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51CTO

全球软件开发技术峰会

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DEVELOPMENT

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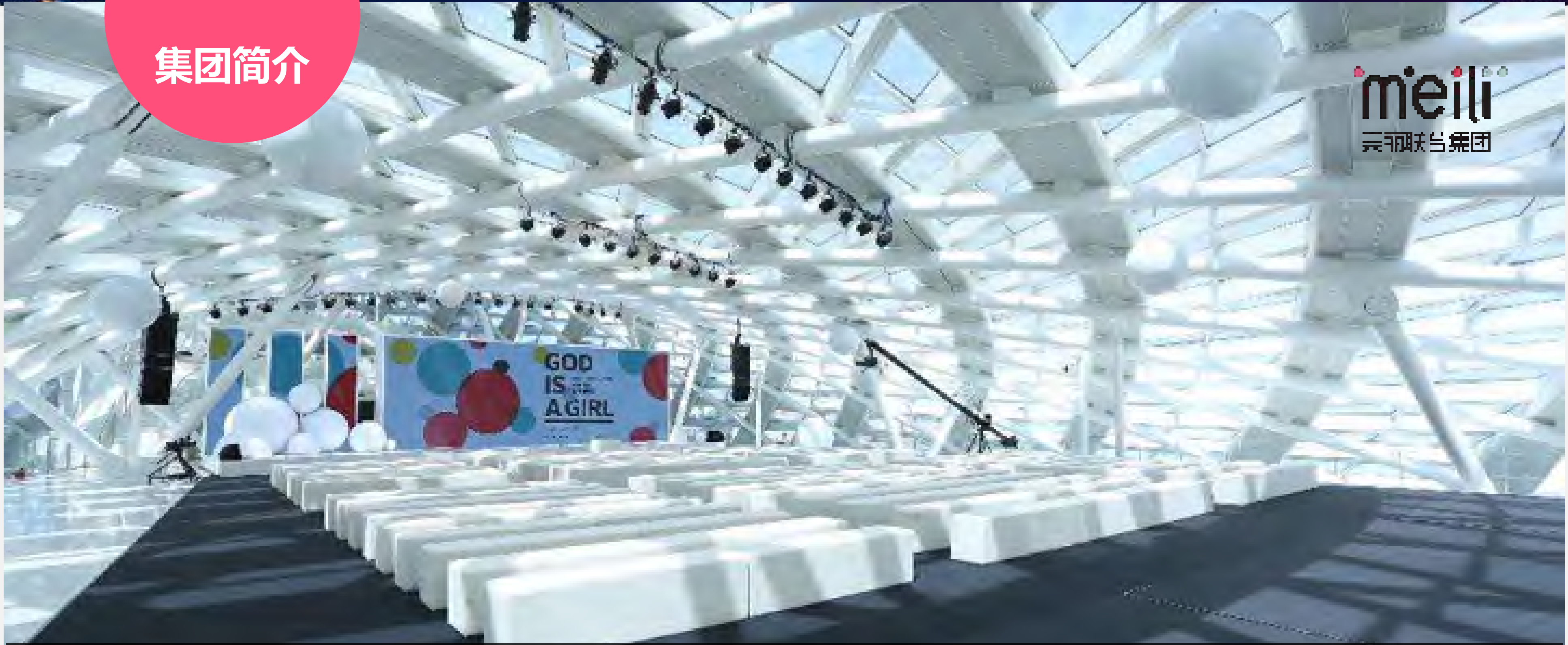
深度学习在移动端的优化实践

黄文波(鬼谷)
美丽联合集团

meili

集团简介



美丽联合集团是专注服务女性的时尚消费平台，成立于2016 年 6 月 15 日。美丽联合集团旗下包括：蘑菇街、美丽说、uni、锐鲨、MOGU STATION等产品与服务。覆盖时尚消费的各个领域，满足不同年龄层、消费力和审美品位的女性用户日常时尚资讯与时尚消费所需。

整体数据

时尚红人
120,000+

日活用户
10,000,000+

注册用户数
200,000,000+

移动用户占比
95%+

女性用户占比
95%+

成交规模
¥20,000,000,000+

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主要内容

01

背景及现状

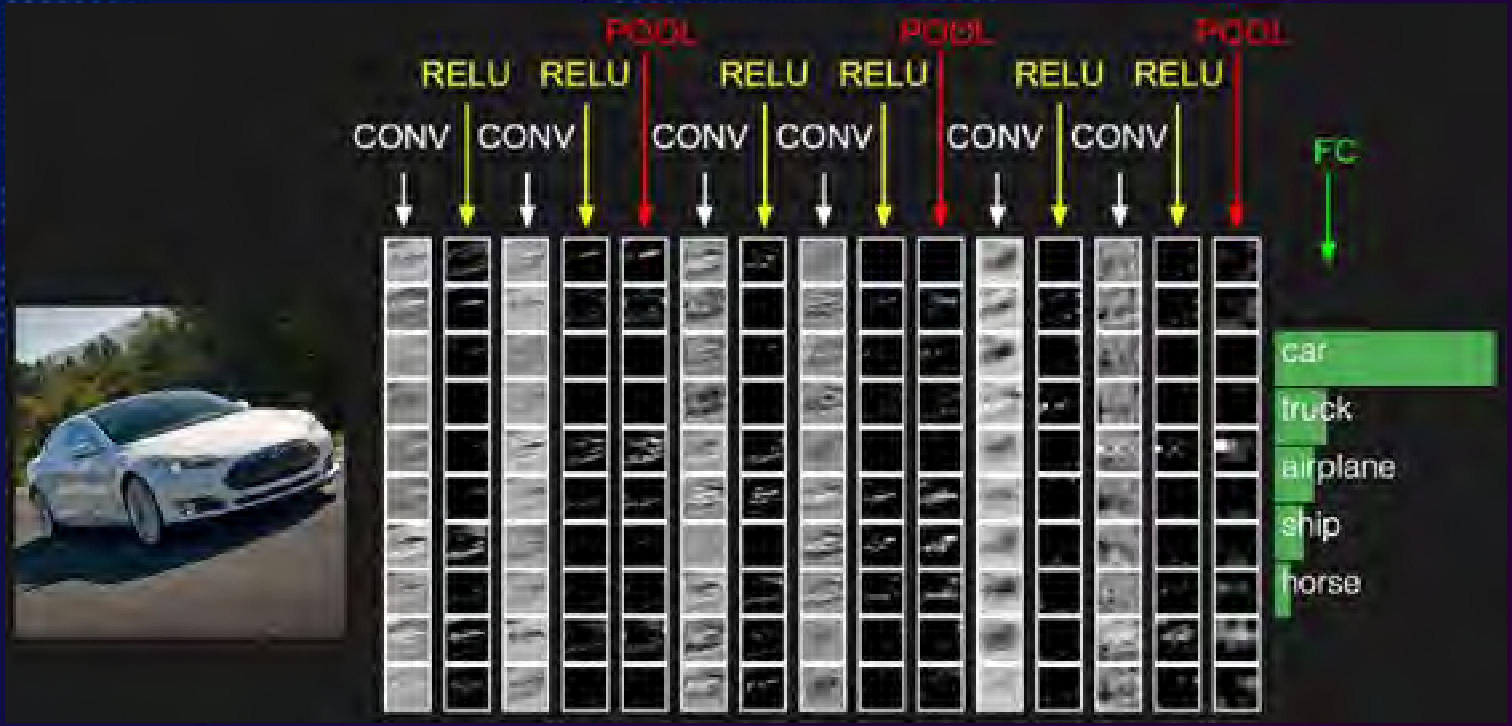
深度学习：从云端到边缘计算

蘑菇街为什么做深度学习优化？

服务器
- 减少训练、预测的时间
- 节约GPU资源，节约电

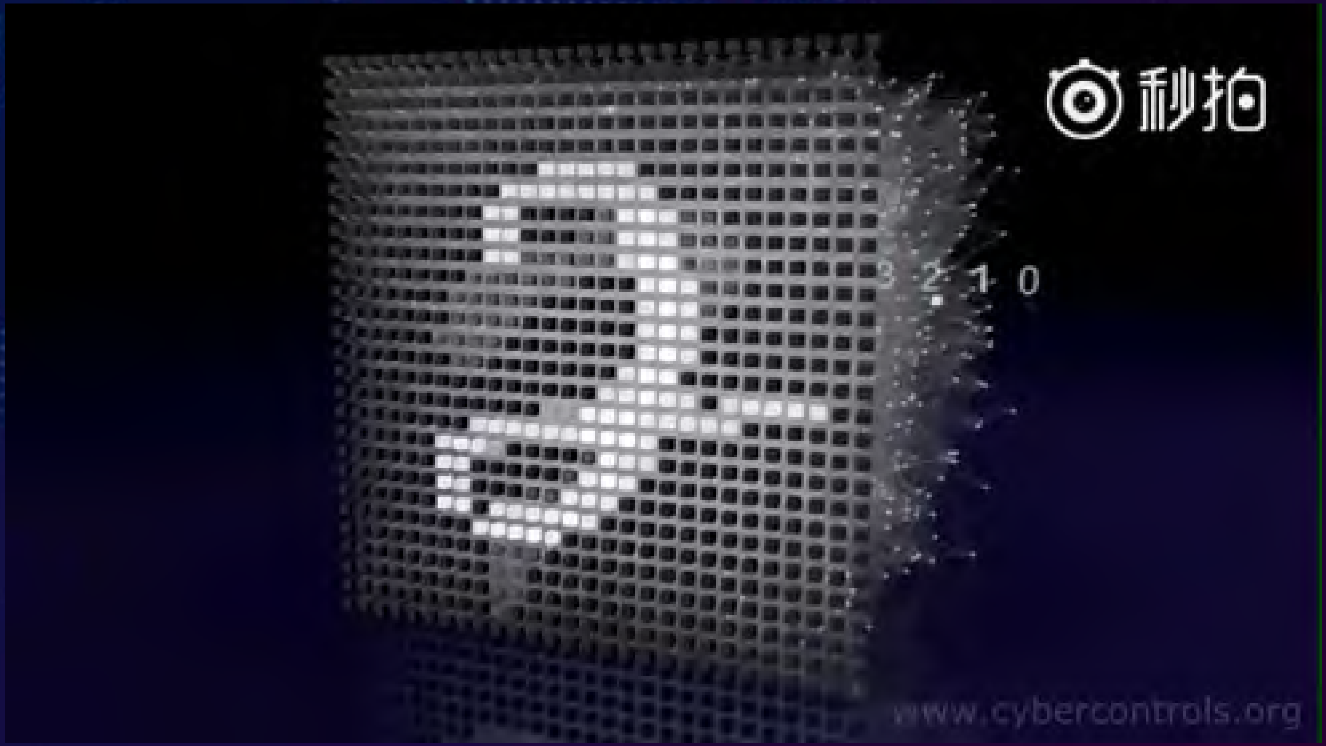
移动端
- 实时响应需求
- 本地化运行，减少服务器压力
- 保护用户隐私

CNN基础



POOL
POOL
POOL
RELU
RELU
RELU
RELU
RELU
RELU
CONV
CONV
CONV
CONV
CONV
CONV
FC
car
truck
airplane
ship
horse

CNN基础



Challenge

深度学习：网络越来越深，准确率越来越高

模型越来越大 → 越多的存储和计算 → 耗费越多能量

移动设备：内存有限、计算性能有限、功耗有限

02

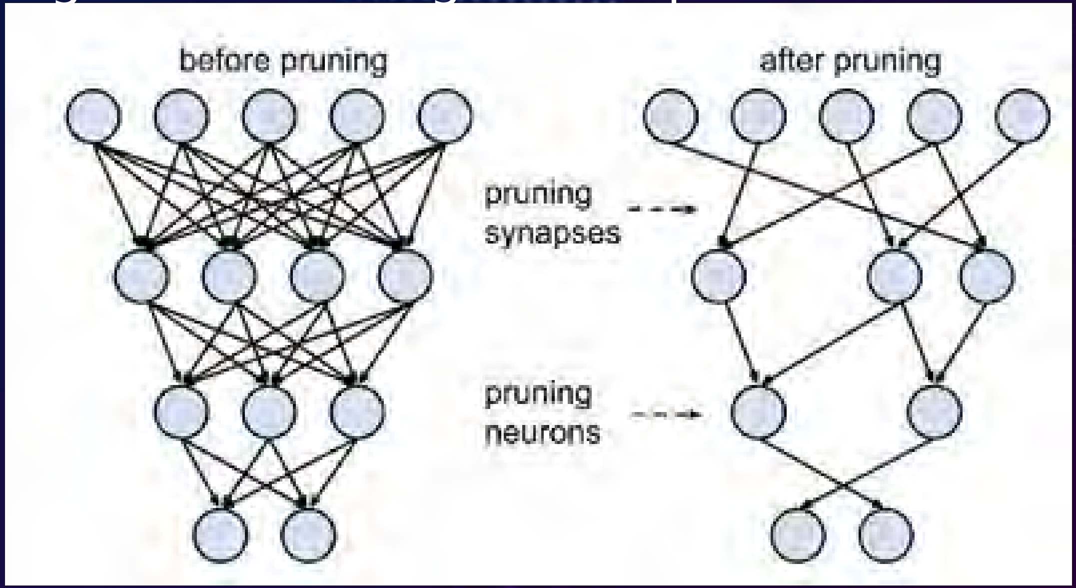
模型压缩与设计

Model Compression

- Pruning
- Quantization
- Huffman Encoding

Pruning

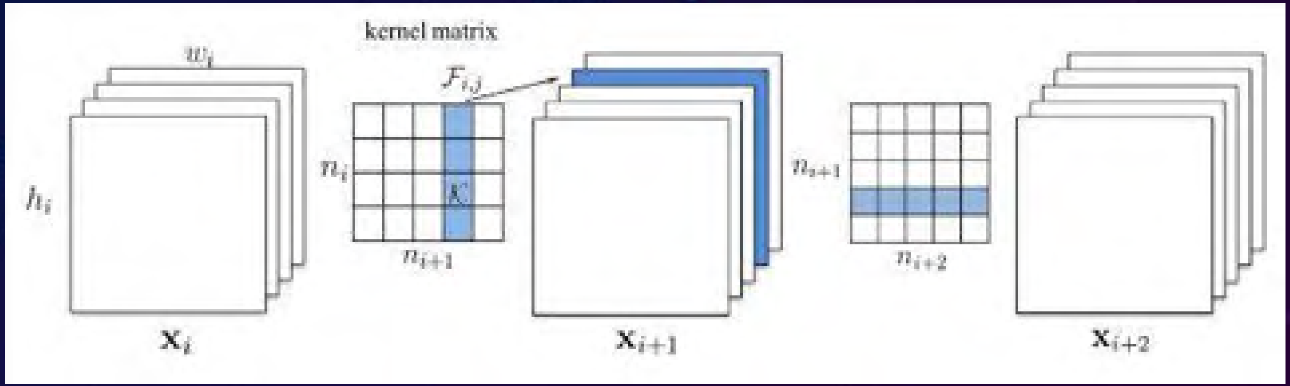
Weight-Level Pruning for the sparse connections



Han et al, “Learning both weights and connections for efficient neural networks”, NIPS 2015

Pruning

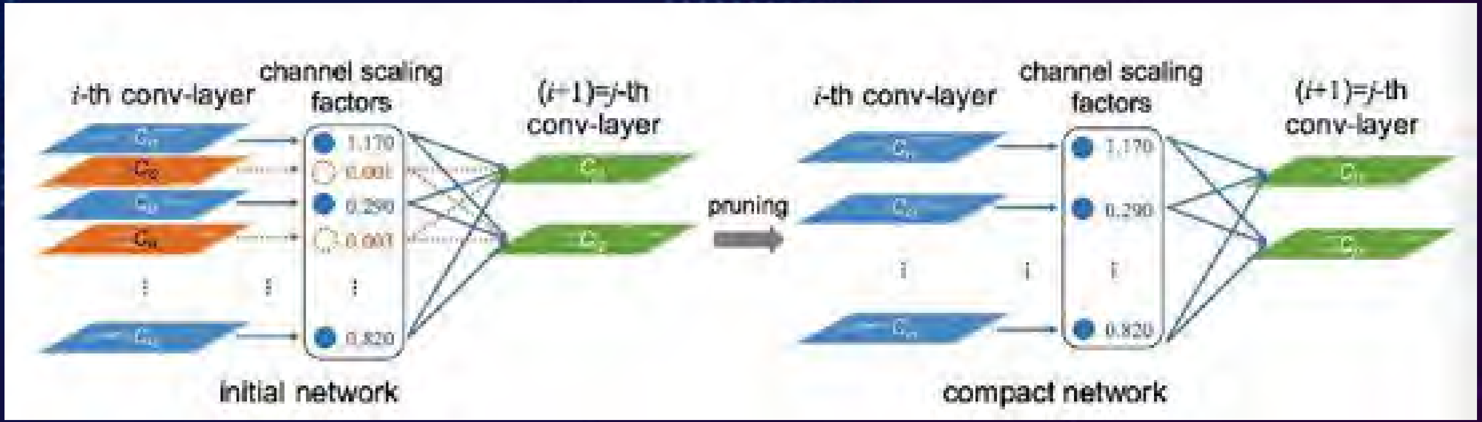
Channel-Level Pruning and retraining iteratively



Li et al, "Pruning filter for efficient convnets", ICLR 2017

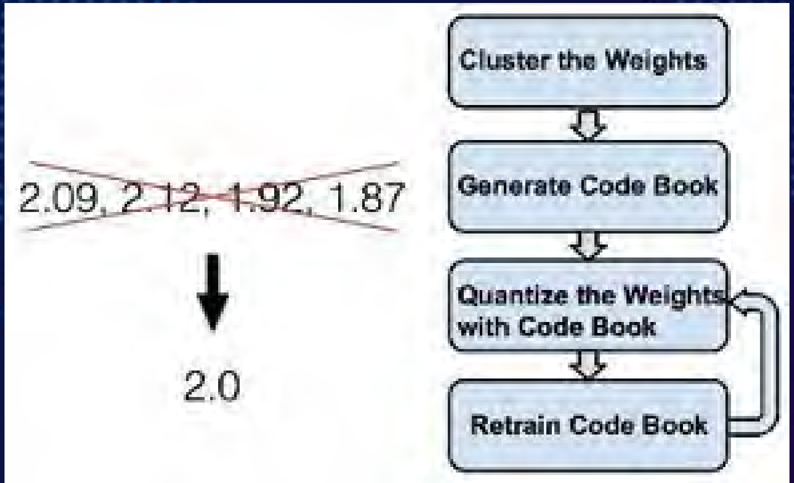
Pruning

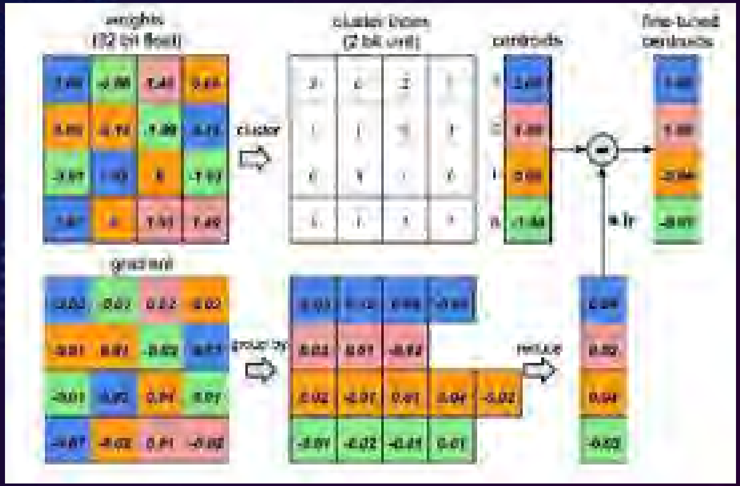
Channel-Level Pruning with L1 regularization



Liu et al, "Learning efficient convolutional networks through network slimming", ICCV 2017

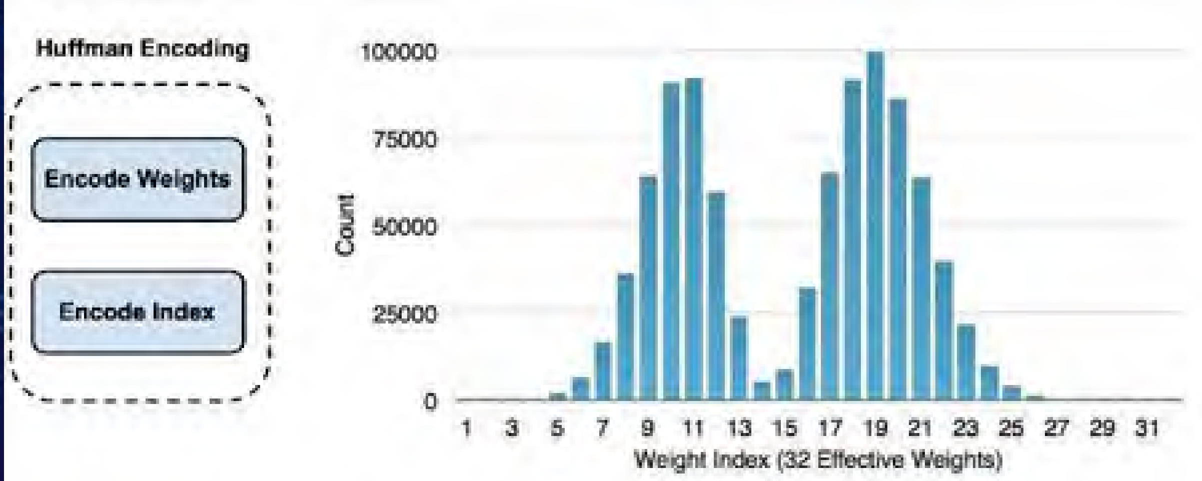
Quantization





Han et al, “Deep Compression: Compressing deep neural networks with pruning, trained quantization and huffman coding”,

Huffman Encoding



- In-frequent weights: use more bits to represent
- Frequent weights: use less bits to represent

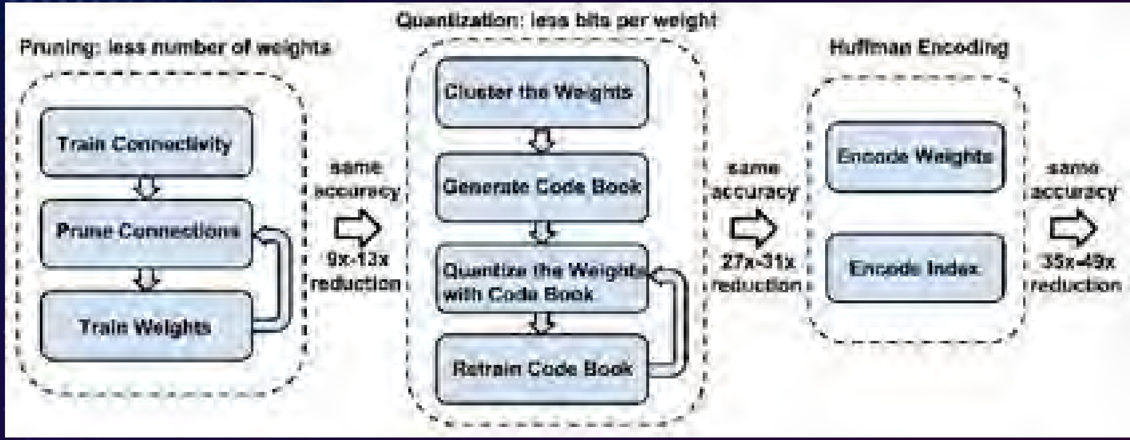
Han et al, “Deep Compression: Compressing deep neural networks with pruning, trained quantization and huffman coding”

Summary of model compression

Pruning: less number of channels

channel-level pruning and retraining iteratively

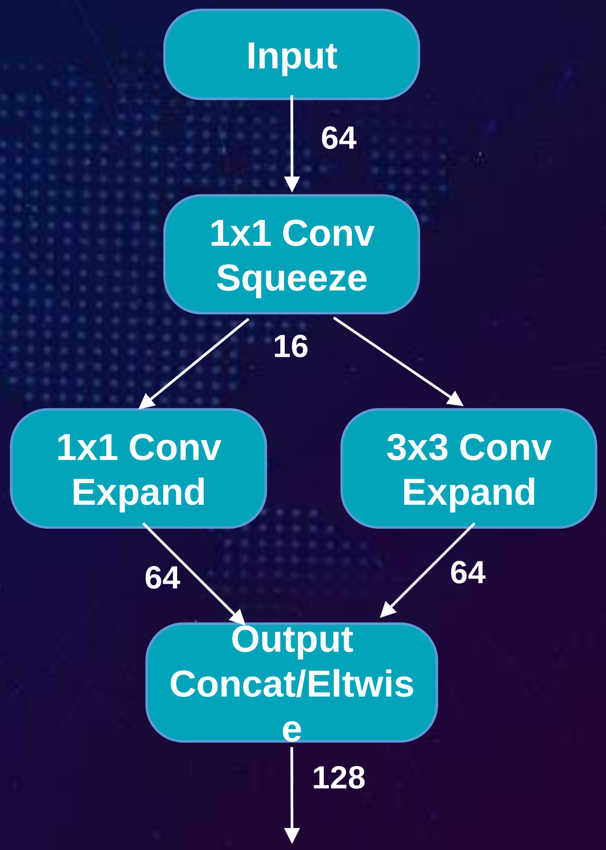
channel-level pruning with L1 regularization



Smaller CNNs architecture design

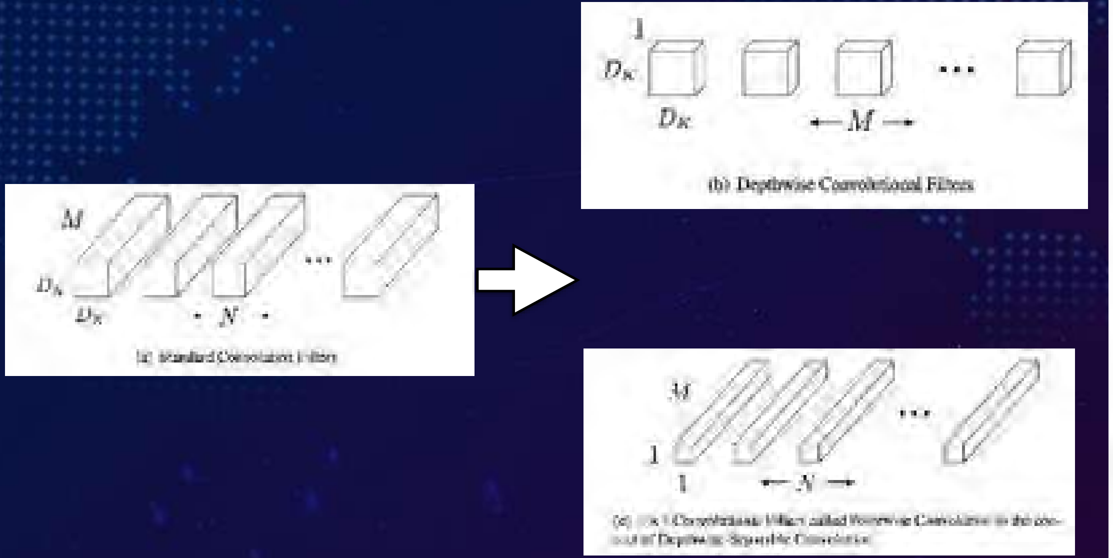
- SqueezeNet
- MobileNet
- ShuffleNet

SqueezeNet



Iandola et al, “SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and < 0.5MB model size”, arXiv 2016

MobileNets



(a) Standard Convolution Filters

(b) Depthwise Convolutional Filters

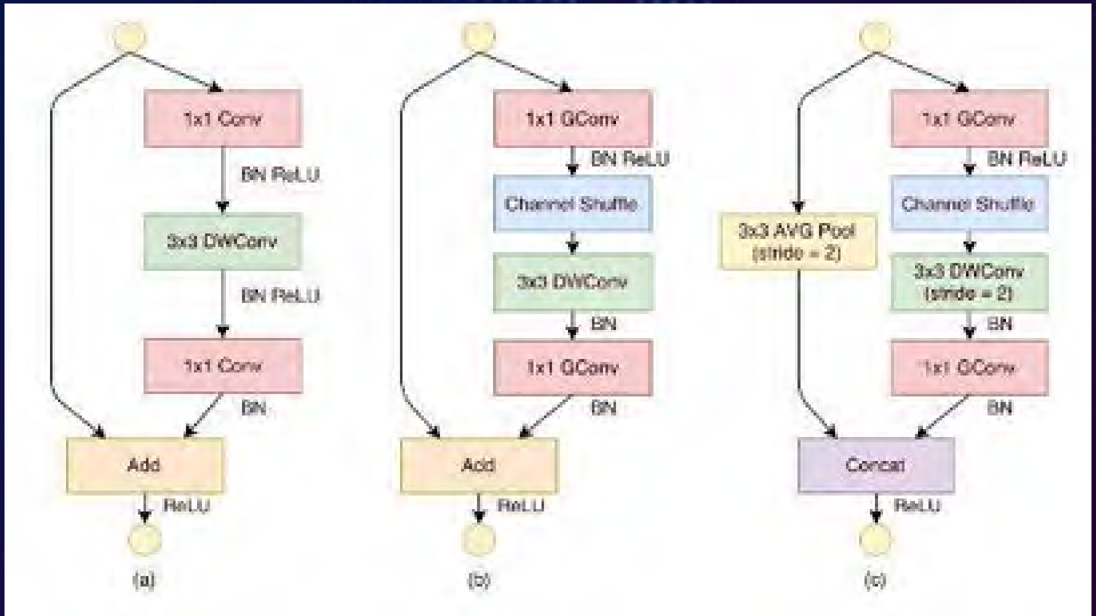
(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

Table 1. MobileNet Body Architecture

Type / Stride	Filter Shape	Input Size
Conv / s2	3 × 3 × 3 × 32	224 × 224 × 3
Conv dw / s1	3 × 3 × 32 dw	112 × 112 × 32
Conv / s1	1 × 1 × 32 × 64	112 × 112 × 32
Conv dw / s2	3 × 3 × 64 dw	112 × 112 × 64
Conv / s1	1 × 1 × 64 × 128	56 × 56 × 64
Conv dw / s1	3 × 3 × 128 dw	56 × 56 × 128
Conv / s1	1 × 1 × 128 × 128	56 × 56 × 128
Conv dw / s2	3 × 3 × 128 dw	56 × 56 × 128
Conv / s1	1 × 1 × 128 × 256	28 × 28 × 128
Conv dw / s1	3 × 3 × 256 dw	28 × 28 × 256
Conv / s1	1 × 1 × 256 × 256	28 × 28 × 256
Conv dw / s2	3 × 3 × 256 dw	28 × 28 × 256
Conv / s1	1 × 1 × 256 × 512	14 × 14 × 256
5× Conv dw / s1	3 × 3 × 512 dw	14 × 14 × 512
5× Conv / s1	1 × 1 × 512 × 512	14 × 14 × 512
Conv dw / s2	3 × 3 × 512 dw	14 × 14 × 512
Conv / s1	1 × 1 × 512 × 1024	7 × 7 × 512
Conv dw / s2	3 × 3 × 1024 dw	7 × 7 × 1024
Conv / s1	1 × 1 × 1024 × 1024	7 × 7 × 1024
Avg Pool / s1	Pool 7 × 7	7 × 7 × 1024
FC / s1	1024 × 1000	1 × 1 × 1024
Softmax / s1	Classifier	1 × 1 × 1000

Howard et al, "MobileNets: Efficient convolutional neural networks for mobile vision applications", arXiv 2017

ShuffleNet



Zhang et al, "ShuffleNet: An extremely efficient convolutional neural network for mobile devices", arXiv 2017

Our practice

Overall Performance of Pruning ResNet50 on ImageNet

Model	strategy	Top-1	Top-5	Model Size
Original	-	75%	92.27%	98M
Pruned-50	Pruning	72.5%	90.9%	49M
Pruned-Q-50	Pruning + Quantization	72.4%	90.6%	15M

Our practice

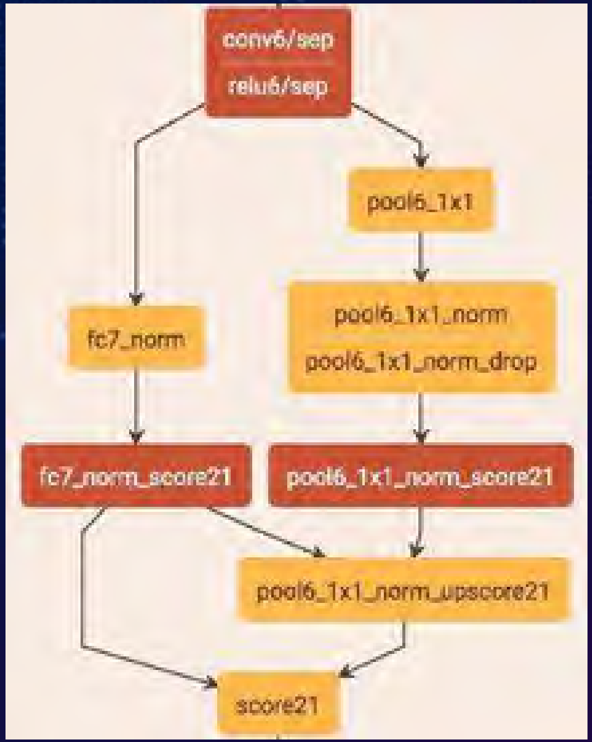
Performance of Pruning ResNet-34 on Our Dataset

Model	Top-1	Top-5	Inference Time	Model Size
Original	48.92%	82.2%	96ms	86M
Pruned-64	48.27%	81.5%	45ms	31M

(2319 categories, 1200W samples)

Our practice

ParseNet 18类(基础网络：MobileNet)



Model	mIOU	Pixel-Level-Accuracy	Model Size
ParseNet	56%	93.5%	13M

03

移动端工程实践

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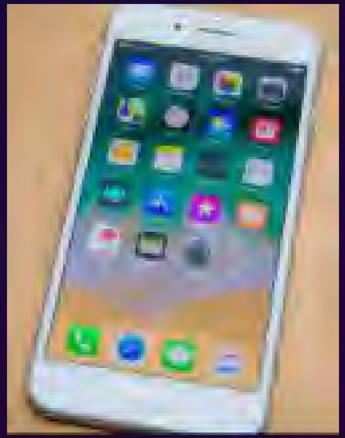
移动端服务端分工

Training

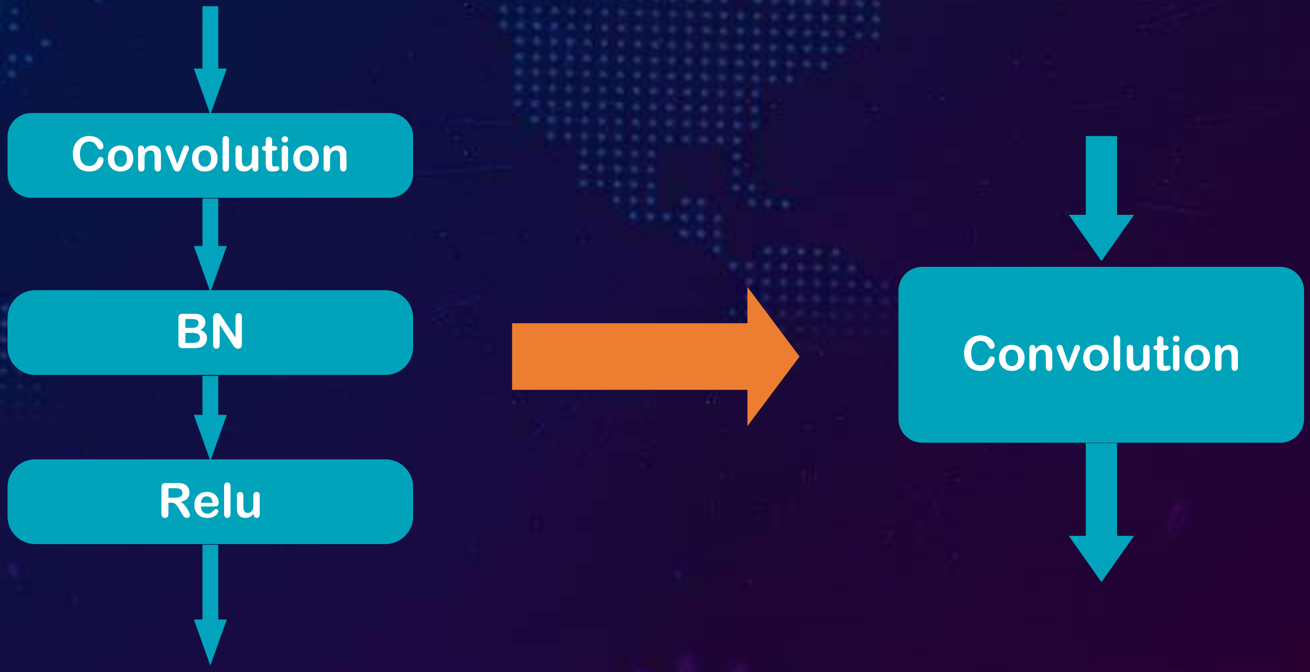


Inference

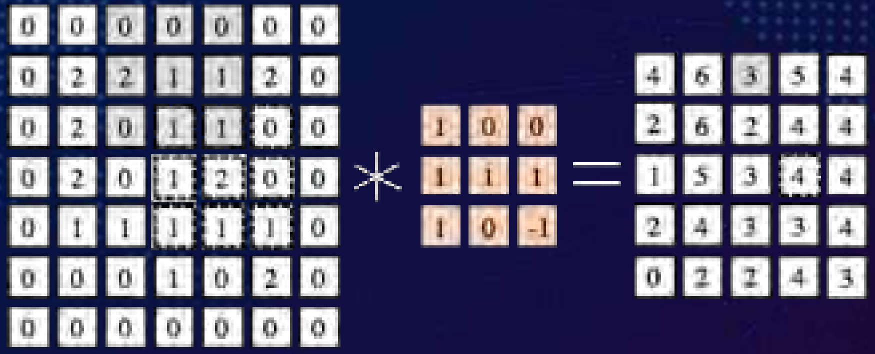
DL frameworks

- Caffe Caffe2 MXNet Tensorflow Torch ....
- NCNN、MDL
- CoreML
- Tensorflow Lite

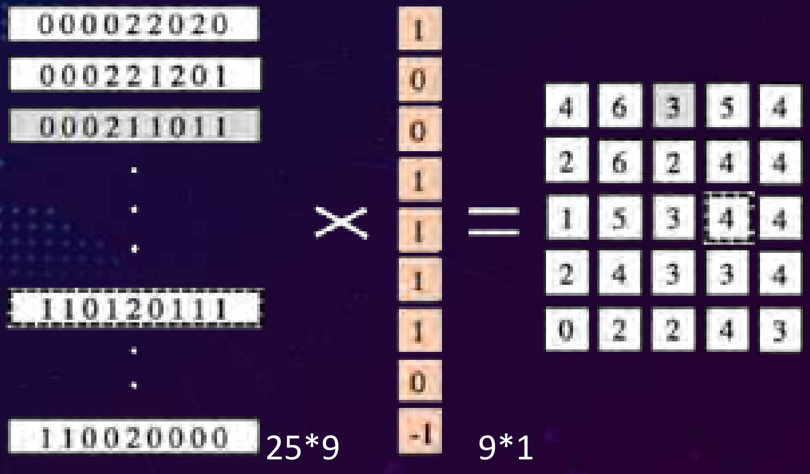
From training to inference



优化卷积计算

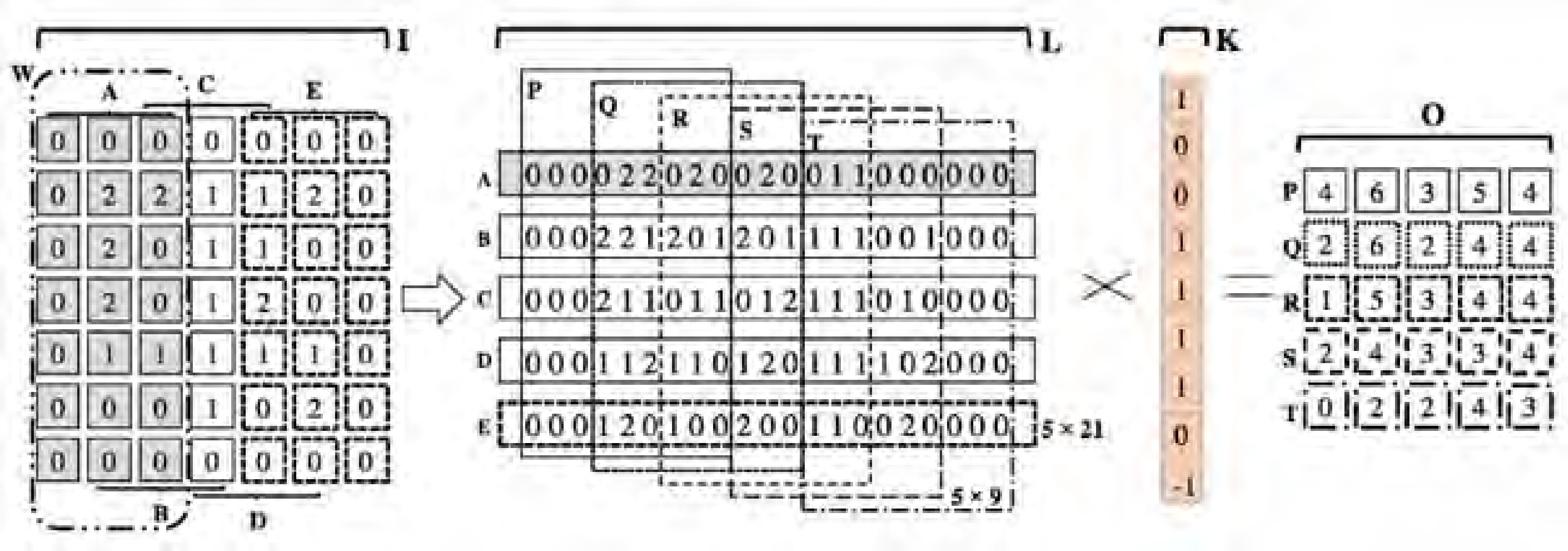


Direct convolution



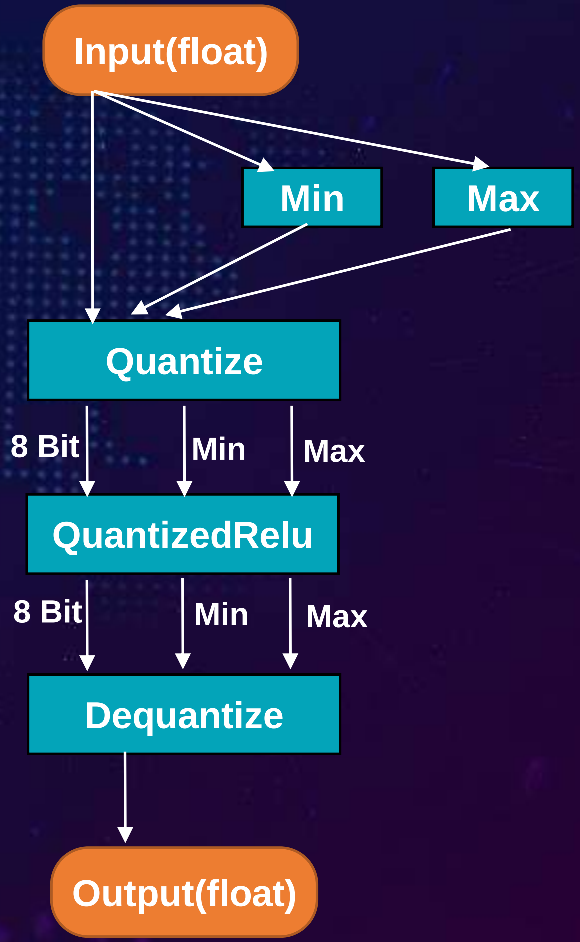
im2col-based convolution

优化卷积计算



Cho et al, “MEC: Memory-efficient convolution for deep neural network”,

浮点运算定点化



Input(float)
Min
Max
Quantize
8 Bit
Min
Max
QuantizedRelu
8 Bit
Min
Max
Dequantize
Output(float)

卷积计算还能怎么进化？

- 再牛逼的优化算法，都不如硬件实现来得直接
- 通用卷积 VS 特定卷积

Android端深度学习框架

NCNN vs MDL

FrameWork	单线程	四线程	内存
NCNN	370ms	200ms	25M
MDL	360ms	190ms	30M

MobileNet on HuaweiP9

Tensorflow Lite

Quantize MobileNet	Float Mobilenet
85ms	400ms

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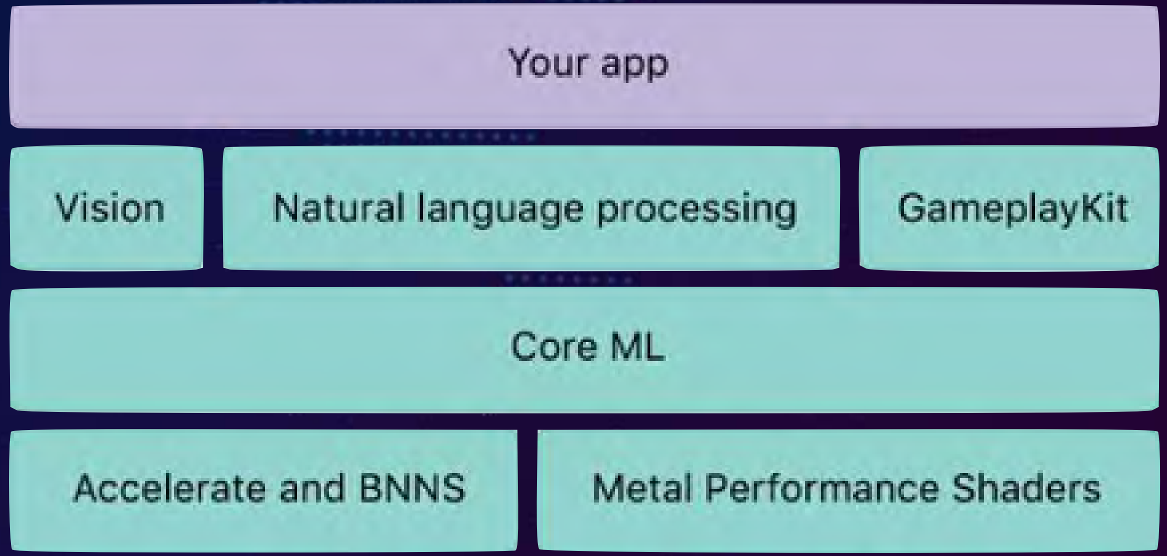
iOS 上的DL

CoreM
L



可扩展性不强，不适合部署新算法；需要iOS 11+

MPSCNN

- 充分利用GPU资源，不用抢占CPU
- 利用Metal开发新的层很方便

Tips： 半精度计算；权重存储格式为NHWC

MPSCNN

MPSImage

The layout of a 9-channel CNN image with a width of 3 and a height of 2.

Metal Performance Shader

```
kernel void eltwiseSum_array(
                texture2d_array<half, access::sample> inTexture1 [[texture(0)]],
                texture2d_array<half, access::sample> inTexture2 [[texture(1)]],
                texture2d_array<half, access::write> outTexture [[texture(2)]],
                ushort3 gid [[thread_position_in_grid]])
 {
    if (gid.x >= outTexture.get_width() ||
       gid.y >= outTexture.get_height() ||
       gid.z >= outTexture.get_array_size()) return;
    constexpr sampler s(coord::pixel, filter::nearest, address::clamp_to_zero);
    const ushort2 pos = gid.xy;
    const ushort slice = gid.z;
    half4 in[2];
    in[0] = inTexture1.sample(s, float2(pos.x, pos.y), slice);
    in[1] = inTexture2.sample(s, float2(pos.x, pos.y), slice);
    float4 out = float4(0.0f);
    out =float4( in[0]+in[1]);
    outTexture.write(half4(out), gid.xy, gid.z);
 }
```

MPSCNN VS NCNN on iPhone

FrameWork	Time
NCNN	110ms
MPSCNN	45ms

Device: iPhone 6s

How to create a new framework

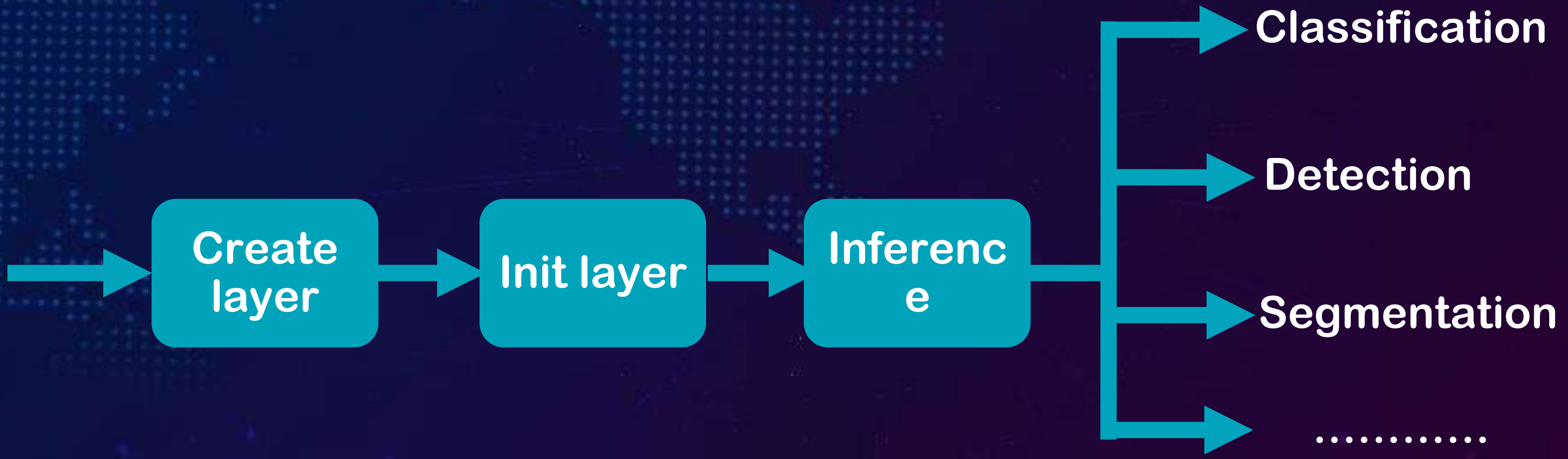
- 优化inference网络结构
- GPU加速
- 指令集加速
- 多线程
- 内存布局优化 NCHW—
- >NHWC
  浮点运算定点化

Mogu Deep Learning Toolkit

Mogu DL Toolkit

- For professional
- Highly Flexible
- High Cohesion & Low Coupling
- Easy to use

Mogu Deep Learning Toolkit



Mogu DL Toolkit-Example

MobileNet

```
class MobileNet{
public:
    Input           input;
    Convolution        fc7;

    int Init(const char* modelpath);
    int infer(Mat &input,Mat &output);

private:
    Convolution        conv1_s2;
    ReLU              relu1;
    ConvolutionDepthWise conv2_1_dw;
    ReLU              relu2_1_dw;
    Convolution        conv2_1_s1;
    ReLU              relu2_1_s1;
    ConvolutionDepthWise conv2_2_dw;
    …….
}
```

Demo

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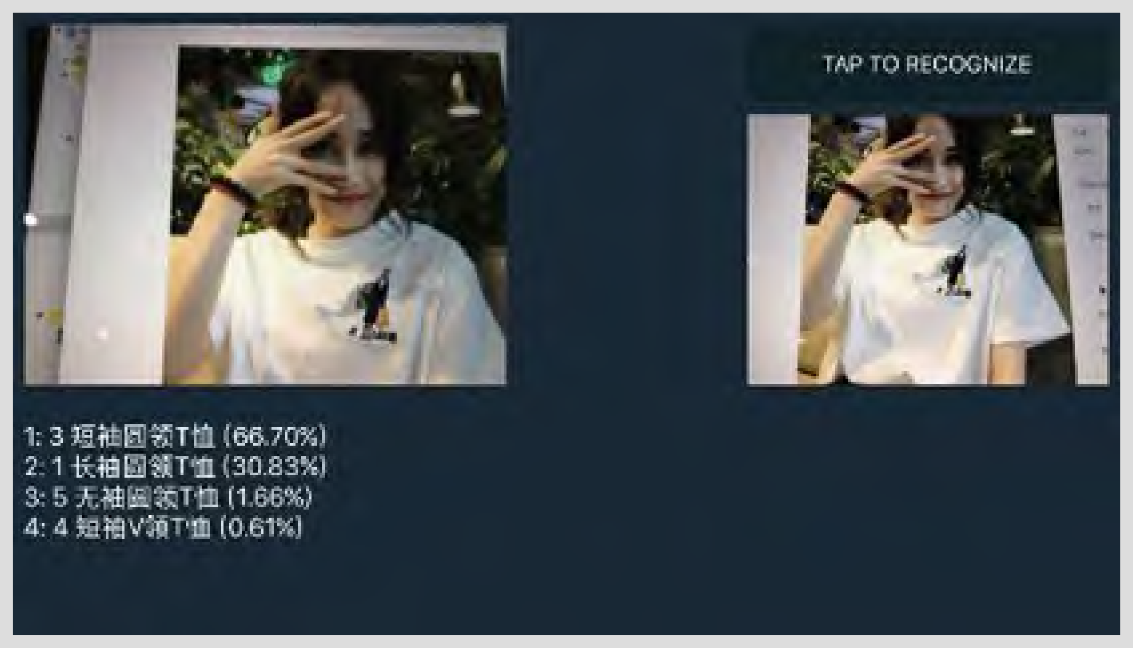
Demo



总结

- 模型压缩的两类方式
- 移动端优化实践
- Mogu DL Toolkit
- 深度学习优化在蘑菇街业务中的尝试

致谢

- 感谢蘑菇街图像算法部门深度学习优化小组全体成员的共同努力！！

Thanks!

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