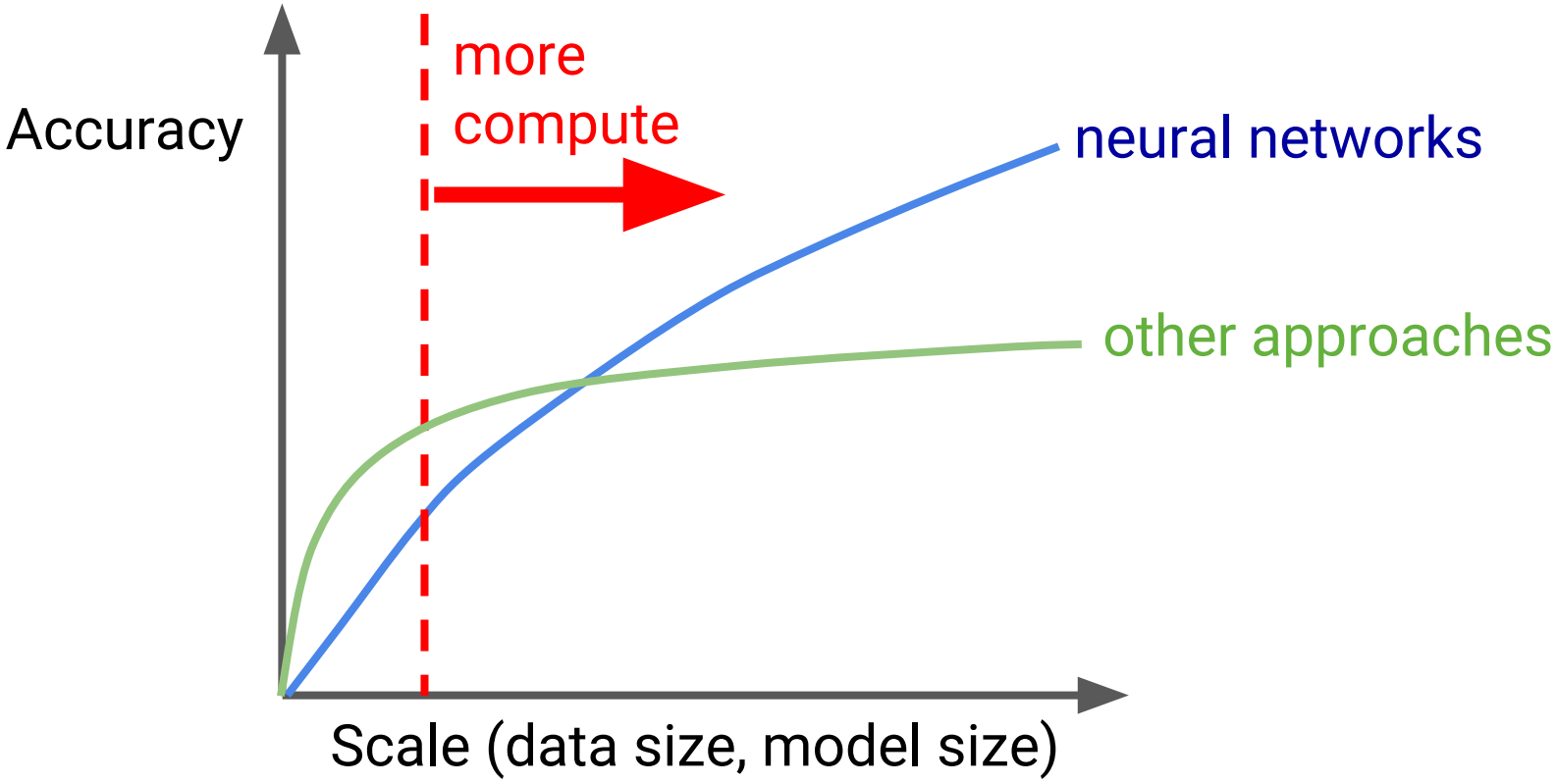
1980s and 1990s

在1980年-1990年计算模型规模、数据量下神经网络比其他方法的准确率低



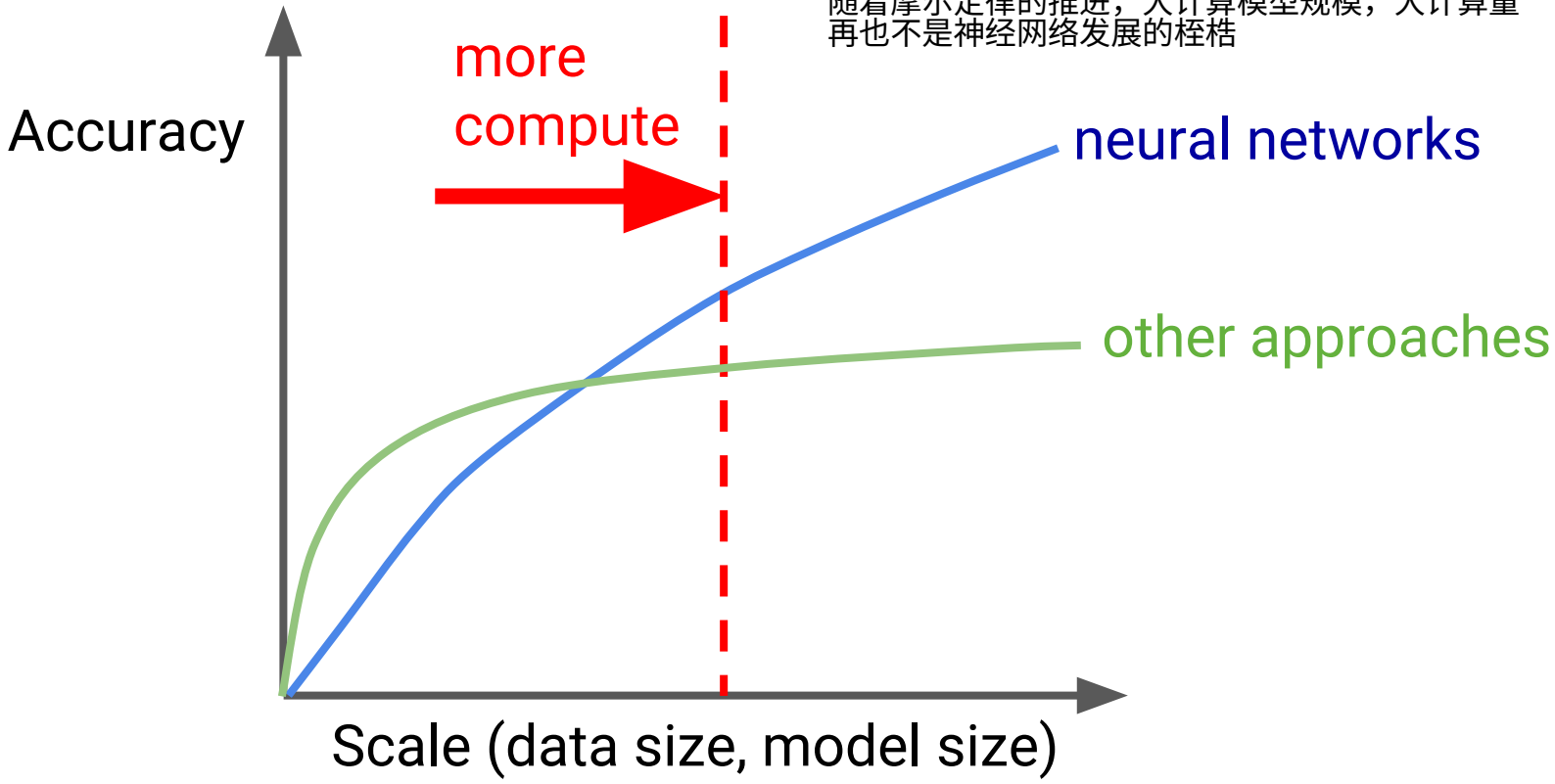
1980s and 1990s

计算模型规模越大、数据量越大计算量越多

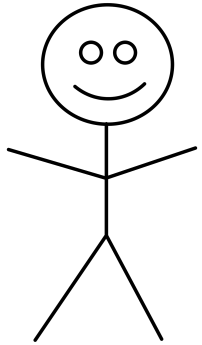


Now

随着摩尔定律的推进，大计算模型规模，大计算量再也不是神经网络发展的桎梏



humans

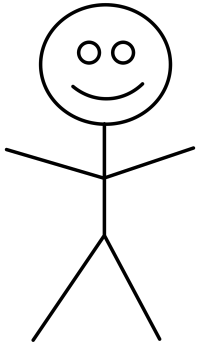


5% errors

2011

26% errors

humans



5% errors

2016

3% errors

2008: NAE Grand Engineering Challenges for 21st Century

2008年美国国家工程院评选出的21世纪14个工程学上的巨大的挑战

- Make solar energy affordable
  让太阳能变得廉价可用
- Provide energy from fusion
  利用核聚变产生的能源
- Develop carbon sequestration methods
  让大气中的碳固化的方法
- Manage the nitrogen cycle
  控制氮循环
- Provide access to clean water
  让净水更容易
- Restore & improve urban infrastructure
  修复和升级城市基础设施
- Advance health informatics
  人体生理指标信息化
- Engineer better medicines
  拓展医学医药工程
- Reverse-engineer the brain
  人脑逆向工程
- Prevent nuclear terror
  研究更安全的核能使用方法
- Secure cyberspace
  使网络世界更加安全
- Enhance virtual reality
  提高虚拟现实技术
- Advance personalized learning
  提高个性化学习
- Engineer the tools for scientific discovery
  升级科学发现的工

www.engineeringchallenges.org/challenges.aspx

2008: NAE Grand Engineering Challenges for 21st Century

红色是通过神经网络方法获得巨大进展的

- Make solar energy affordable
- Provide energy from fusion
- Develop carbon sequestration methods
- Manage the nitrogen cycle
- Provide access to clean water
- Restore & improve urban infrastructure
  修复和升级城市基础设施
- Advance health informatics
  人体生理指标信息化
- Engineer better medicines
  拓展医学医药工程
- Reverse-engineer the brain
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- Prevent nuclear terror
- Secure cyberspace
- Enhance virtual reality
- Advance personalized learning
- Engineer the tools for scientific discovery
  升级科学发现的工

www.engineeringchallenges.org/challenges.aspx

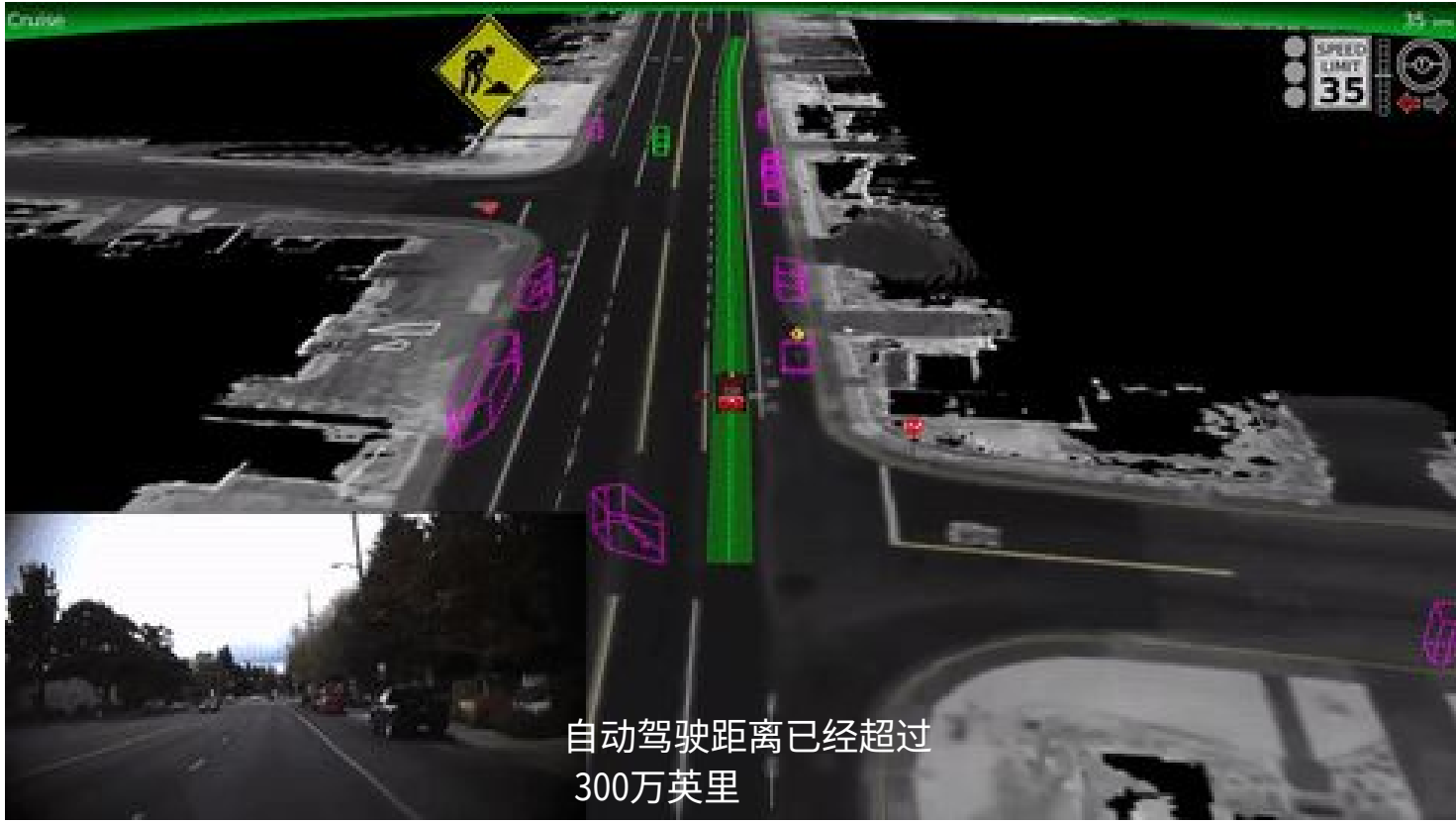
Restore & improve urban infrastructure

修复和提升城市基础设施

WAYMO

3 million miles self-driven

We drive more than 25,000 autonomous miles each week, largely on complex city streets. That's on top of 1 billion simulated miles we drove just in 2016.



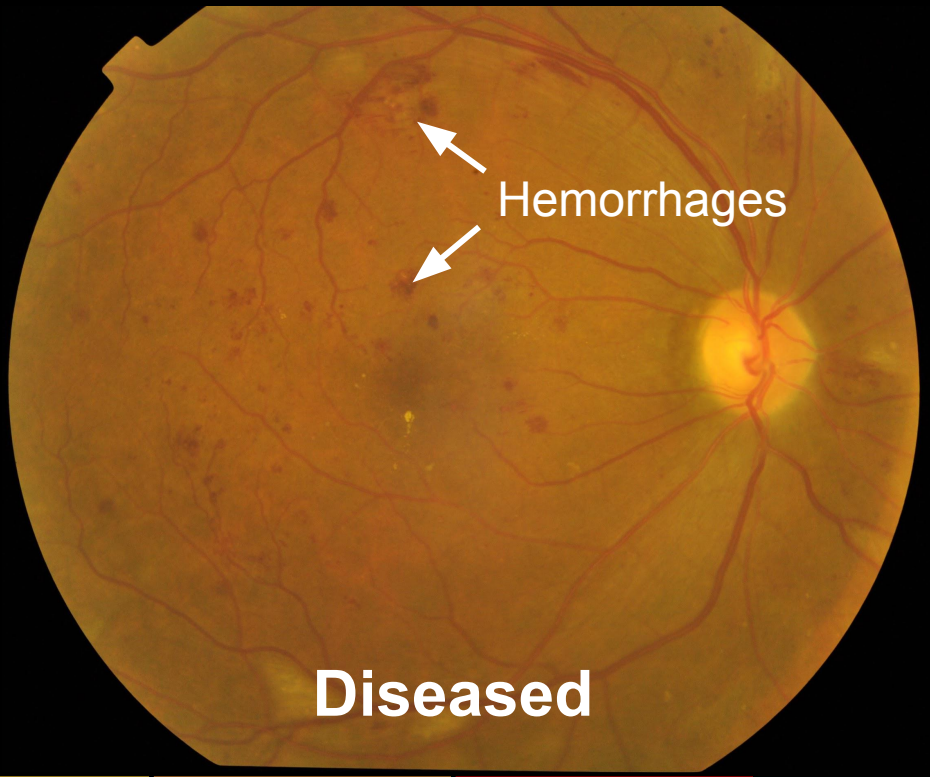
自动驾驶距离已经超过
300万英里

https://waymo.com/tech/

Advance health informatics

人体生理指标信息化

Healthy



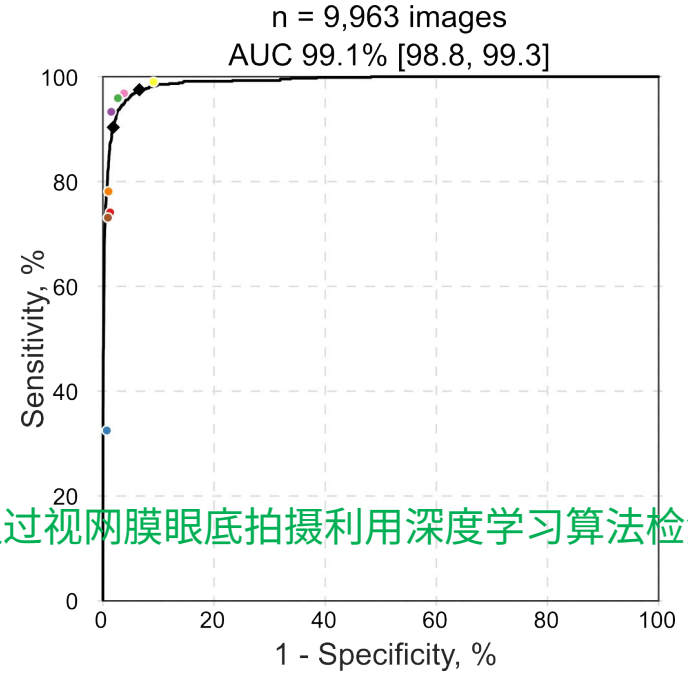
Diseased

No DR	Mild DR	Moderate DR	Severe DR	Proliferative DR
1	2	3	4	5

JAMA The Journal of the American Medical Association

JAMA | Original Investigation | INNOVATIONS IN HEALTH CARE DELIVERY

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs



论文：通过视网膜眼底拍摄利用深度学习算法检测和诊断糖尿病视网膜病变

F-score

0.95	0.91
Algorithm	Ophthalmologist (median)

深度学习算法比眼科医生还准

"The study by Gulshan and colleagues **truly represents the brave new world in medicine.**"

Dr. Andrew Beam, Dr. Isaac Kohane
Harvard Medical School

"Google just published this paper in JAMA (impact factor 37) [...] **It actually lives up to the hype.**"

Dr. Luke Oakden-Rayner
University of Adelaide

Pathology

Detecting Cancer Metastases on Gigapixel Pathology Images

检测高像素照片的癌细胞区域：算法比病理家准

Yun Liu[1]*, Krishna Gadepalli[1], Mohammad Norouzi[1], George E. Dahl[1], Timo Kohlberger[1], Aleksey Boyko[1], Subhashini Venugopalan[2]**, Aleksei Timofeev[2], Philip Q. Nelson[2], Greg S. Corrado[1], Jason D. Hipp[3], Lily Peng[1], and Martin C. Stumpe[1]

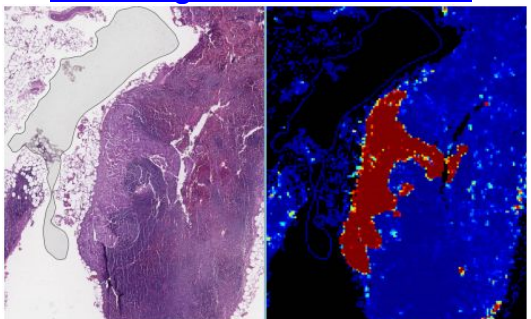
{liuyun,mnorouzi,gdahl,lhpeng,mstumpe}@google.com

[1]Google Brain, [2]Google Inc, [3]Verily Life Sciences, Mountain View, CA, USA

Tumor localization score (FROC):

model:	**0.89**
pathologist:	0.73

arxiv.org/abs/1703.02442



Radiology

Acta Orthopaedica

Research-article

Artificial intelligence for analyzing orthopedic trauma radiographs 利用人工智能通过X光片分析骨伤

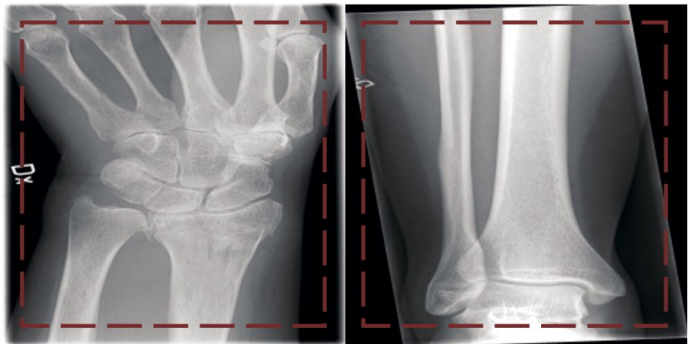
Deep learning algorithms—are they on par with humans for diagnosing fractures?

Jakub Olczak, Niklas Fahlberg, Atsuto Maki, Ali Sharif Razavian, Anthony Jilert, André Stark, Olof Sköldenberg & Max Gordon ...show less

Pages 1-6 | Received 01 Mar 2017, Accepted 06 Jun 2017, Published online: 06 Jul 2017

"The network performed similarly to senior orthopedic surgeons when presented with images at the same resolution as the network."

www.tandfonline.com/doi/full/10.1080/17453674.2017.1344459



Engineer better medicines

拓展医学医药工程

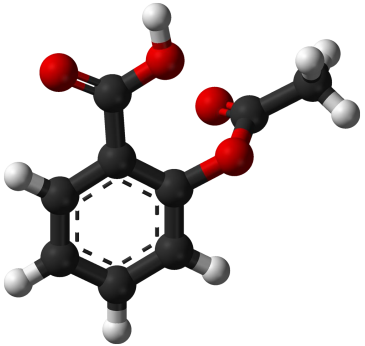
and maybe...

Make solar energy affordable

Develop carbon sequestration methods

Manage the nitrogen cycle

Predicting Properties of Molecules 预测分子的性质



DFT (density functional theory) simulator

Toxic? 是否有毒

Bind with a given protein?
是否针对特定蛋白质毒性为显性

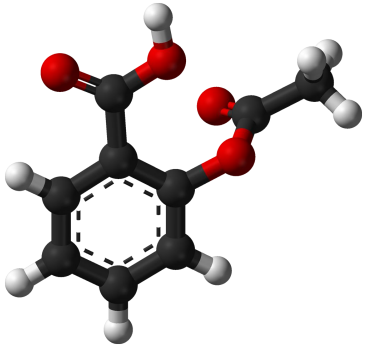
Quantum properties: $E, \omega_0, \ldots$
量子性参数

$\sim 10^3$ seconds

密度泛函模拟需要计算1000秒

密度泛函理论 （英语：Density functional theory (DFT)）是一种研究多电子体系电子结构的量子力学方法。密度泛函理论在物理和化学上都有广泛的应用，特别是用来研究分子和凝聚态的性质，是凝聚态物理和计算化学领域最常用的方法之一。

Predicting Properties of Molecules 预测分子的性质



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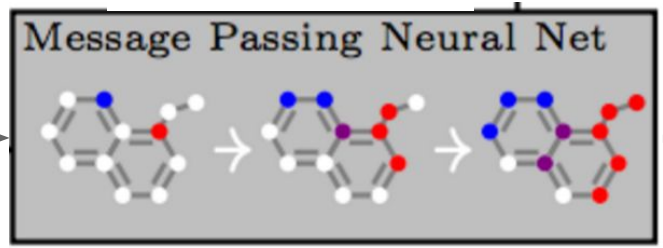
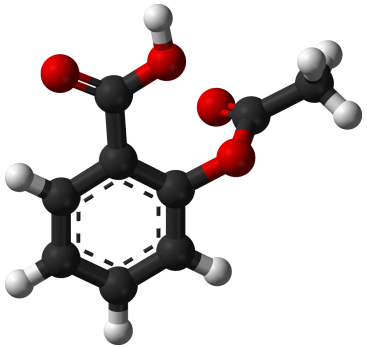


利用神经网络进行分析只需0.01秒

$\sim 10^{-2}$ seconds

Predicting Properties of Molecules 预测分子的性质



DFT (density functional theory) simulator

密度泛函模拟需要计算1000秒

$\sim 10^3$ seconds

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Bind with a given protein?
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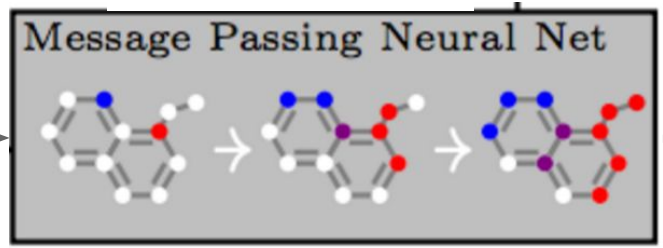
Quantum properties: $E, \omega_0, \ldots$
量子性参数



利用神经网络进行分析只需0.01秒

$\sim 10^{-2}$ seconds

- State of the art results predicting output of expensive quantum chemistry calculations, but **~300,000 times faster**

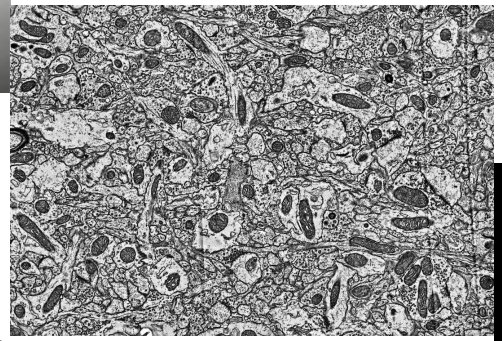
https://research.googleblog.com/2017/04/predicting-properties-of-molecules-with.html and https://arxiv.org/abs/1702.05532 and https://arxiv.org/abs/1704.01212 (appeared in ICML 2017)

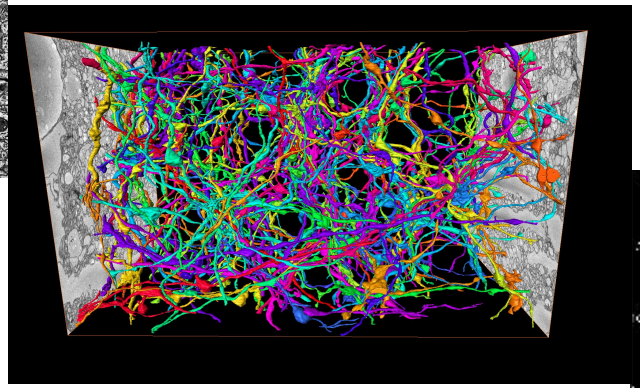
Reverse engineer the brain

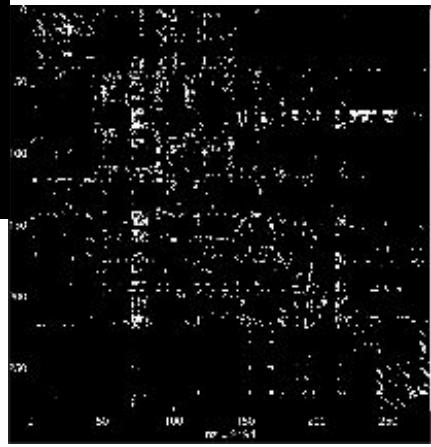
人脑逆向工程

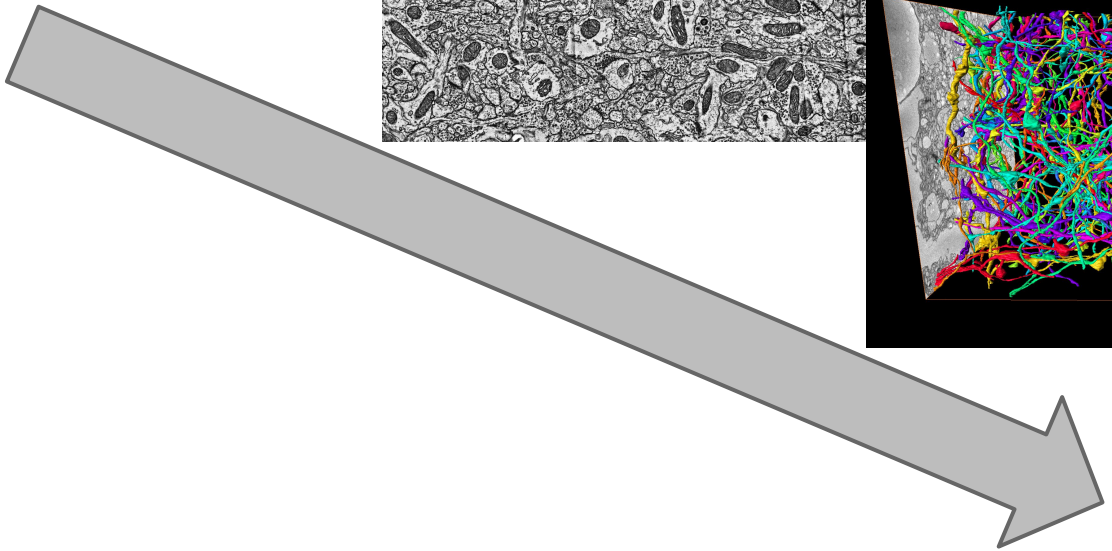
Connectomics: Reconstructing Neural Circuits from High-Resolution Brain Imaging

分子连接分析：通过高分辨率人脑图片重构大脑神经回路



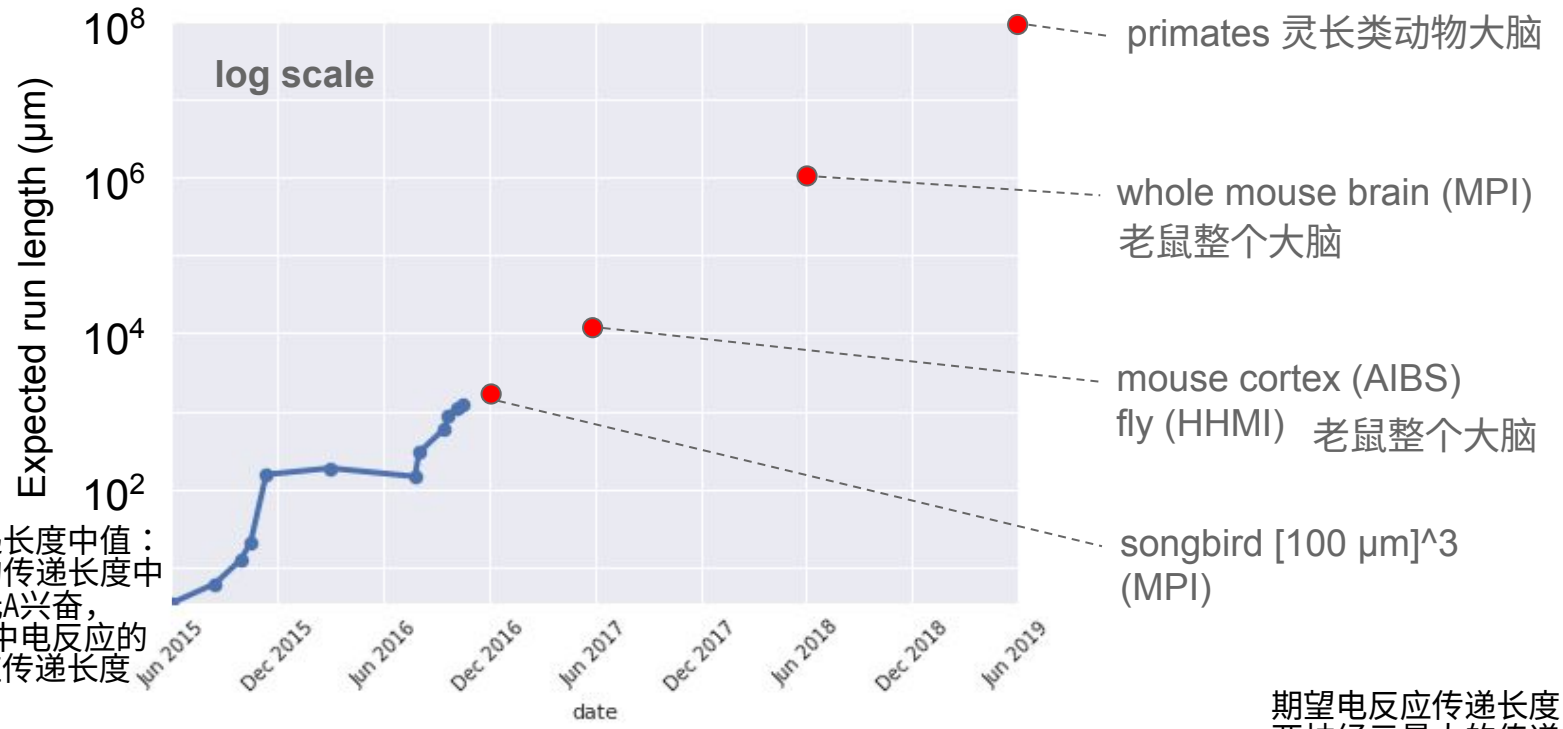






Automated Reconstruction Progress at Google

Google的人脑神经回路自动重构进展



期望电反应传递长度中值：
两神经元最大的传递长度中值，例如神经元A兴奋，
神经元B兴奋其中电反应的
空间长度为反应传递长度

Metric: Expected Run Length (ERL) 期望电反应传递长度
"mean microns between failure" of automated neuron tracing

期望电反应传递长度中值：
两神经元最大的传递长度中值，例如神经元A兴奋，
神经元B兴奋其中电反应的
空间长度为反应传递长度

New Technology: Flood Filling Networks

新技术：灌注网络

Flood-Filling Networks

Michał Januszewski
Google
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Jeremy Maitin-Shepard
Google
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Peter Li
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phli@google.com

Jörgen Kornfeld
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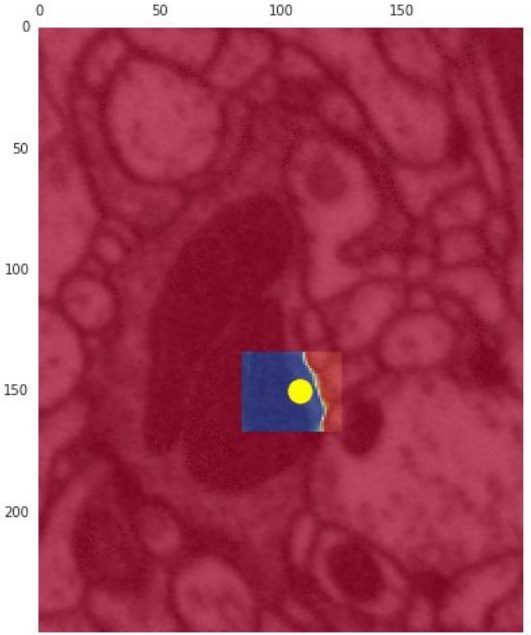
Viren Jain
Google
viren@google.com

2d Inference

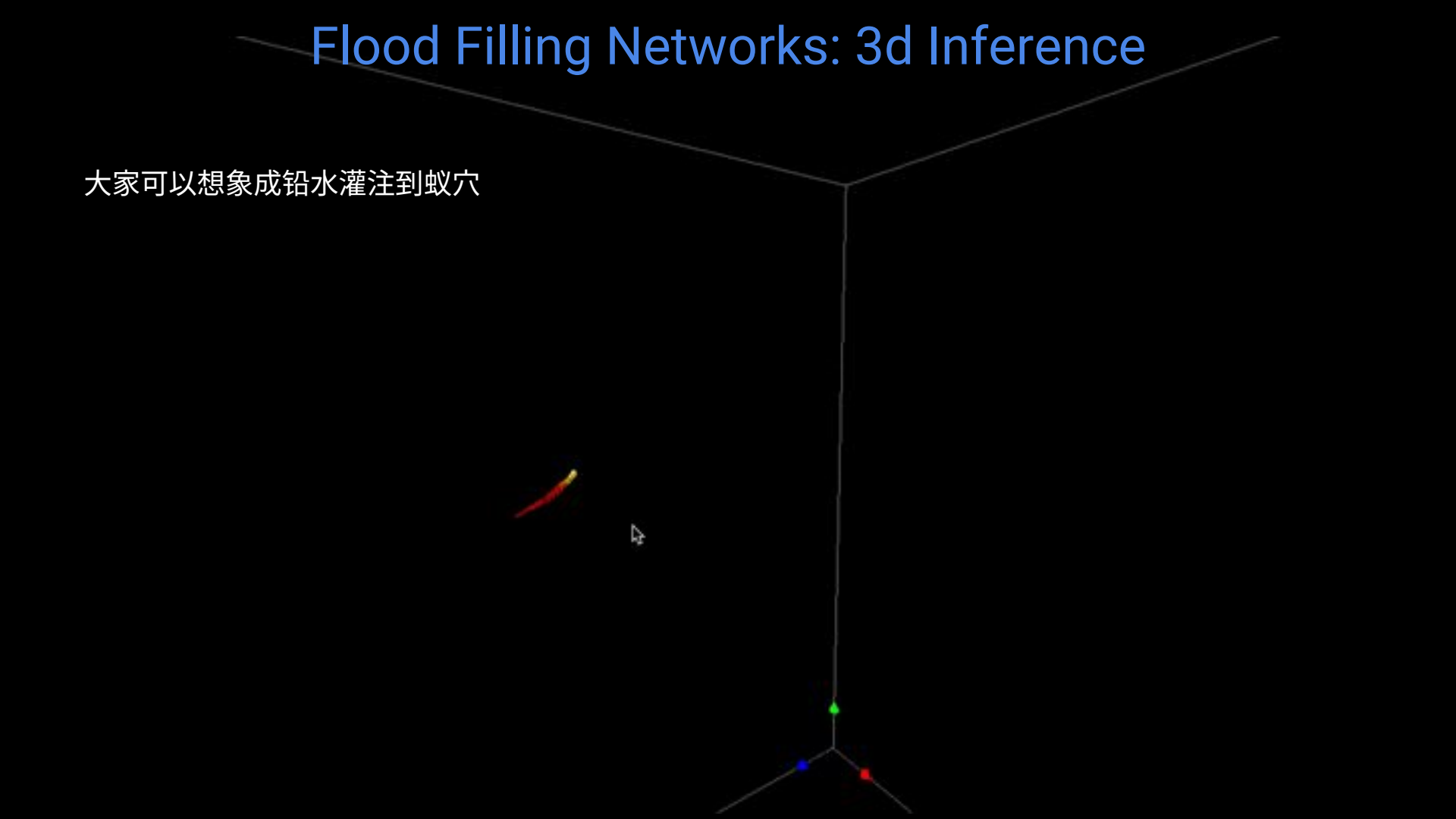


- Start with a seed point
  从种子点开始
- Recurrent neural network iteratively fills out an object based on image content and its own previous predictions
  根据图像内容以及以前的预测结果循环迭代到神经网络中

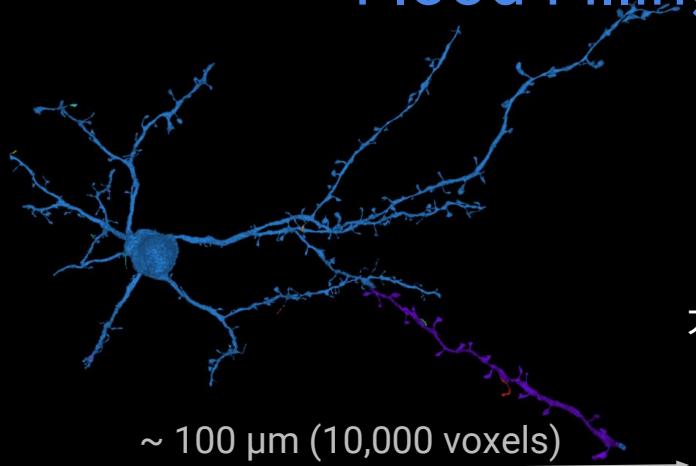
https://arxiv.org/abs/1611.00421

Flood Filling Networks: 3d Inference

大家可以想象成铅水灌注到蚁穴

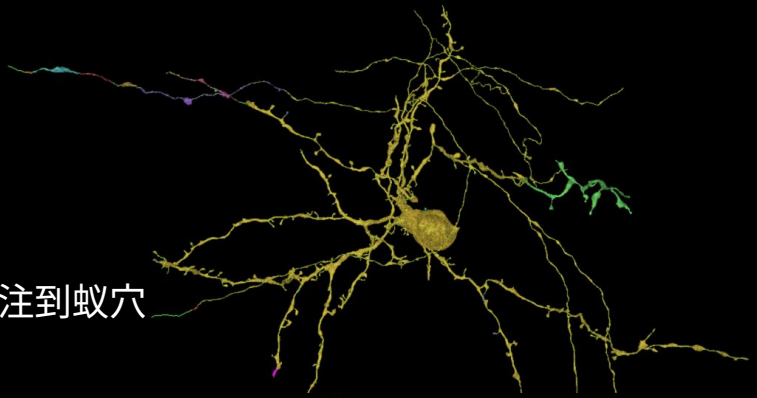


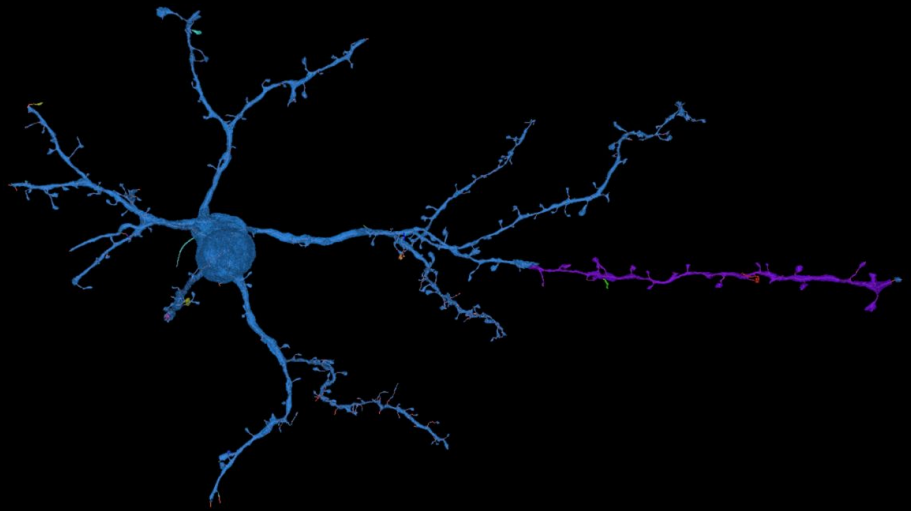
Flood Filling Networks: 3d Inference

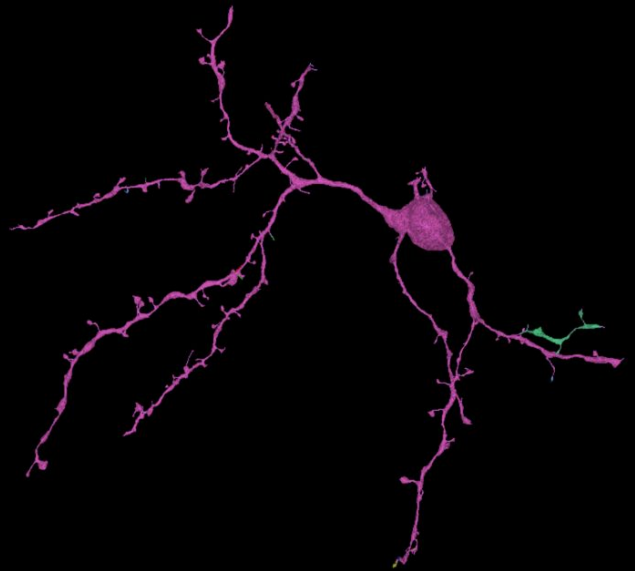


~ 100 µm (10,000 voxels)

大家可以想象成铅水灌注到蚁穴







Google

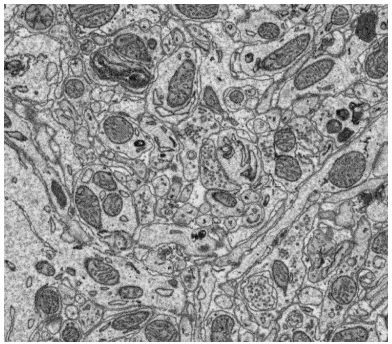
Songbird Brain Wiring Diagram

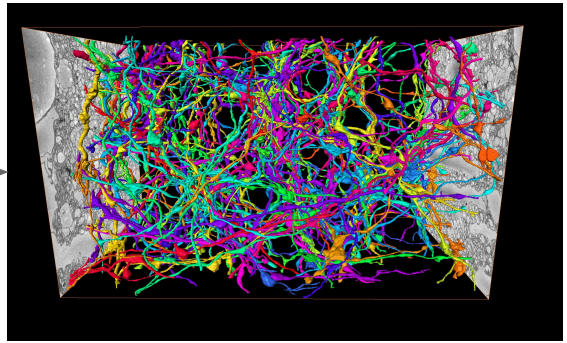
小鸟大脑神经回路图

- Raw data produced by Max Planck Institute for Neurobiology using serial block face scanning electron microscopy 原始数据来自串行面扫描电子显微镜
- 10,600 × 10,800 × 5,700 voxels = ~600 billion voxels

10600 * 10800 * 5700 约 6000亿立体像素

- Goal: Reconstruct **complete connectivity** and use to **test specific hypotheses** related to how biological nervous systems produce precise, sequential motor behaviors and perform reinforcement learning.





Courtesy Jorgen Kornfeld & Winfried Denk, MPI

目标：基于生物神经系统如何产生精确的顺序运动行为以及强化学习重构神经元的连接

Engineer the tools for scientific discovery

升级科学研究工具

http://tensorflow.org/

and

https://github.com/tensorflow/tensorflow

Open, standard software for general machine learning

斯坦福开源的通用机器学习框架

Great for Deep Learning in particular

{对深度学习特适合}

First released Nov 2015

Apache 2.0 license

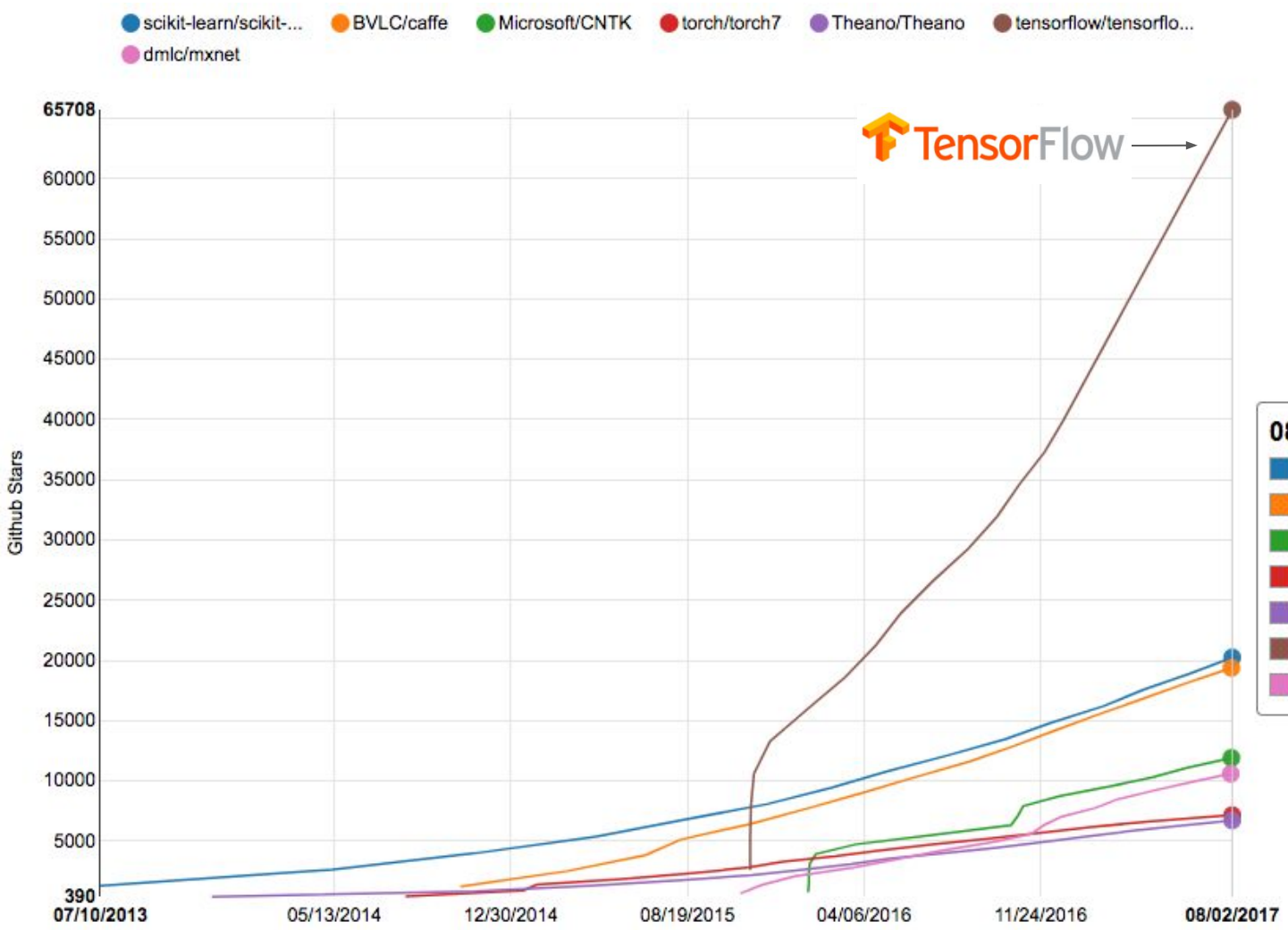
TensorFlow Goals

Establish **common platform** for expressing machine learning ideas and systems

Open source it so that it becomes a **platform for everyone**, not just Google

Make this platform the **best in the world** for both research and production use

构建一个能清晰表达机器学习构思和系统结构的通用框架
开源的话人人都能用，不单单是google
使这个平台成为研究和商用最好的机器学习框架



{各个框架github中被点赞数}

TensorFlow: A Vibrant Open-Source Community

TensorFlow还有个充满活力的开源社区

- **Rapid development, many outside contributors**
  - ~800+ non-Google contributors to TensorFlow
  - 21,000+ commits in 21 months
  - Many community created tutorials, models, translations, and projects
    - ~16,000 GitHub repositories with ‘TensorFlow’ in the title

- **Direct engagement between community and TensorFlow team**
  - 5000+ Stack Overflow questions answered
  - 80+ community-submitted GitHub issues responded to weekly

- **Growing use in ML classes: Toronto, Berkeley, Stanford, ...**

More computational power needed

越来越多的能源投入到计算中

Deep learning is transforming how we design computers

深度学习正在改变我们设计计算机的思路

Special computation properties

reduced precision ok

about 1.2
× about 0.6
about 0.7

NOT

1.21042
× 0.61127
0.73989343

为了省电，我们阉割了精度

Special computation properties

reduced precision ok

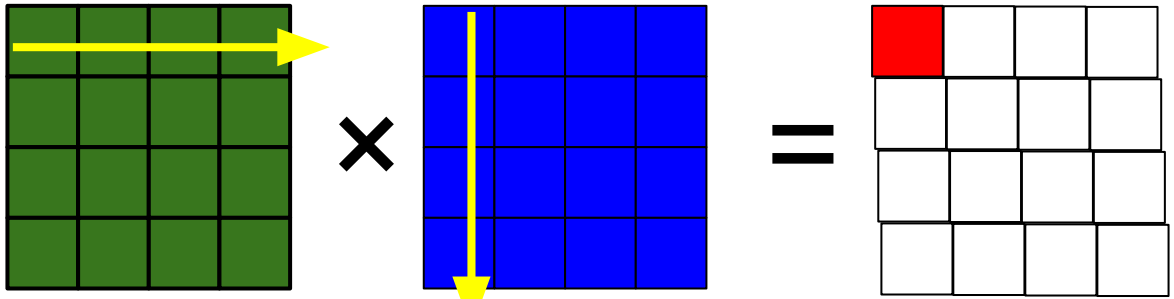
about 1.2
× about 0.6
about 0.7

NOT

1.21042
× 0.61127
0.73989343

为了省电，我们阉割了精度

handful of specific operations

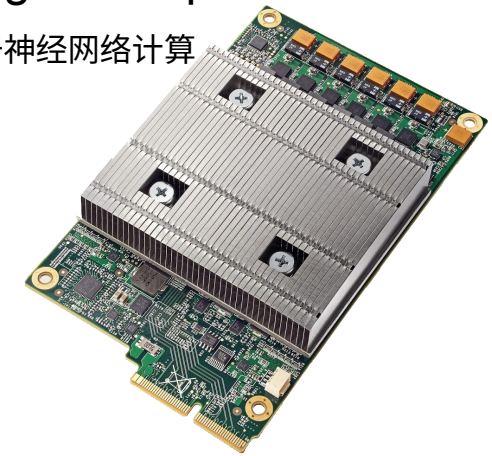


固化矩阵相乘等特定操作，我们就不用传统的指令操作了

Tensor Processing Unit v1

Google-designed chip for neural net **inference**

Google设计的用于神经网络计算的模块，：TPU v1



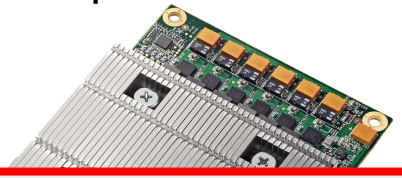
In production use for >30 months: used on search queries, for neural machine translation, for AlphaGo match, …

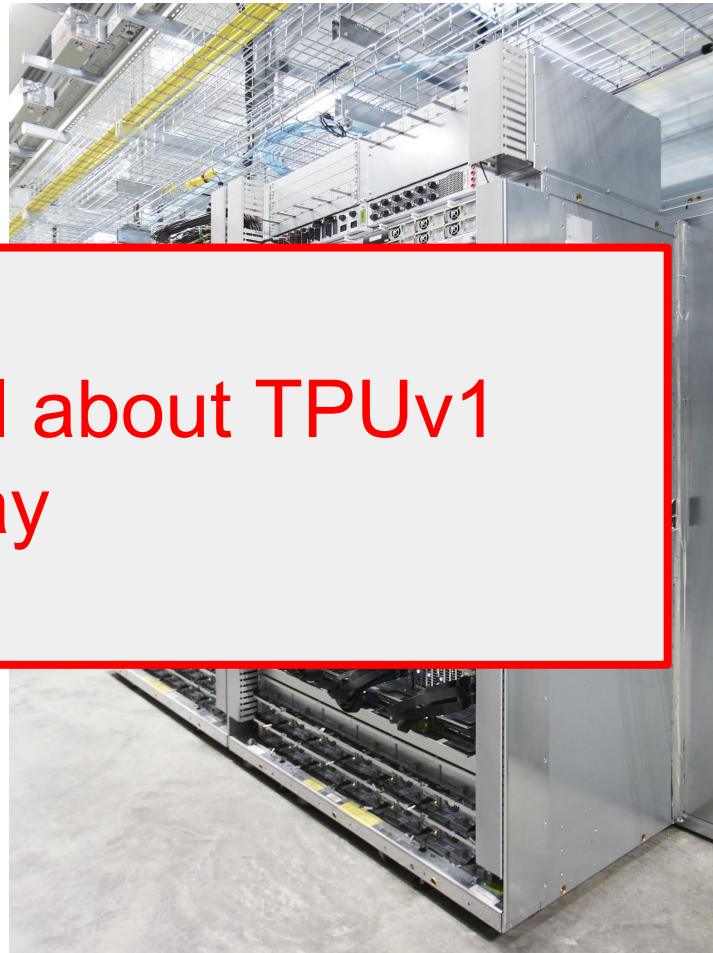
TPUv1已经稳定使用30个月，甚至AlphaGo的围棋比赛也是用它的

In-Datacenter Performance Analysis of a Tensor Processing Unit, Jouppi, Young, Patil, Patterson et al., ISCA 2017, arxiv.org/abs/1704.04760

Tensor Processing Unit v1

Google-designed chip for neural net **inference**





Cliff Young will tell you all about TPUv1 at 3 PM today

In pro
querie
for AlphaGo match, …

In-Datacenter Performance Analysis of a Tensor Processing Unit, Jouppi, Young, Patil, Patterson et al., ISCA 2017, arxiv.org/abs/1704.04760

TPUv1 is a huge help for inference

TPU v1确实在推理计算方面很有用

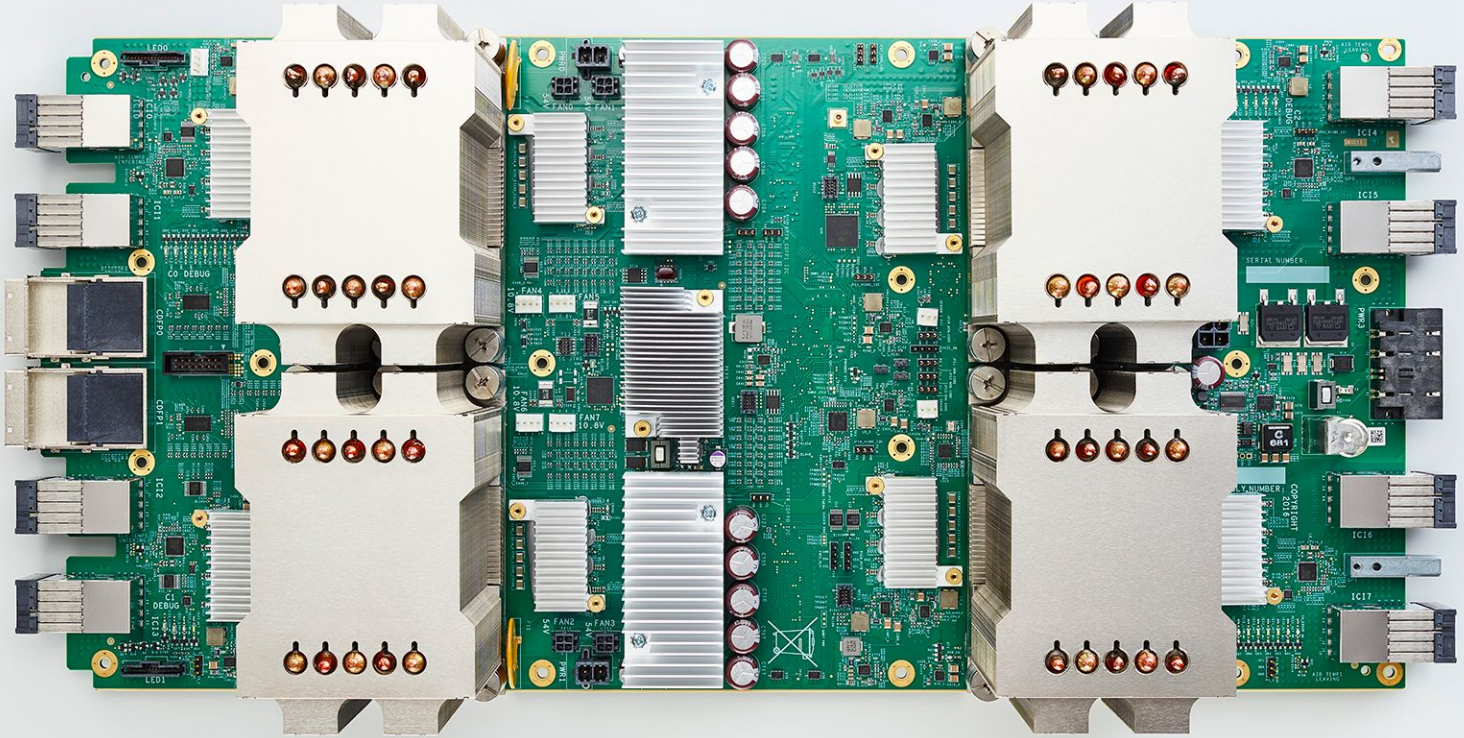
But what about training?

但是训练呢？

Speeding up training hugely important:
for researcher productivity, and
for increasing scale of problems that can be tackled

加快训练速度很有价值：不仅能加快研究转化成产品，而且有助于提高问题复杂度得出更好的计算结果

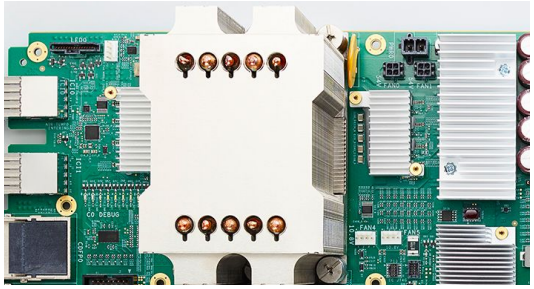
Tensor Processing Unit v2



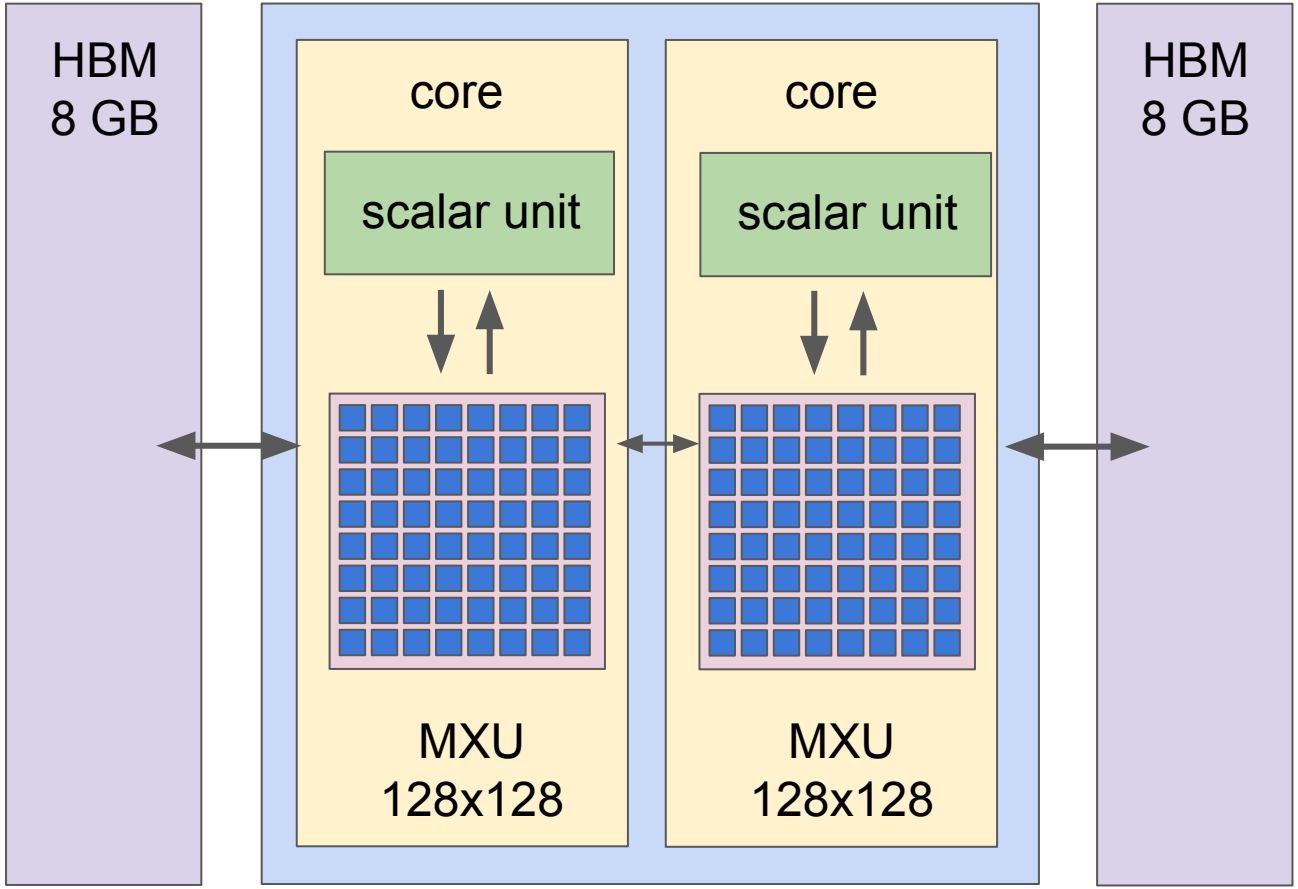
Google-designed device for neural net **training** and **inference**

TPU V2 不仅能训练，而且能做推导计算

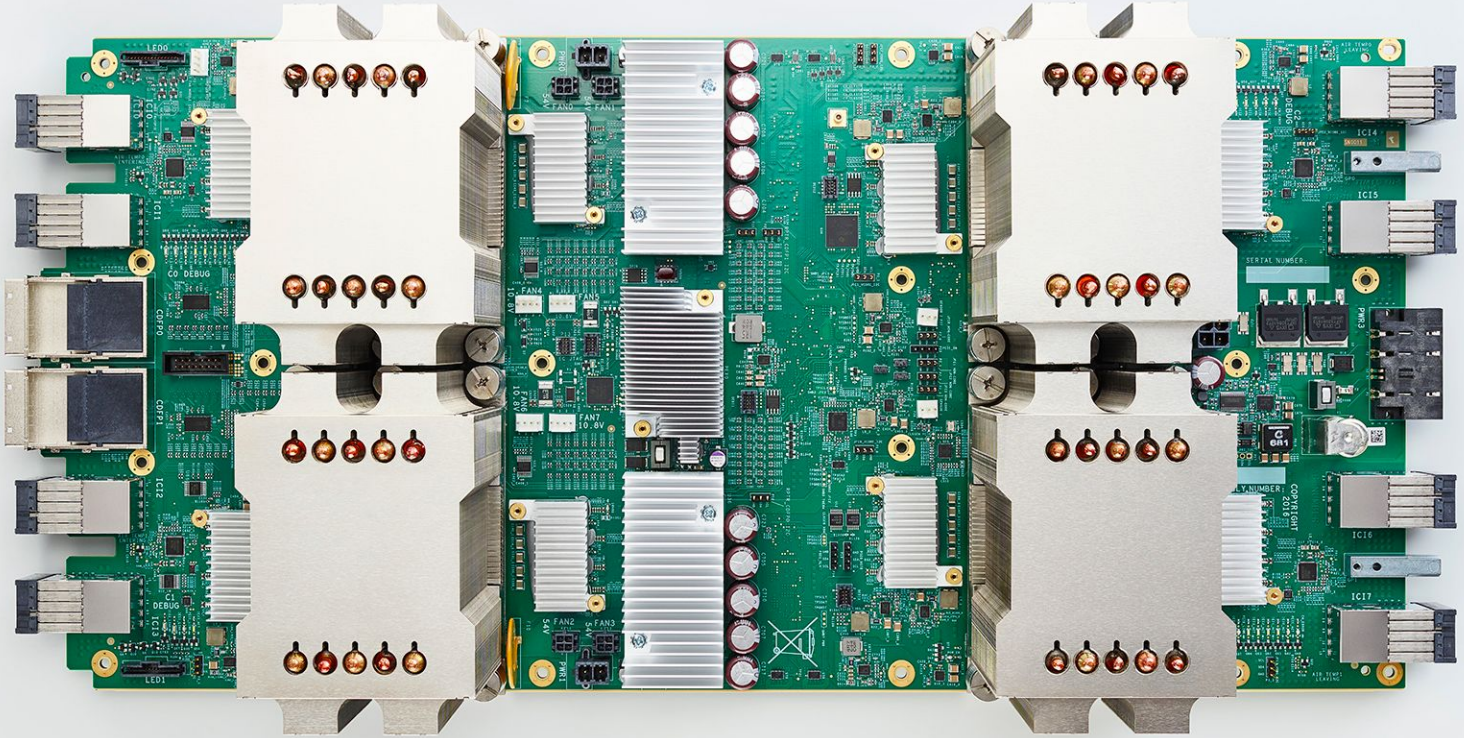
TPUv2 Chip



- 16 GB of HBM
- 600 GB/s mem BW
- Scalar unit: 32b float
- MXU: 32b float accumulation but reduced precision for multipliers
- 45 TFLOPS



Tensor Processing Unit v2



TPU V2芯片之间能像XEON Phi一样连接起来，提供更强的计算能力

- **180 teraflops of computation, 64 GB of HBM memory, 2400 GB/s mem BW**
- **Designed to be connected together into larger configurations**

TPU Pod

64 2nd-gen TPUs

11.5 petaflops

4 terabytes of HBM memory

Programmed via TensorFlow

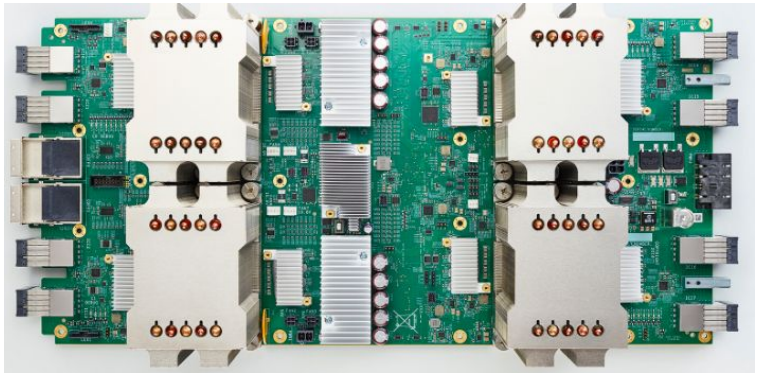
TPU V2通过TensorFlow编程使用

Same program will run with only minor modifications on CPUs, GPUs, & TPUs

Will be Available through Google Cloud

将在Google云开放使用

Cloud TPU - virtual machine w/180 TFLOPS TPUv2 device attached



TensorFlow
RESEARCH CLOUD

Making 1000 **Cloud TPUs** available **for free** to top researchers who are committed to **open machine learning research**

We’re excited to see what researchers will do with much more computation!

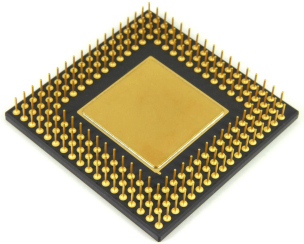
要申请使用TPUV2的可以到这里登记 g.co/tpusignup

Machine learning needs to run in a growing set of environments

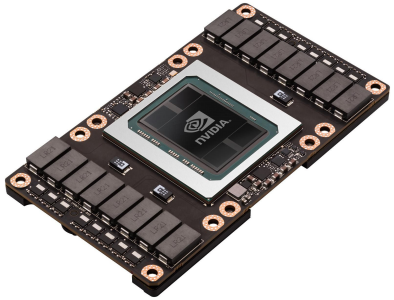
机器学习需要运行在弹性的计算环境中

TensorFlow supports many platforms

TensorFlow可以运行在下面平台中

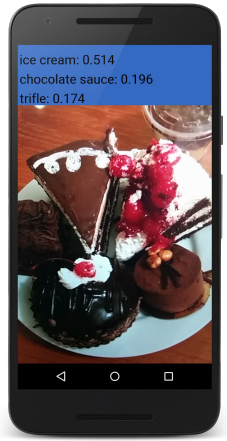


CPU

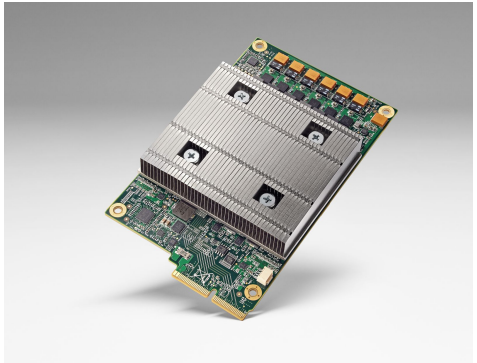


GPU

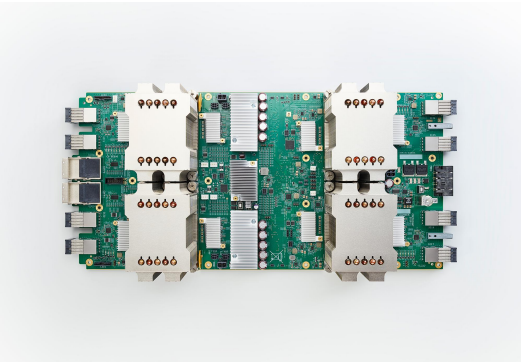
iOS



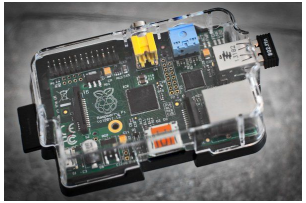
Android



1st-gen TPU



Cloud TPU



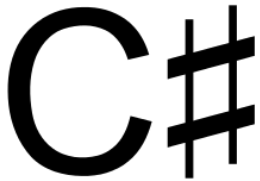
Raspberry Pi

TensorFlow supports many languages

TensorFlow支持以下编程语言

Java

Go



TensorFlow Graph

Python Program

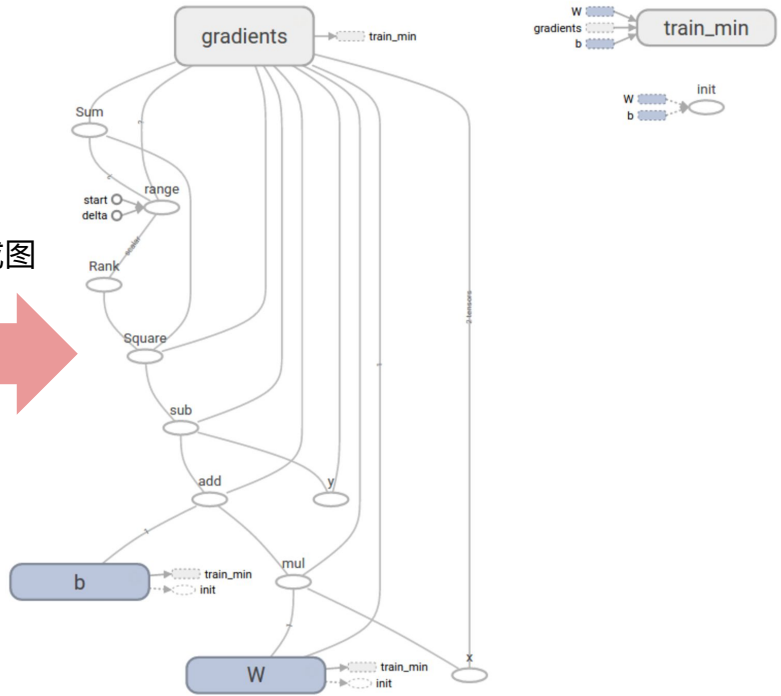
```
import numpy as np
import tensorflow as tf

# Model parameters
W = tf.Variable([.3], tf.float32)
b = tf.Variable([-.3], tf.float32)
# Model input and output
x = tf.placeholder(tf.float32)
linear_model = W * x + b
y = tf.placeholder(tf.float32)
# loss
loss = tf.reduce_sum(tf.square(linear_model - y)) # sum of the squares
# optimizer
optimizer = tf.train.GradientDescentOptimizer(0.01)
train = optimizer.minimize(loss)
# training data
x_train = [1,2,3,4]
y_train = [0,-1,-2,-3]
# training loop
init = tf.global_variables_initializer()
sess = tf.Session()
sess.run(init) # reset values to wrong
for i in range(1000):
  sess.run(train, {x:x_train, y:y_train})

# evaluate training accuracy
curr_W, curr_b, curr_loss  = sess.run([W, b, loss], {x:x_train, y:y_train})
print("W: %s b: %s loss: %s"%(curr_W, curr_b, curr_loss))
```

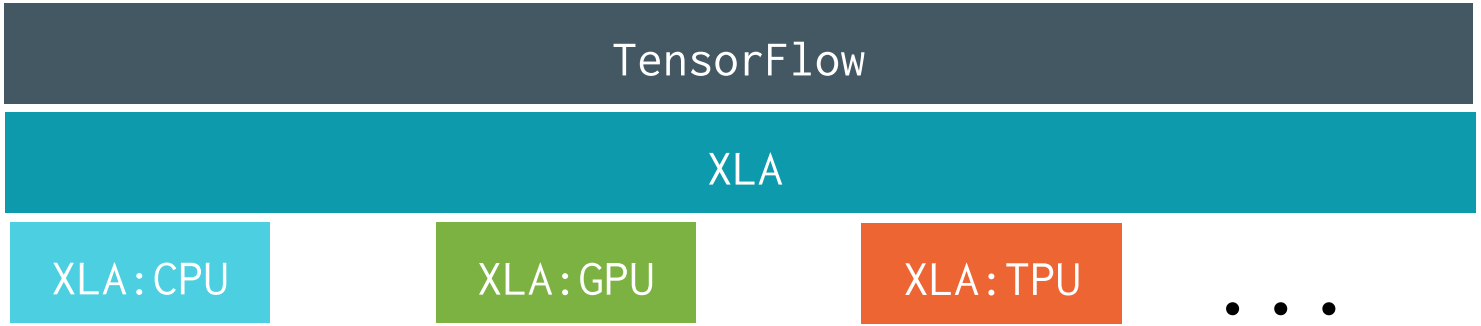
将代码生成图

TensorFlow Graph



https://www.tensorflow.org/get_started/get_started

TensorFlow + XLA Compiler



XLA - TensorFlow 编译器:XLA 利用 JIT 编译技术分析用户在运行时创建的 TensorFlow 图表，根据实际运行时维度和类型将其专门化，将多个运算融合在一起并为它们生成高效的本机代码——适用于 CPU、GPU 之类的设备和自定义加速器（例如，Google 的 TPU）。

See: https://www.tensorflow.org/performance/xla/

Open-sourced code in
https://github.com/tensorflow/tensorflow/tree/master/tensorflow/compiler

Why XLA?

TensorFlow Strengths

Interpreted

Dynamic

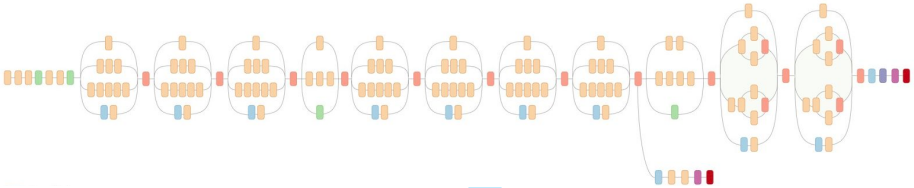
Stateful

"Black-Box" Modular

TensorFlow 的其中一个设计目标和核心优势是它的灵活性。TensorFlow 的设计目标是成为一个灵活并且可扩展的系统，用于定义任意数据流图，以及利用异构计算设备（例如 CPU 和 GPU）分布式地高效执行它们。
但灵活性往往与性能存在矛盾。尽管 TensorFlow 旨在让您定义任何种类的数据流图，但让所有图表都高效执行颇具挑战，因为 TensorFlow 会单独优化每一个运算。如果运算具有高效实现，或者每个运算都是相对重量级的运算，一切还好；否则，虽然用户仍可利用低级别运算组合该运算，却不能保证这个组合出的运算能够以最高效的方式运行。

How do we keep the strengths but add more performance?

JIT Compilation via XLA



XLA program: static, decomposed TF ops

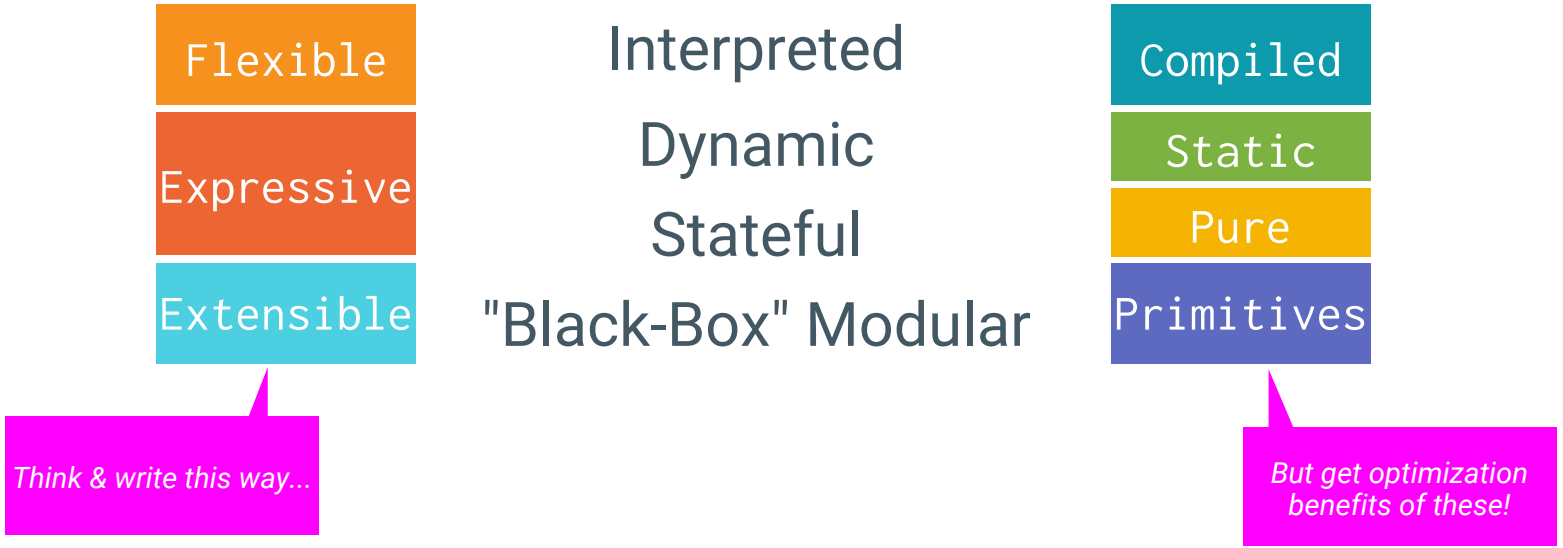
- Static data types
- Math-looking primitive ops

```
0x00000000      movq    (%rdx), %rax
0x00000003      vmovaps (%rax), %xmm0
0x00000007      vmulps  %xmm0, %xmm0, %xmm0
0x0000000b      vmovaps %xmm0, (%rdi)
                    ...
```

XLA - TensorFlow 编译器:XLA 利用 JIT 编译技术分析用户在运行时创建的 TensorFlow 图表，根据实际运行时维度和类型将其专门化，将多个运算融合在一起并为它们生成高效的本机代码——适用于 CPU、GPU 之类的设备和自定义加速器（例如，Google 的 TPU）。

The Best of Both Worlds

TensorFlow Strengths



Machine Learning for Higher Performance Machine Learning Models

通过机器学习加速机器学习模型

Google

For large models, model parallelism is important

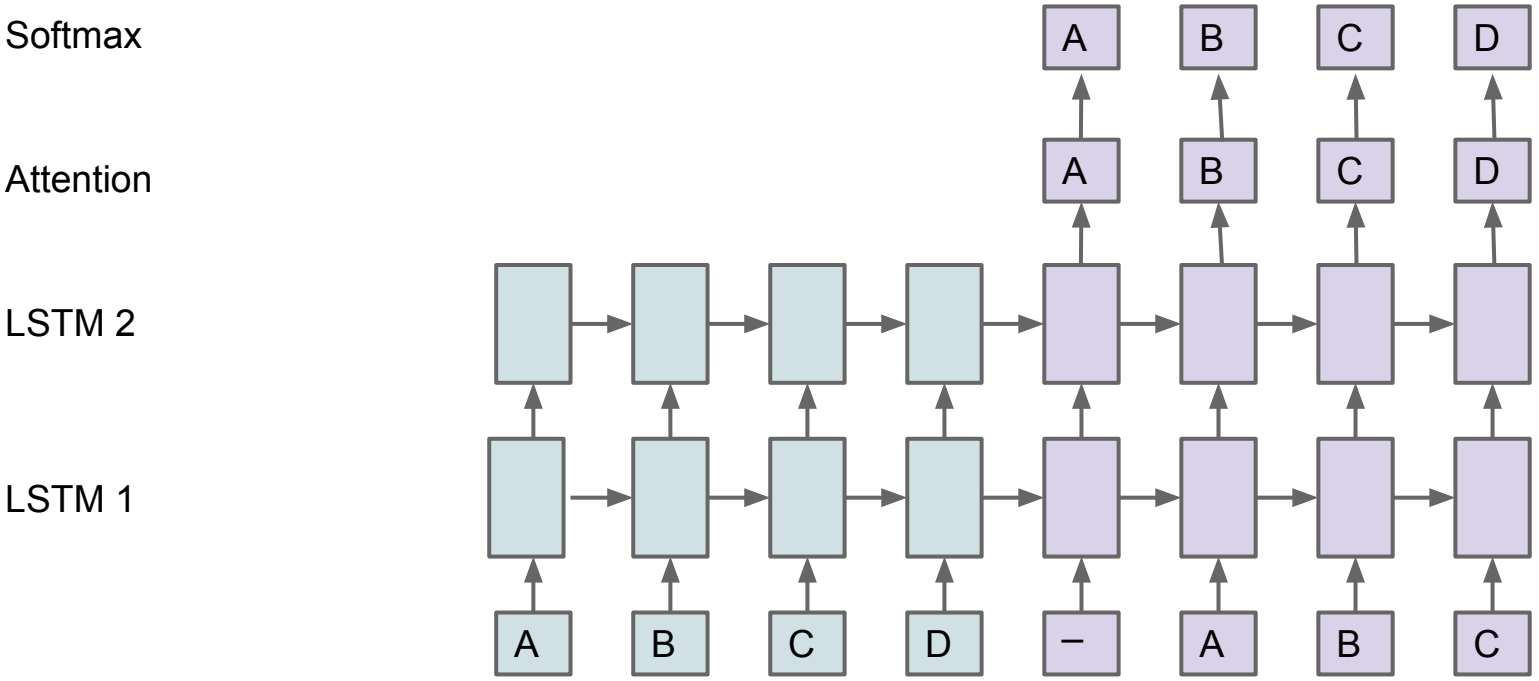
对于巨型计算模型，模型计算的并行化非常重要

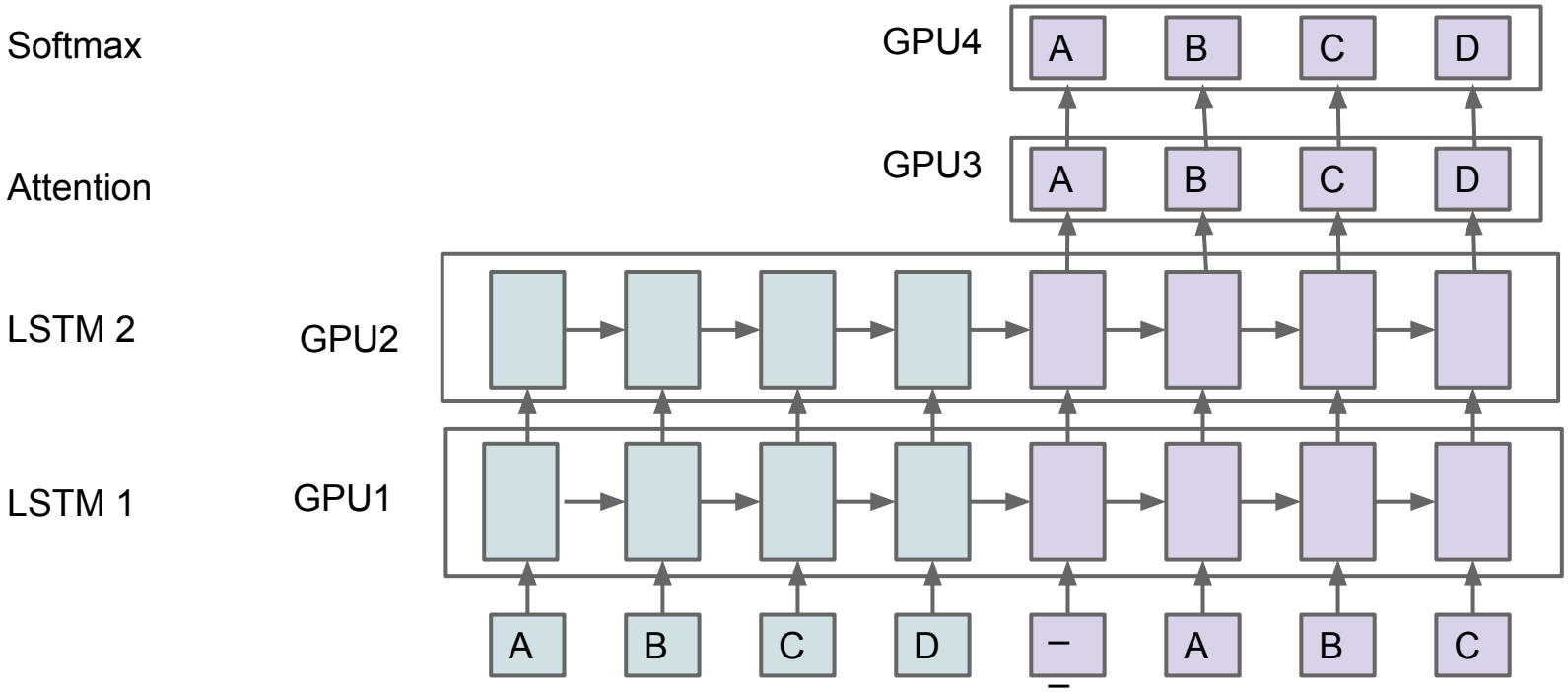
For large models, model parallelism is important

对于巨型计算模型，模型计算的并行化非常重要

But getting good performance given multiple computing devices is non-trivial and non-obvious

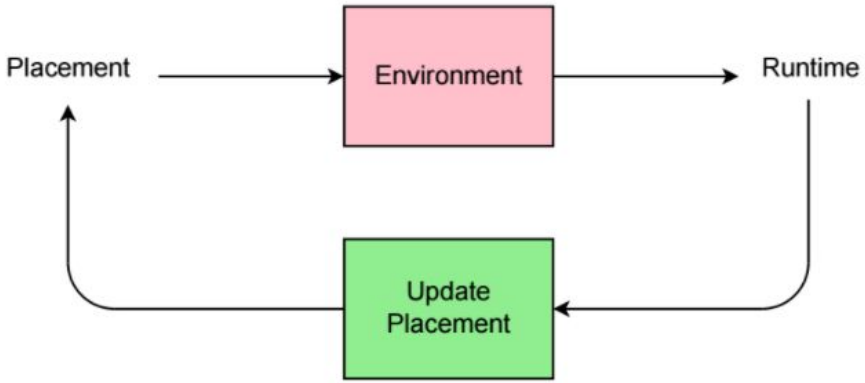
但是好的计算性能并非简单的计算设备堆砌就可以了


Softmax
Attention
LSTM 2
LSTM 1
A
B
C
D
–
A
B
C
D
A
B
C
D
A
B
C
D


Softmax
Attention
LSTM 2
LSTM 1
GPU4
GPU3
GPU2
GPU1
A
B
C
D
A
B
C
D
A
B
C
D
–
A
B
C

Reinforcement Learning for Higher Performance Machine Learning Models

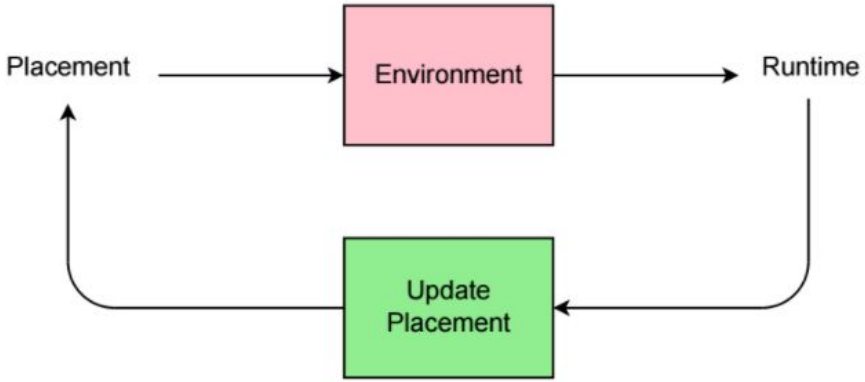
基于增强学习的高性能机器学习模型



Device Placement Optimization with Reinforcement Learning,
Azalia Mirhoseini, Hieu Pham, Quoc Le, Mohammad Norouzi, Samy Bengio, Benoit Steiner, Yuefeng Zhou, Naveen Kumar, Rasmus Larsen, and Jeff Dean, ICML 2017, arxiv.org/abs/1706.04972

Reinforcement Learning for Higher Performance Machine Learning Models

Placement model (trained via RL) gets graph as input + set of devices, outputs device placement for each graph node



Device Placement Optimization with Reinforcement Learning,
Azalia Mirhoseini, Hieu Pham, Quoc Le, Mohammad Norouzi, Samy Bengio, Benoit Steiner, Yuefeng Zhou, Naveen Kumar, Rasmus Larsen, and Jeff Dean, ICML 2017, arxiv.org/abs/1706.04972

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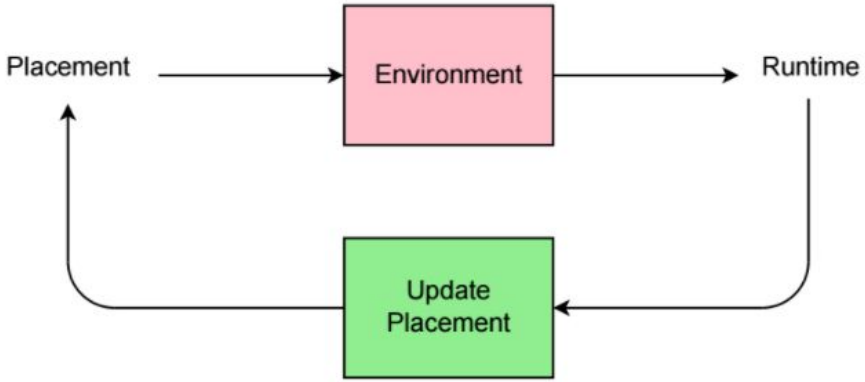

Measured time per step gives RL reward signal

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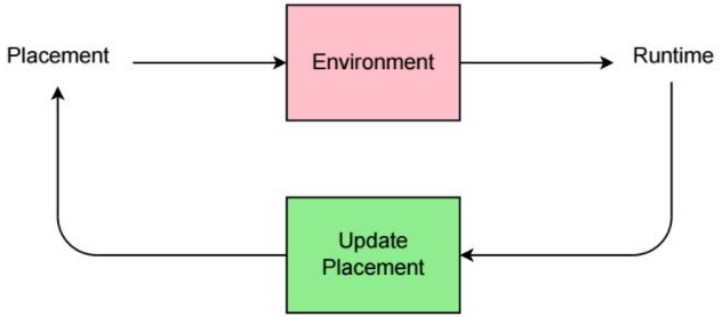


Measured time per step gives RL reward signal

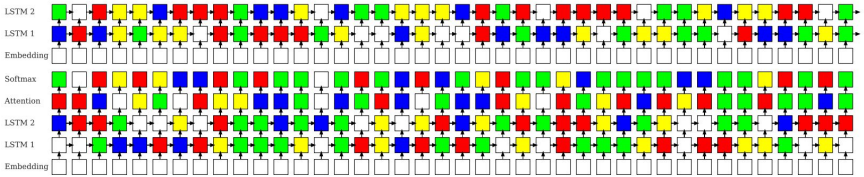


Figure 4. RL-based placement of Neural MT graph. Above: encoder, Below: decoder. Devices are denoted by colors, where the transparent color represents an operation on a CPU and each other unique color represents a different GPU. This placement achieves an improvement of 19.3% in running time compared to the fine-tuned hand-crafted placement.

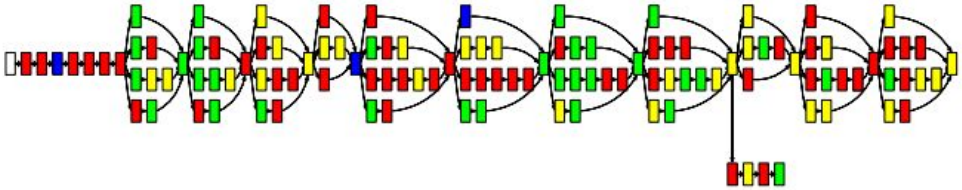


Figure 5. RL-based placement of Inception-V3. Devices are denoted by colors, where the transparent color represents an operation on a CPU and each other unique color represents a different GPU. RL-based placement achieves the improvement of 19.7% in running time compared to expert-designed placement.

+19.3% faster vs. expert human for neural translation model

+19.7% faster vs. expert human for InceptionV3 image model

Device Placement Optimization with Reinforcement Learning,
Azalia Mirhoseini, Hieu Pham, Quoc Le, Mohammad Norouzi, Samy Bengio, Benoit Steiner, Yuefeng Zhou, Naveen Kumar, Rasmus Larsen, and Jeff Dean, ICML 2017, arxiv.org/abs/1706.04972

Reducing inference cost

Reducing inference cost

- **Bad feeling:** *“I have an awesomely good model that requires too much (computation, power, memory) to deploy! Oh no!”*

Fear not, there are lots of tricks:

- **Quantize**! Most models tolerate very low precision for weights (8 bits or even less).
  - 4X memory reduction, 4X computation efficiency

Distillation

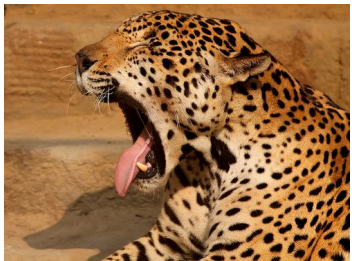
- Suppose you have a giant, highly accurate model
  - (Or maybe an ensemble of many such models)
- Now you want a smaller, cheaper model with almost the same accuracy (maybe to run on a phone)

Distilling the Knowledge in a Neural Network, Hinton, Vinyals, and Dean. NIPS Deep Learning Workshop, 2014. http://arxiv.org/abs/1503.02531

.001	.04	.95	…	10^{-6}
Cow	Lion	Jaguar	…	Car

Softmax output

Expensive
but
accurate
model or
ensemble



The Main Idea

The ensemble implements a function from input to output. Forget the models in the ensemble and the way they are parameterized and focus on the function.

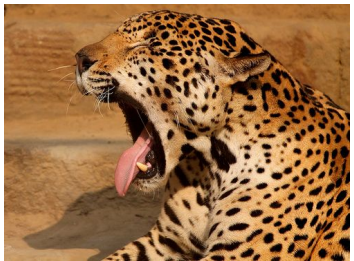
- After learning the ensemble, we have our hands on the function.
- Can we transfer the knowledge in the function into a single smaller model?

Training

0	0	**1**	0
Cow	Lion	**Jaguar**	… Car

Hard targets

Small model for deployment



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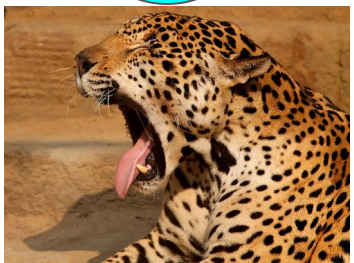
Cow	Lion	Jaguar	…	Car

Softmax output

Expensive but accurate model or ensemble



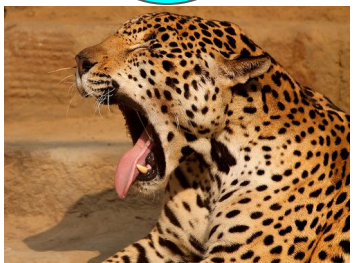
.001	.04	.95	…	10^{-6}
Cow	Lion	Jaguar	…	Car

Softmax output

If we have the ensemble, we can divide the averaged logits from the ensemble by a "temperature" *T* to get a much softer distribution.

$$p_i = \frac{\exp\left(\frac{z_i}{T}\right)}{\sum_j \exp\left(\frac{z_j}{T}\right)}$$

Expensive but accurate model or ensemble



.001	.04	.95	10^{-6}
Cow	Lion	Jaguar	… Car

Softmax output

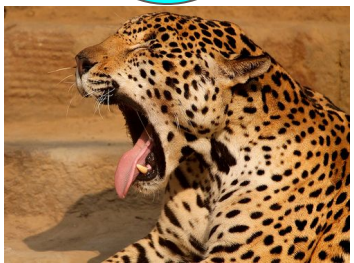
.1	.2	.6	0
Cow	Lion	Jaguar	… Car

Softened softmax output

If we have the ensemble, we can divide the averaged logits from the ensemble by a “temperature” *T* to get a much softer distribution.

$$p_i = \frac{\exp\left(\frac{z_i}{T}\right)}{\sum_j \exp\left(\frac{z_j}{T}\right)}$$

Expensive but accurate model or ensemble



.001	.04	.95	…	10^{-6}
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Softmax output

.1	.2	.6	…	0
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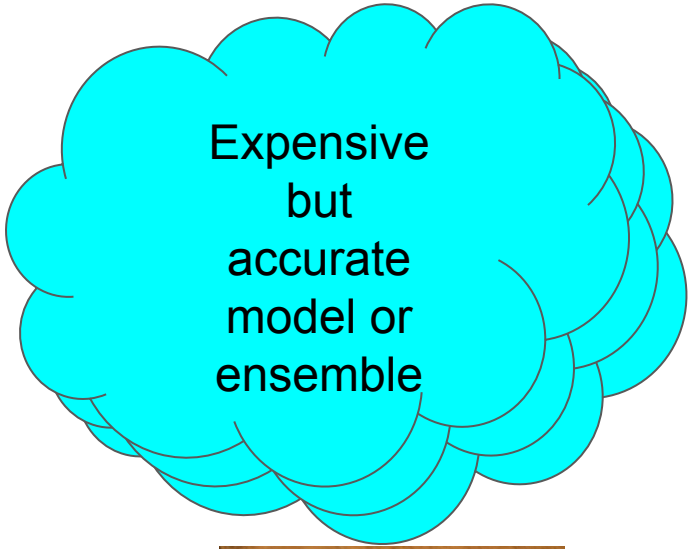
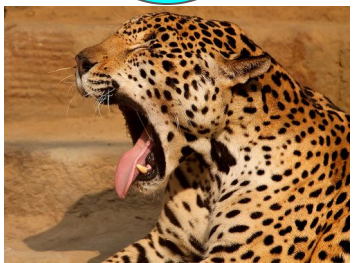




This full distribution conveys lots of information about the function implemented by the large ensemble!

Distillation

Softened softmax output

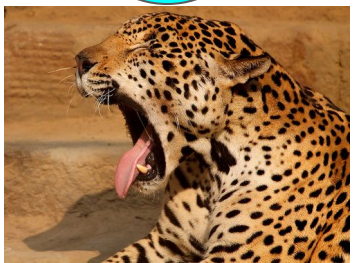
.1	.2	.6	…	0
Cow	Lion	Jaguar	…	Car

Hard targets

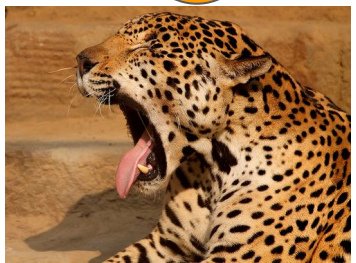
0	0	**1**	…	0
Cow	Lion	**Jaguar**	…	Car

Training objective tries to match both of these

Expensive but accurate model or ensemble



Small model for deployment



Some Results on Speech

Start with a model that classifies 58.9% of frames correctly.

Use that model to provide soft targets for smaller model (that also sees hard targets)

- The new model gets 57.0% correct even when trained on only 3% of the data
- With just hard targets, it only gets to 44.5% correct and then gets much worse.

Soft targets are a VERY good regularizer!
Also trains much faster (soft targets enrich gradients)

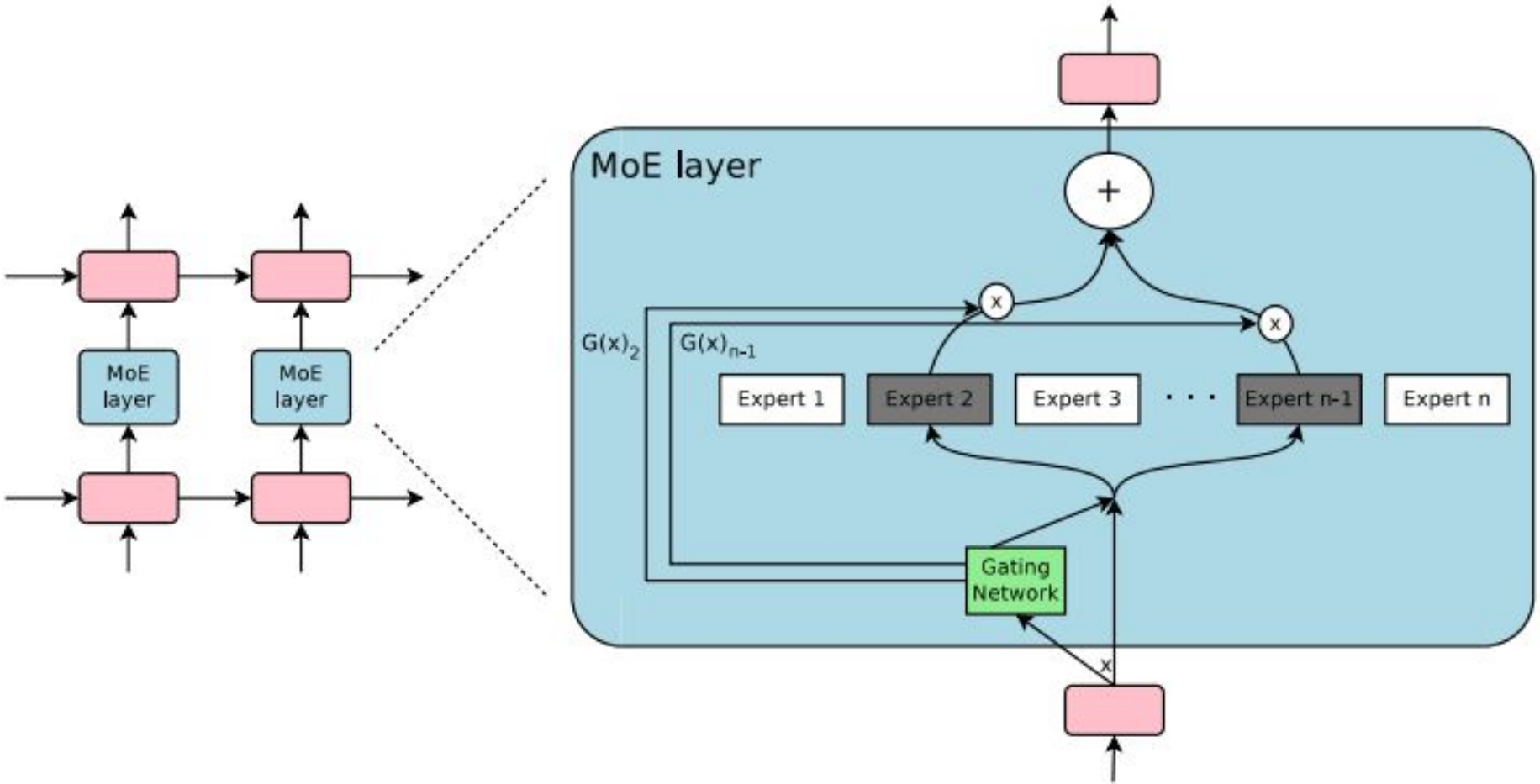
A few trends in the kinds of models we want to train

Bigger models, but sparsely activated

Bigger models, but sparsely activated

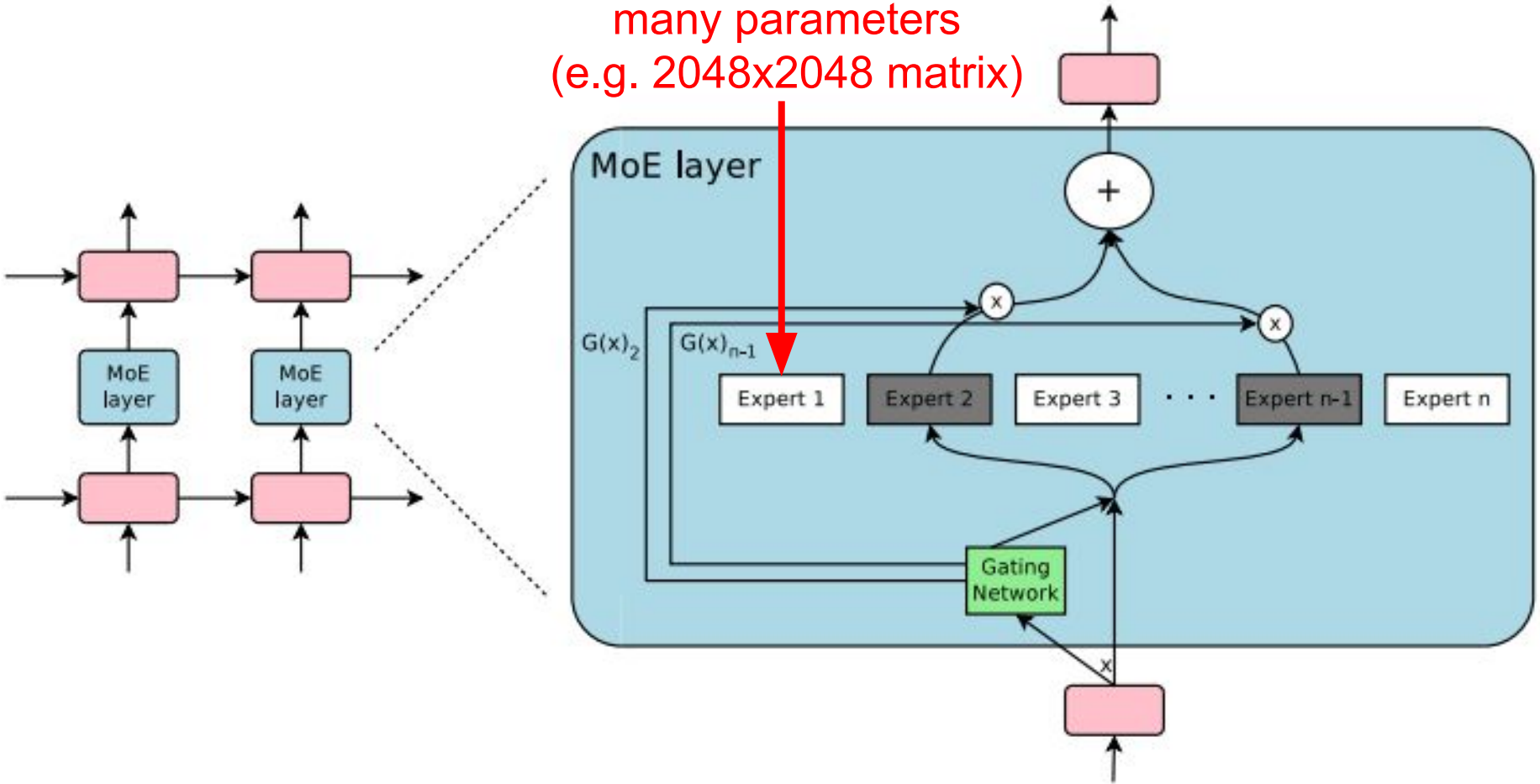
Motivation:
Want **huge model capacity** for large datasets, but want individual example to **only activate tiny fraction** of large model

Per-Example Routing

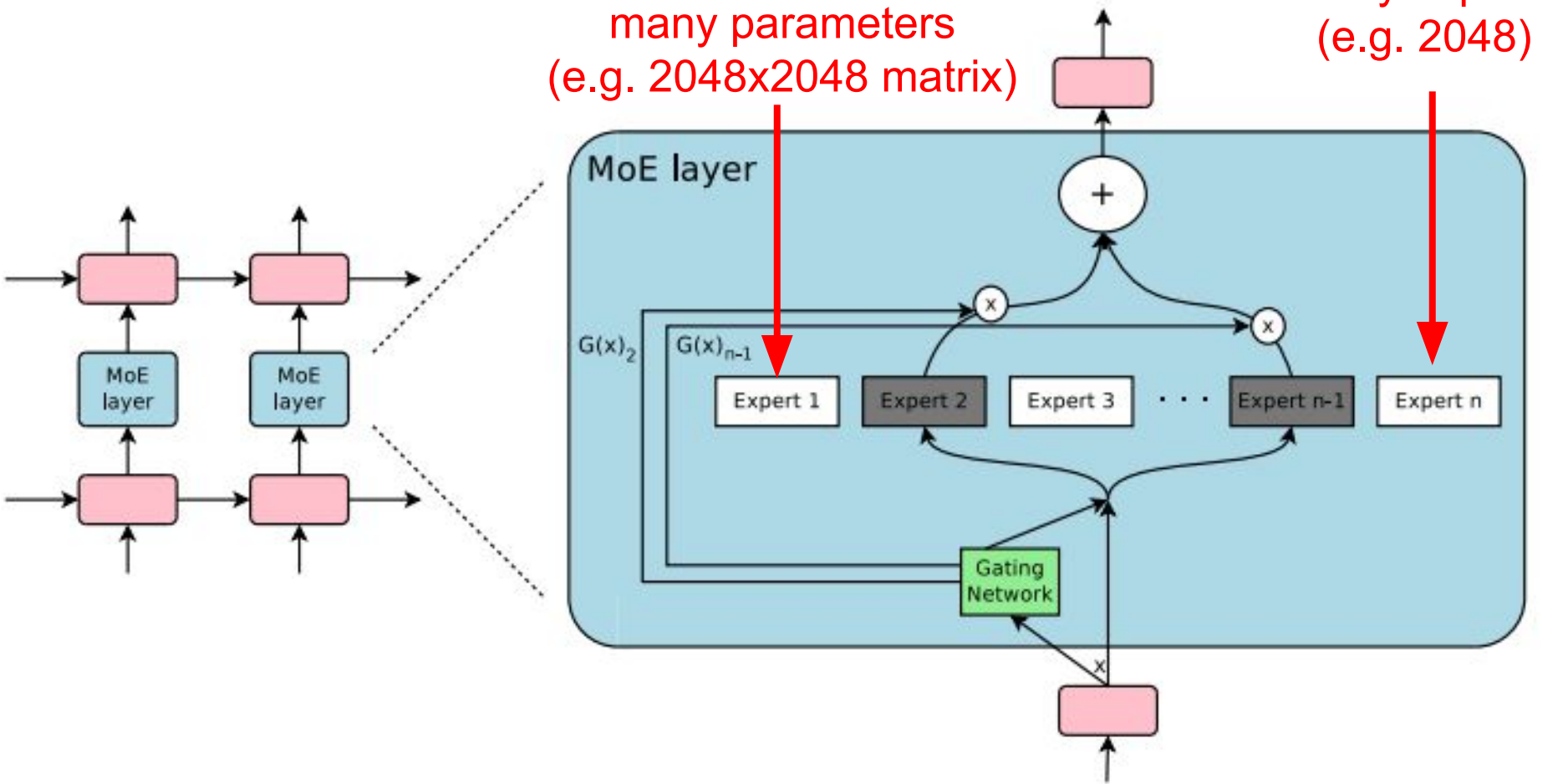


Per-Example Routing

Each expert has
many parameters
(e.g. 2048x2048 matrix)



Per-Example Routing



Per-Example Routing

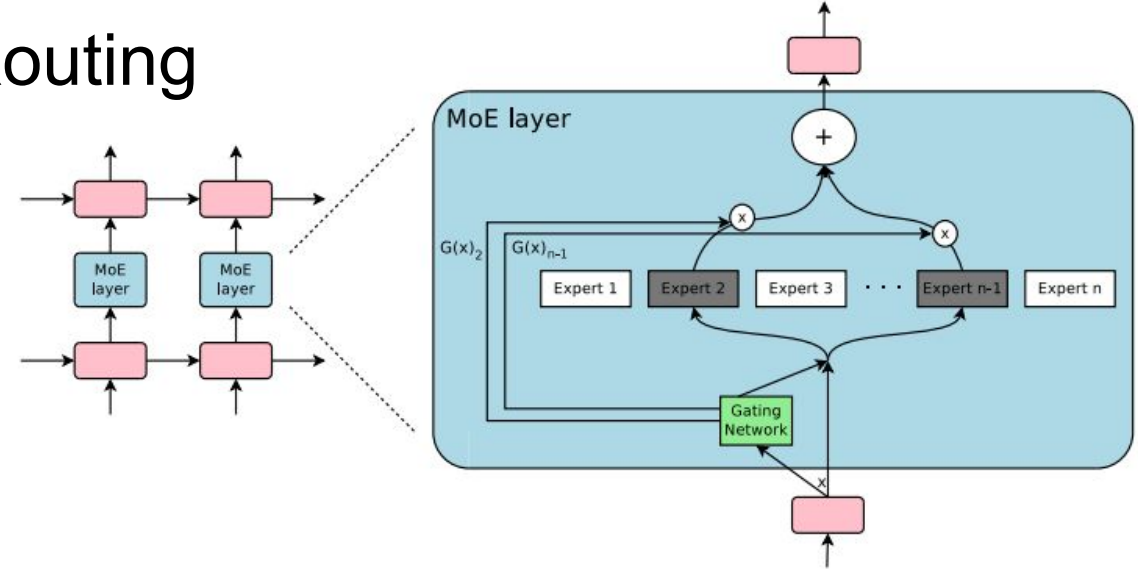


Table 7: Perplexity and BLEU comparison of our method against previous state-of-art methods on the Google Production En→ Fr dataset.

Model	Eval Perplexity	Eval BLEU	Test Perplexity	Test BLEU	Computation per Word	Total #Parameters	Training Time
MoE with 2048 Experts	2.60	37.27	2.69	36.57	100.8M	8.690B	1 day/64 k40s
GNMT (Wu et al., 2016)	2.78	35.80	2.87	35.56	214.2M	246.9M	6 days/96 k80s

Outrageously Large Neural Networks: The Sparsely-gated Mixture-of-Experts Layer, Noam Shazeer, Azalia Mirhoseini, Krzysztof Maziarz, Andy Davis, Quoc Le & Jeff Dean Appeared in ICLR 2017, https://openreview.net/pdf?id=B1ckMDqlg

Automated machine learning ("learning to learn")

Current:

Solution = ML expertise + data + computation

Current:

Solution = ML expertise + data + computation

Can we turn this into:

Solution = data + 100X computation

???

Early encouraging signs

(1) Reinforcement learning-based architecture search
(2) Learn how to optimize

NEURAL ARCHITECTURE SEARCH WITH REINFORCEMENT LEARNING

Barret Zoph, **Quoc V. Le**
Google Brain
{barretzoph,qvl}@google.com

Appeared in ICLR 2017

Idea: model-generating model trained via RL

(1) Generate ten models
(2) Train them for a few hours
(3) Use loss of the generated models as reinforcement learning signal

arxiv.org/abs/1611.01578

CIFAR-10 Image Recognition Task

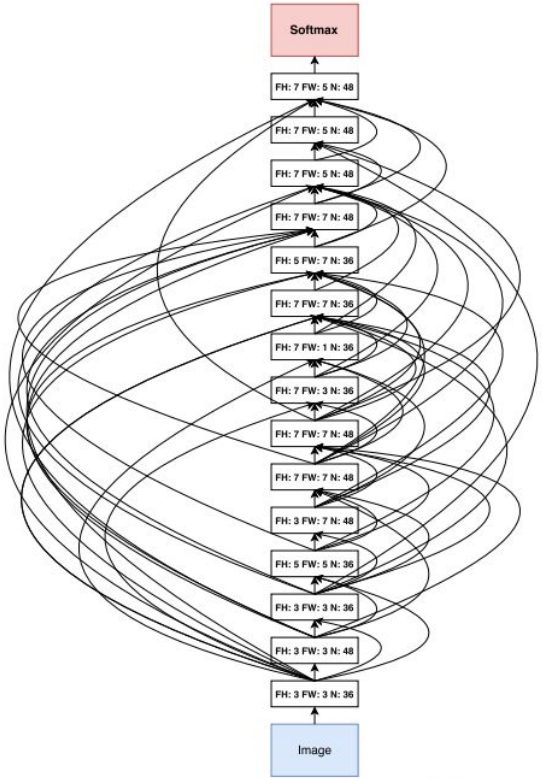


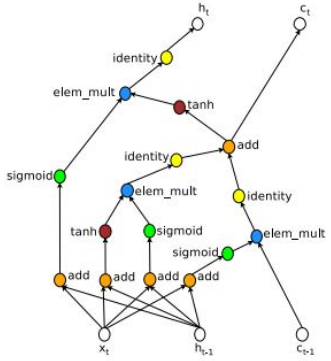
Figure 7: Convolutional architecture discovered by our method, when the search space does not have strides or pooling layers. FH is filter height, FW is filter width and N is number of filters.

Model	Depth	Parameters	Error rate (%)
Network in Network (Lin et al., 2013)	-	-	8.81
All-CNN (Springenberg et al., 2014)	-	-	7.25
Deeply Supervised Net (Lee et al., 2015)	-	-	7.97
Highway Network (Srivastava et al., 2015)	-	-	7.72
Scalable Bayesian Optimization (Snoek et al., 2015)	-	-	6.37
FractalNet (Larsson et al., 2016)	21	38.6M	5.22
with Dropout/Drop-path	21	38.6M	4.60
ResNet (He et al., 2016a)	110	1.7M	6.61
ResNet (reported by Huang et al. (2016b))	110	1.7M	6.41
ResNet with Stochastic Depth (Huang et al., 2016b)	110	1.7M	5.23
	1202	10.2M	4.91
Wide ResNet (Zagoruyko & Komodakis, 2016)	16	11.0M	4.81
	28	36.5M	4.17
ResNet (pre-activation) (He et al., 2016b)	164	1.7M	5.46
	1001	10.2M	4.62
DenseNet $(L = 40, k = 12)$ Huang et al. (2016a)	40	1.0M	5.24
DenseNet$(L = 100, k = 12)$ Huang et al. (2016a)	100	7.0M	4.10
DenseNet $(L = 100, k = 24)$ Huang et al. (2016a)	100	27.2M	3.74
Neural Architecture Search v1 no stride or pooling	15	4.2M	5.50
Neural Architecture Search v2 predicting strides	20	2.5M	6.01
Neural Architecture Search v3 max pooling	39	7.1M	4.47
Neural Architecture Search v3 max pooling + more filters	39	32.0M	3.84

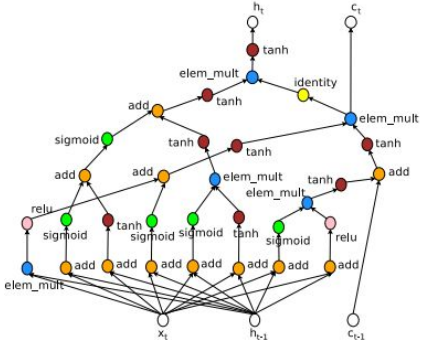
Table 1: Performance of Neural Architecture Search and other state-of-the-art models on CIFAR-10.

Penn Tree Bank Language Modeling Task

"Normal" LSTM cell



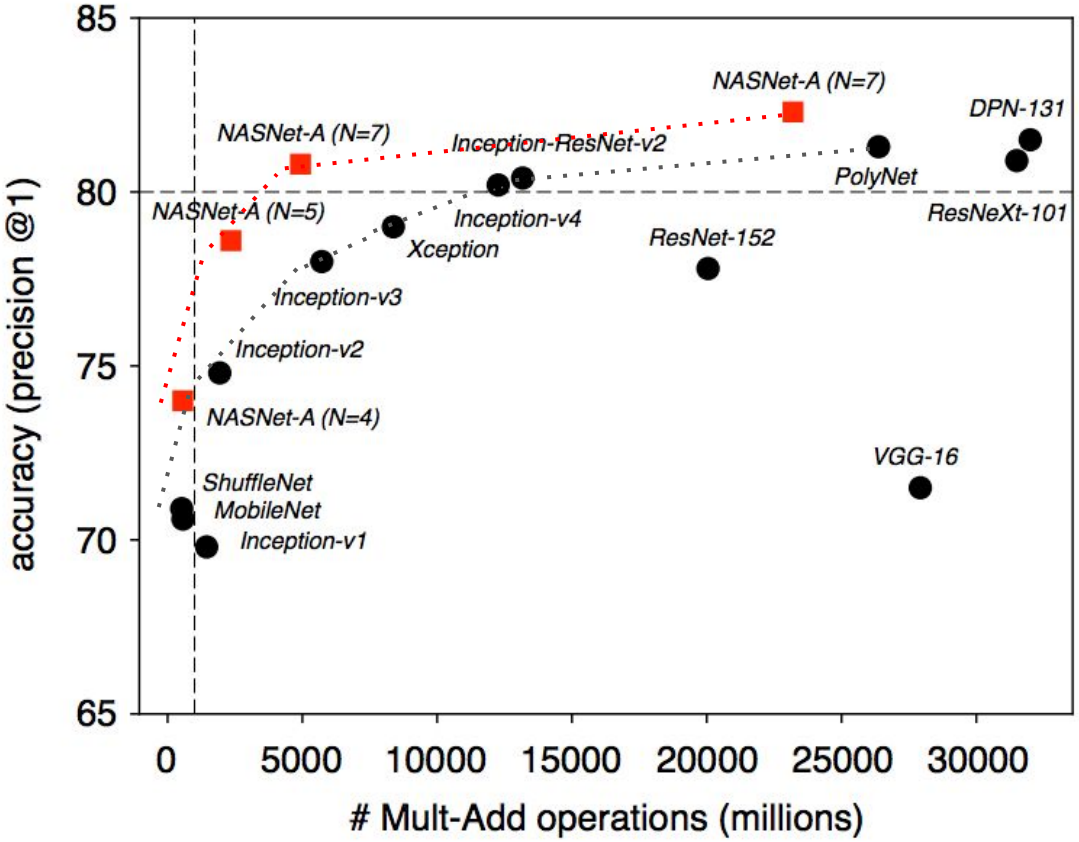
Cell discovered by architecture search



Model	Parameters	Test Perplexity
Mikolov & Zweig (2012) - KN-5	2M‡	141.2
Mikolov & Zweig (2012) - KN5 + cache	2M‡	125.7
Mikolov & Zweig (2012) - RNN	6M‡	124.7
Mikolov & Zweig (2012) - RNN-LDA	7M‡	113.7
Mikolov & Zweig (2012) - RNN-LDA + KN-5 + cache	9M‡	92.0
Pascanu et al. (2013) - Deep RNN	6M	107.5
Cheng et al. (2014) - Sum-Prod Net	5M‡	100.0
Zaremba et al. (2014) - LSTM (medium)	20M	82.7
Zaremba et al. (2014) - LSTM (large)	66M	78.4
Gal (2015) - Variational LSTM (medium, untied)	20M	79.7
Gal (2015) - Variational LSTM (medium, untied, MC)	20M	78.6
Gal (2015) - Variational LSTM (large, untied)	66M	75.2
Gal (2015) - Variational LSTM (large, untied, MC)	66M	73.4
Kim et al. (2015) - CharCNN	19M	78.9
Press & Wolf (2016) - Variational LSTM, shared embeddings	24M	73.2
Merity et al. (2016) - Zoneout + Variational LSTM (medium)	20M	80.6
Merity et al. (2016) - Pointer Sentinel-LSTM (medium)	21M	70.9
Zilly et al. (2016) - Variational RHN, shared embeddings	24M	66.0
Neural Architecture Search with base 8	32M	67.9
Neural Architecture Search with base 8 and shared embeddings	25M	64.0
Neural Architecture Search with base 8 and shared embeddings	54M	62.4

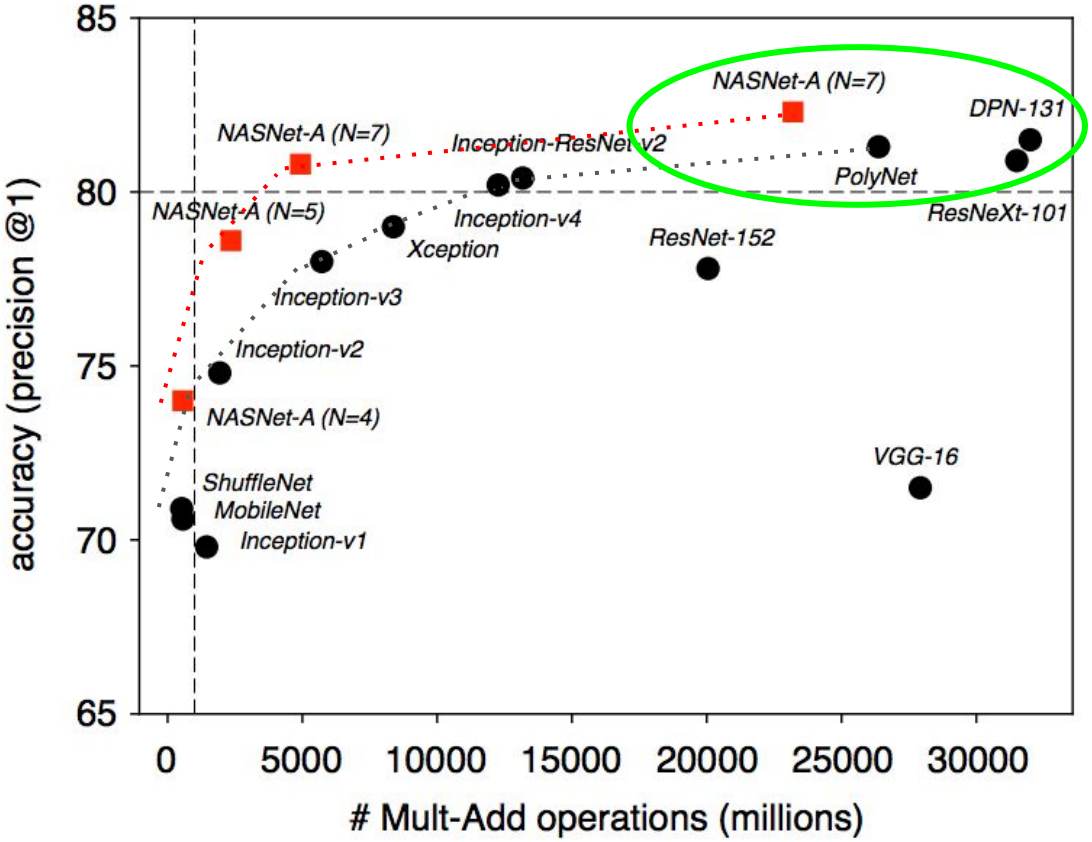
Table 2: Single model perplexity on the test set of the Penn Treebank language modeling task. Parameter numbers with ‡ are estimates with reference to Merity et al. (2016).

Scaling to Imagenet



Learning Transferable Architectures for Scalable Image Recognition, Barret Zoph, Vijay Vasudevan, Jonathon Shlens and Quoc Le, https://arxiv.org/abs/1707.07012

Scaling to Imagenet



Learning Transferable Architectures for Scalable Image Recognition, Barret Zoph, Vijay Vasudevan, Jonathon Shlens and Quoc Le, https://arxiv.org/abs/1707.07012

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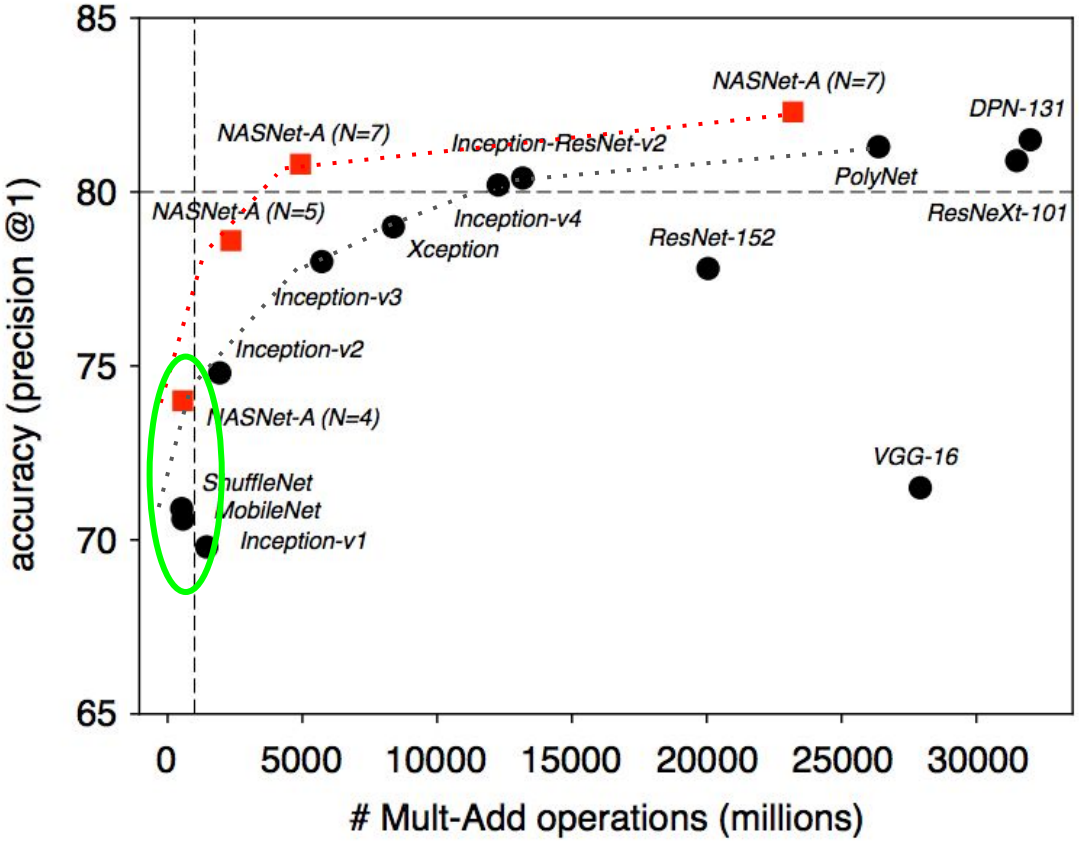


Learning Transferable Architectures for Scalable Image Recognition, Barret Zoph, Vijay Vasudevan, Jonathon Shlens and Quoc Le, https://arxiv.org/abs/1707.07012

Learn the Optimization Update Rule

Commonly Used Human-Designed Optimizers

parameters += *learning_rate* * ***expression***

SGD: g

Momentum: $g + \gamma \hat{m}$

ADAM: $\hat{m} / \sqrt{\hat{v}}$

RMSProp: $g / \sqrt{\hat{v}}$

Where:

g gradient

$\hat{m}$ bias-corrected running average of the gradient

$\hat{v}$ bias-corrected running average of the squared gradient

Learn the Optimization Update Rule

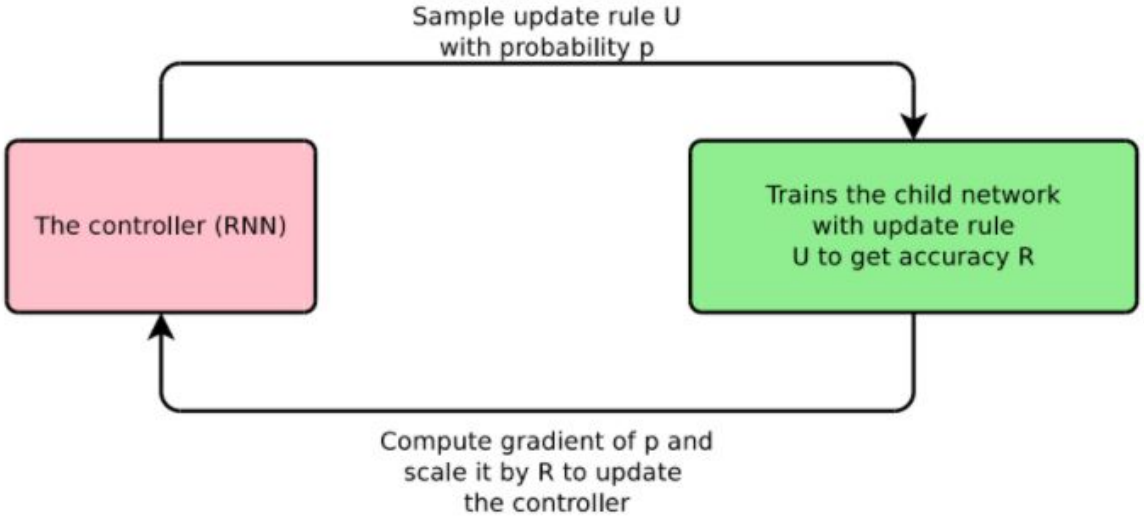


Figure 1. Overview of Neural Optimizer Search.

Neural Optimizer Search using Reinforcement Learning, Irwan Bello, Barret Zoph, Vijay Vasudevan, and Quoc Le, ICML 2017, proceedings.mlr.press/v70/bello17a/bello17a.pdf

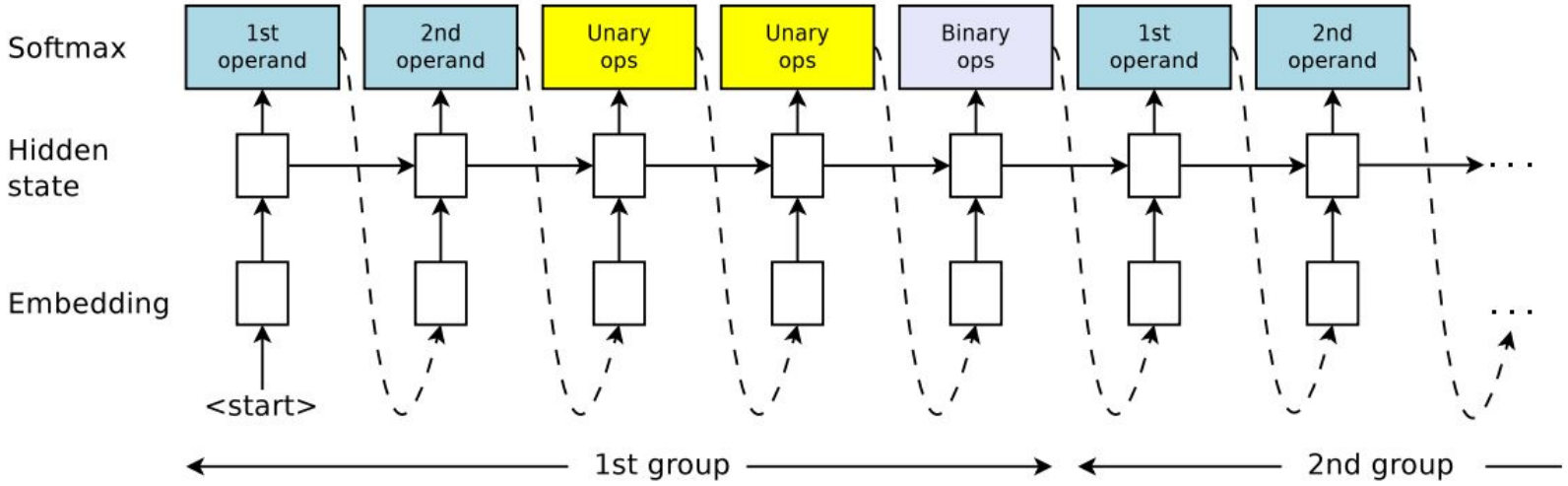


Figure 3. Overview of the controller RNN. The controller iteratively selects subsequences of length 5. It first selects the 1st and 2nd operands op_1 and op_2, then 2 unary functions u_1 and u_2 to apply to the operands and finally a binary function b that combines the outputs of the unary functions. The resulting $b(u_1(op_1), u_2(op_2))$ then becomes an operand that can be selected in the subsequent group of predictions or becomes the update rule. Every prediction is carried out by a softmax classifier and then fed into the next time step as input.

The operands, unary functions and binary functions that are accessible to our controller are as follows:

- Operands: g, g^2, g^3, $\hat{m}$, $\hat{v}$, $\hat{\gamma}$, $sign(g)$, $sign(\hat{m})$, $sign(g) * sign(m)$, 1, small constant noise, $10^{-4}w$, $10^{-3}w$, $10^{-2}w$, $10^{-1}w$, ADAM and RMSProp.

- Unary functions which map input x to: x, e^x, $\log|x|$, $clip(x, 10^{-5})$, $clip(x, 10^{-4})$, $clip(x, 10^{-3})$, $drop(x, 0.1)$, $drop(x, 0.3)$ or $drop(x, 0.5)$.

- Binary functions which map (x, y) to $x+y$ (addition), $x-y$ (subtraction), $x*y$ (multiplication), $\frac{x}{y+\epsilon}$ (division) or x (keep left).

Optimizer	Final Val	Final Test	Best Val	Best Test
SGD	92.0	91.8	92.9	91.9
Momentum	92.7	92.1	93.1	92.3
ADAM	90.4	90.1	91.8	90.7
RMSProp	90.7	90.3	91.4	90.3

Table 1. Performance of Neural Optimizer Search and standard optimizers on the Wide-ResNet architecture (Zagoruyko & Komodakis, 2016) on CIFAR-10. Final Val and Final Test refer to the final validation and test accuracy after for training for 300 epochs. Best Val corresponds to the best validation accuracy over the 300 epochs and Best Test is the test accuracy at the epoch where the validation accuracy was the highest.

Optimizer	Final Val	Final Test	Best Val	Best Test
SGD	92.0	91.8	92.9	91.9
Momentum	92.7	92.1	93.1	92.3
ADAM	90.4	90.1	91.8	90.7
RMSProp	90.7	90.3	91.4	90.3
$[e^{\text{sign}(g)*\text{sign}(m)} + \text{clip}(g, 10^{-4})] * g$	92.5	92.4	93.8	93.1
$\text{clip}(\hat{m}, 10^{-4}) * e^{\hat{v}}$	93.5	92.5	93.8	92.7
$\hat{m} * e^{\hat{v}}$	93.1	92.4	93.8	92.6
$g * e^{\text{sign}(g)*\text{sign}(m)}$	93.1	92.8	93.8	92.8
$\text{drop}(g, 0.3) * e^{\text{sign}(g)*\text{sign}(m)}$	92.7	92.2	93.6	92.7
$\hat{m} * e^{g^2}$	93.1	92.5	93.6	92.4
$\text{drop}(\hat{m}, 0.1)/(e^{g^2} + \epsilon)$	92.6	92.4	93.5	93.0
$\text{drop}(g, 0.1) * e^{\text{sign}(g)*\text{sign}(m)}$	92.8	92.4	93.5	92.2
$\text{clip}(\text{RMSProp}, 10^{-5}) + \text{drop}(\hat{m}, 0.3)$	90.8	90.8	91.4	90.9
$\text{ADAM} * e^{\text{sign}(g)*\text{sign}(m)}$	92.6	92.0	93.4	92.0
$\text{ADAM} * e^{\hat{m}}$	92.9	92.8	93.3	92.7
$g + \text{drop}(\hat{m}, 0.3)$	93.4	92.9	93.7	92.9
$\text{drop}(\hat{m}, 0.1) * e^{g^3}$	92.8	92.7	93.7	92.8
$g - \text{clip}(g^2, 10^{-4})$	93.4	92.8	93.7	92.8
$e^g - e^{\hat{m}}$	93.2	92.5	93.5	93.1
$\text{drop}(\hat{m}, 0.3) * e^w$	93.2	93.0	93.5	93.2

Table 1. Performance of Neural Optimizer Search and standard optimizers on the Wide-ResNet architecture (Zagoruyko & Komodakis, 2016) on CIFAR-10. Final Val and Final Test refer to the final validation and test accuracy after for training for 300 epochs. Best Val corresponds to the best validation accuracy over the 300 epochs and Best Test is the test accuracy at the epoch where the validation accuracy was the highest.

Optimizer	Train perplexity	Test BLEU
Adam	1.49	24.5
$g * e^{\text{sign}(g)*\text{sign}(m)}$	1.39	25.0

Table 2. Performance of our optimizer versus ADAM in a state-of-the-art GNMT model on WMT 2014 English $\rightarrow$ German.

What might a plausible future look like?

Combine many of these ideas:

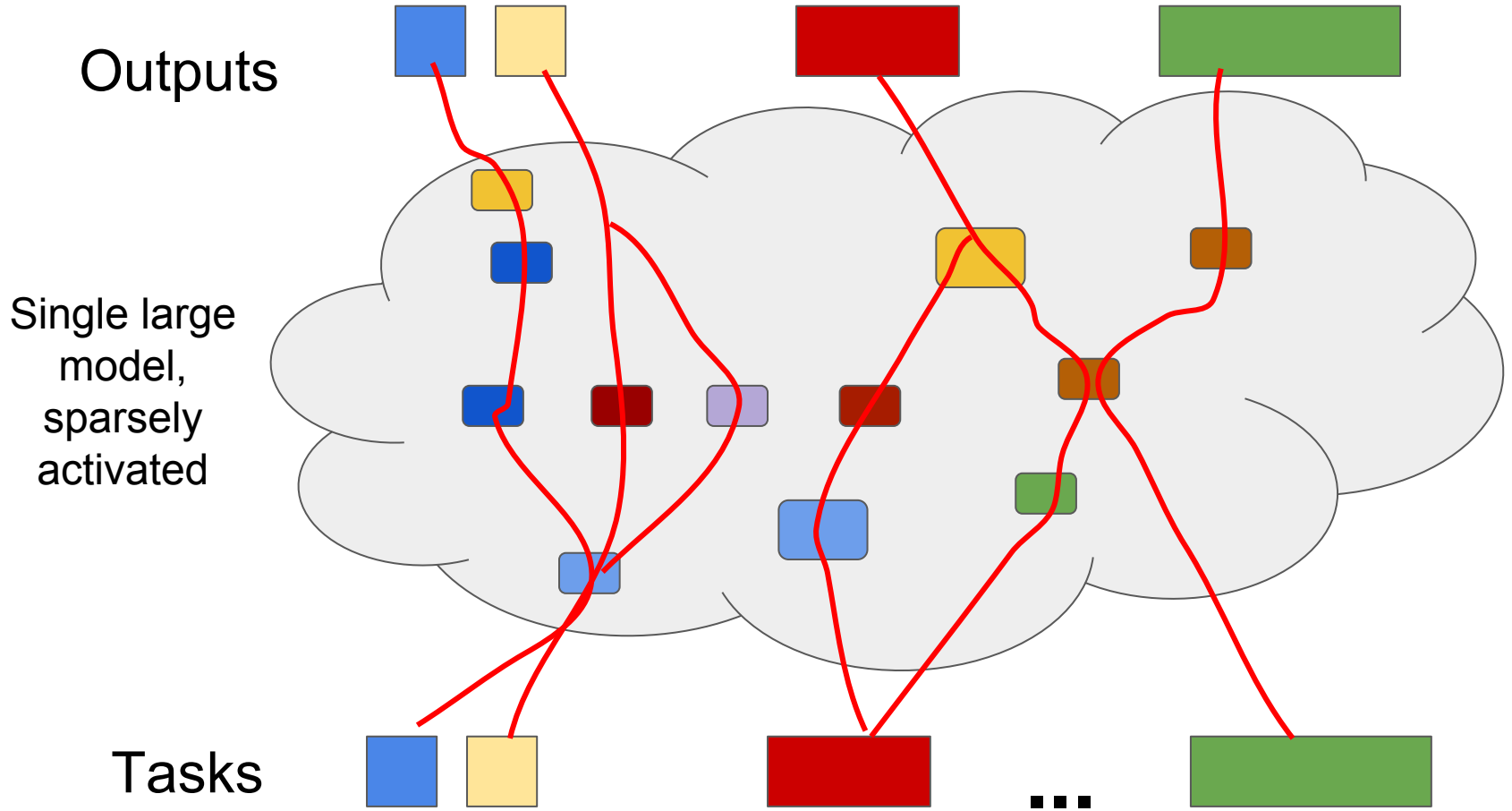
Large model, but **sparsely activated**

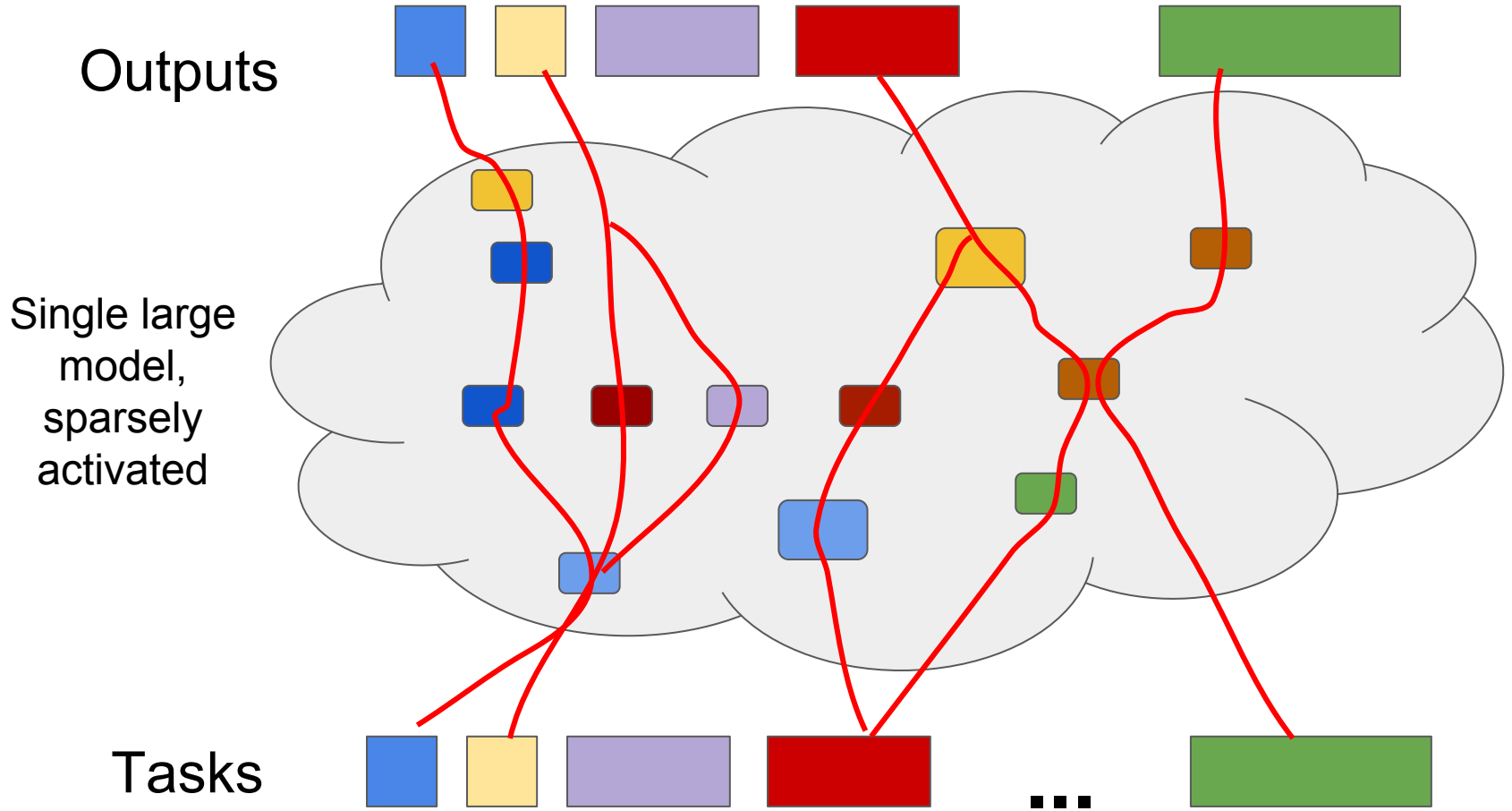
Single model to **solve many tasks** (100s to 1Ms)

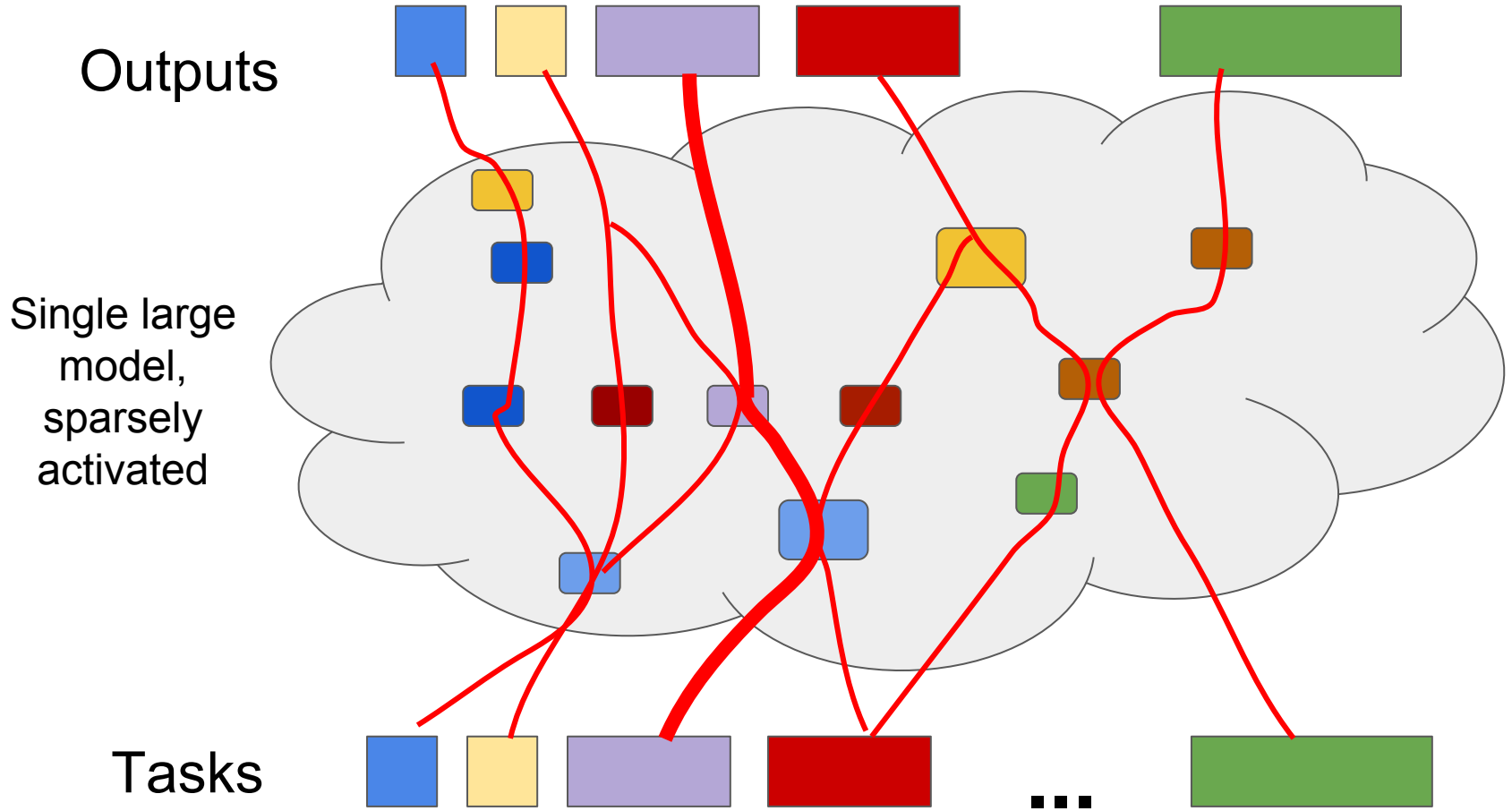
Dynamically learn and **grow pathways** through large model

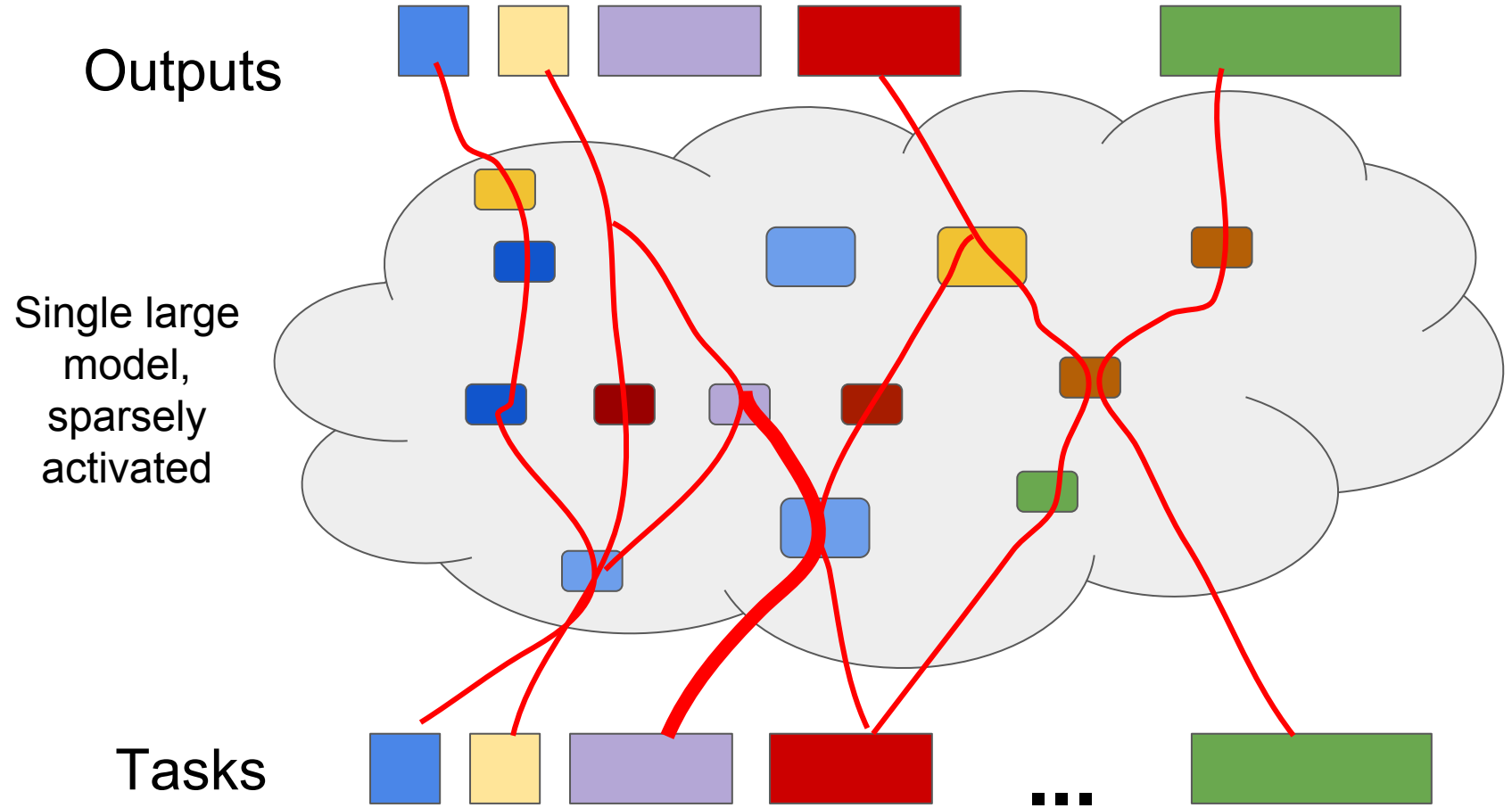
Hardware **specialized for ML supercomputing**

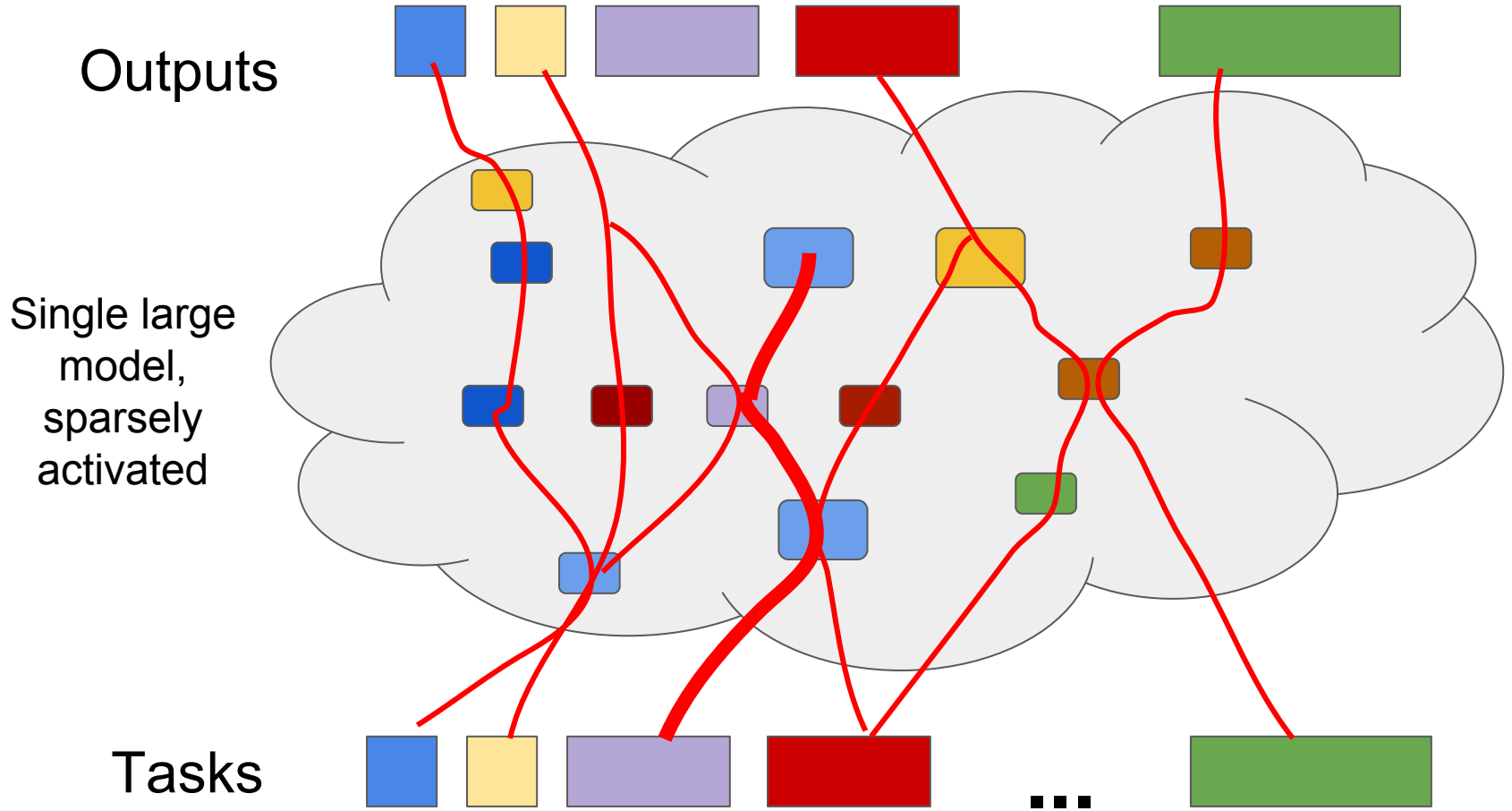
ML for efficient mapping onto this hardware

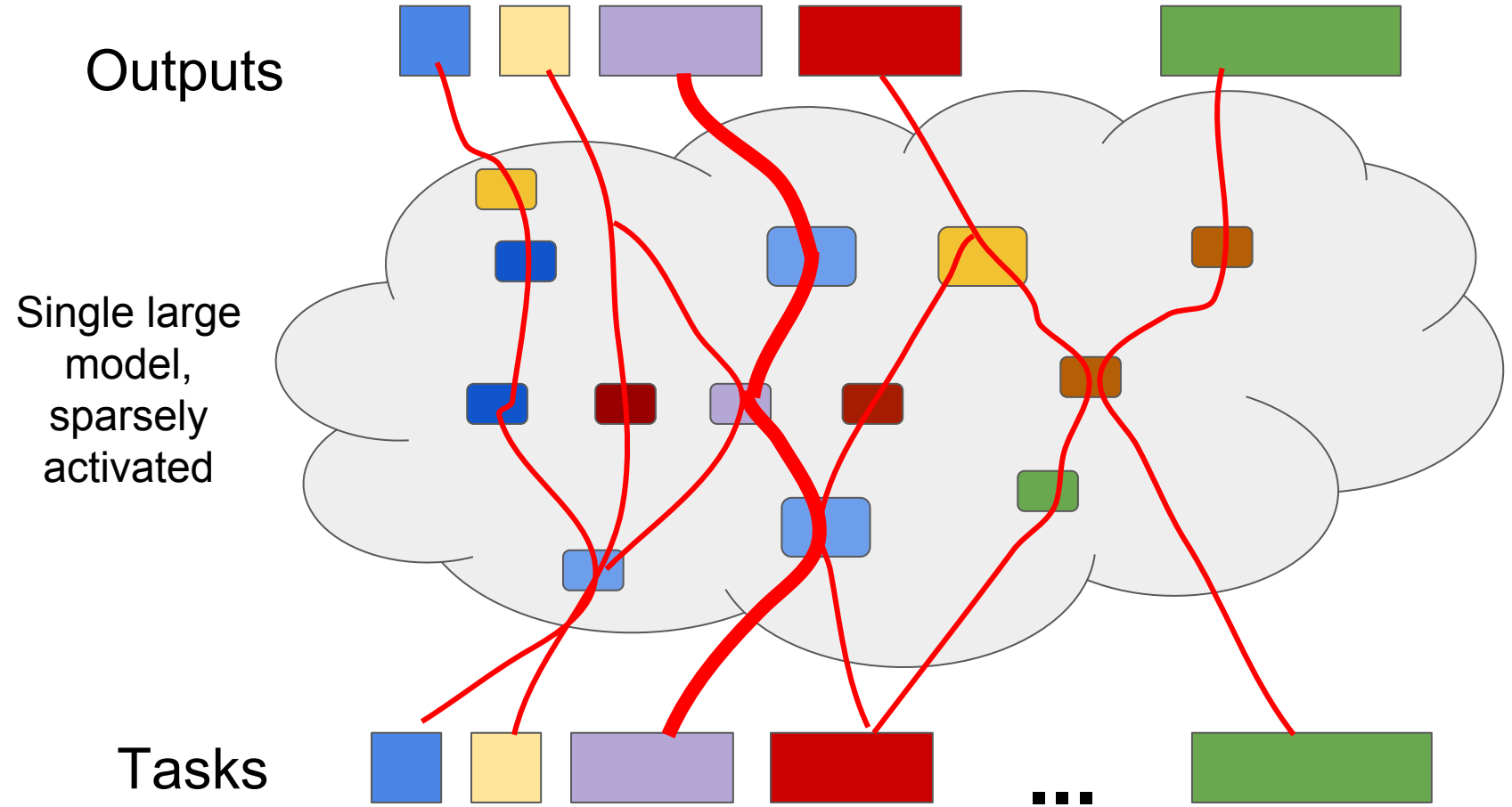

Outputs
Single large model, sparsely activated
Tasks
...


Outputs
Single large model, sparsely activated
Tasks
...


Outputs
Single large model, sparsely activated
Tasks
...


Outputs
Single large model, sparsely activated
Tasks
...


Outputs
Single large model, sparsely activated
Tasks
...

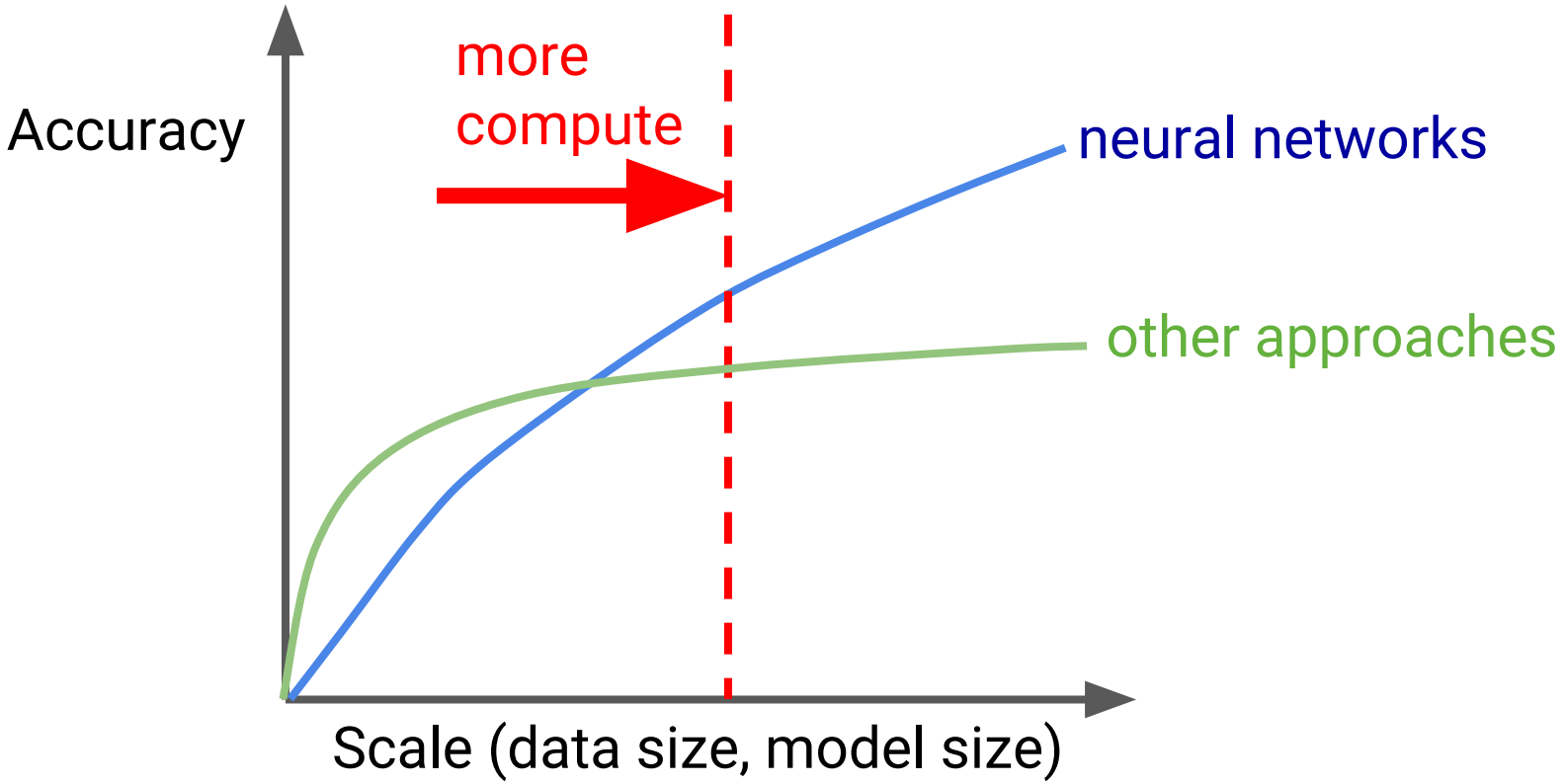

Outputs
Single large model, sparsely activated
Tasks
...

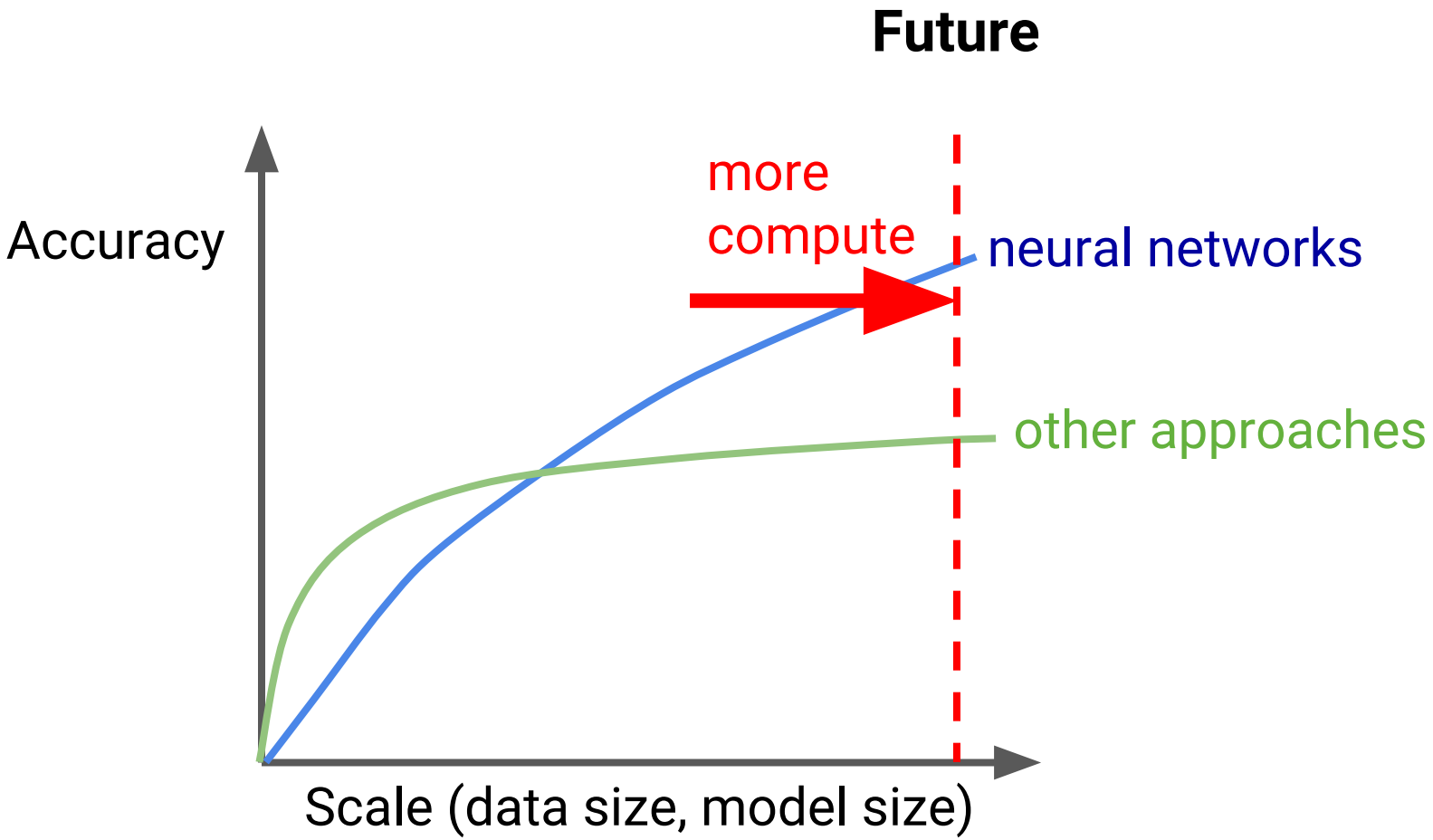
Questions/open-problems at the intersection of machine learning and systems/computer architecture

Questions/Open Issues

- Do **dramatically different numerics** make sense (e.g. 1- or 2-bit activations/parameters?)
- How can we **deal efficiently with very dynamic models** (different graph for every input example), especially on very large scale machines?
- What new approaches can help us with the **problem of diminishing returns from larger batch sizes**?
  - If we could train with batch_size = 1M, that would make things much easier
- What **ML algorithms/approaches will be important in 3-4 years**?

Now


Accuracy
more
compute
neural networks
other approaches
Scale (data size, model size)


Future
Accuracy
more
compute
neural networks
other approaches
Scale (data size, model size)

Conclusions

Deep neural networks are making significant strides in speech, vision, language, search, robotics, healthcare, …

They are also **dramatically reshaping our computational devices**

If you’re not considering how to use deep neural nets to solve your problems, **you almost certainly should be**

g.co/brain

More info about our work

Main Research Areas

- Machine Learning Algorithms and Techniques
- Healthcare
- Computer Systems for Machine Learning
- Robotics
- Natural Language Understanding
- Music and Art Generation
- Perception

MORE PAPERS

BLOG POSTS