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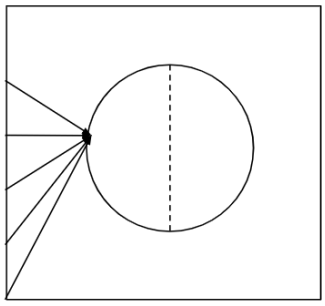
激活（基本属性）

大纲

- 什么是激活
- 非线性差分激活背后的推理



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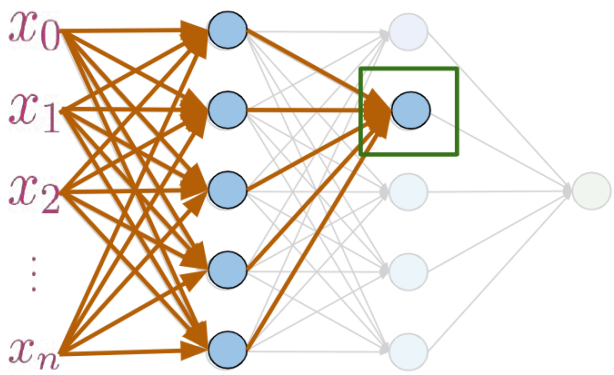
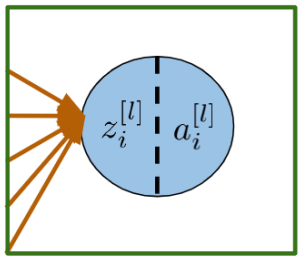
激活





$$z_i^{[l]} = \sum_{i=0} W_i^{[l]} a_i^{[l-1]}$$

$$a_i^{[l]} = \boxed{g^{[l]}}(z_i^{[l]})$$

微

非线性函数

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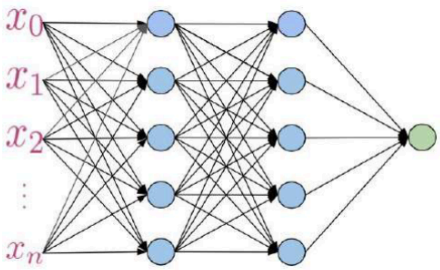
激活

$a_i^{[l]} = \boxed{g^{[l]}}(z_i^{[l]})$ 微非线性函数

1. 可微分反向传播
2. 非线性计算复杂特征，如果不是：



$\equiv$ $WX + b$

线性回归

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总结

- 激活函数是非线性且可微分的
- 可微分反向传播
- 非线性到近似复函数

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常见激活函数

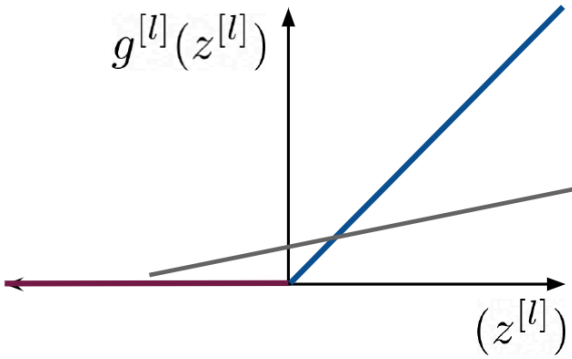
大纲

- 常见激活及其结构
  - ReLU 系列
  - 泄漏的 ReLU
  - 乙状结肠
  - 谭

激活： ReLU

ReLU = 修正线性单位

$$g^{[l]}(z^{[l]}) = \max(0, z^{[l]})$$



垂死的 ReLU 问题

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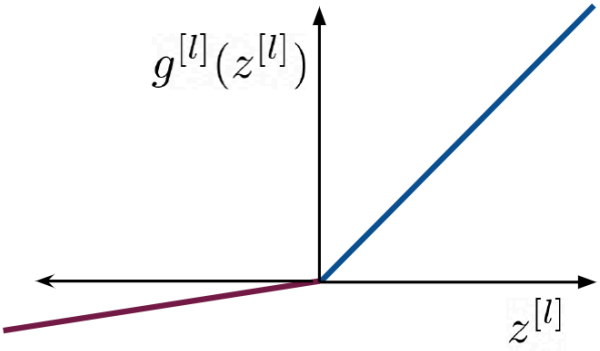
激活：Leaky ReLU

$$g^{[l]}(z^{[l]}) = max(az^{[l]}, z^{[l]})$$



解决垂死的 ReLU 问题

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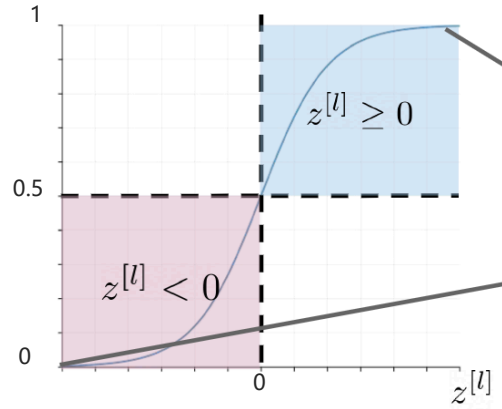
激活： Sigmoid

$$g^{[l]}(z^{[l]}) = \frac{1}{1+e^{-z^{[l]}}}$$



介于 0 之间的值
和 1

梯度消失和饱和度问题

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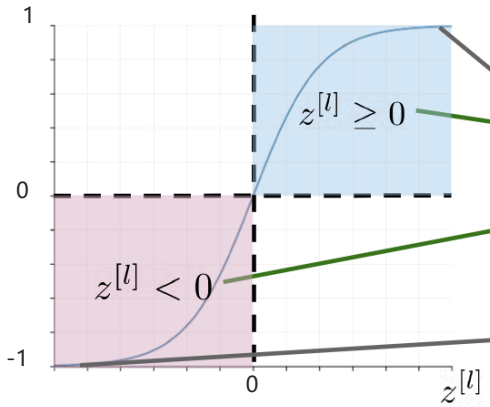
激活： Tanh

$$g^{[l]}(z^{[l]}) = tanh(z^{[l]})$$



介于 -1 之间的值
和 1

保留
输入

与
乙状结肠

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总结

- ReLU 激活会因 ReLU 的死亡而受到影响
- Leaky ReLU 解决了垂死的 ReLu 问题
- Sigmoid 和 Tanh 存在梯度消失和饱和度问题

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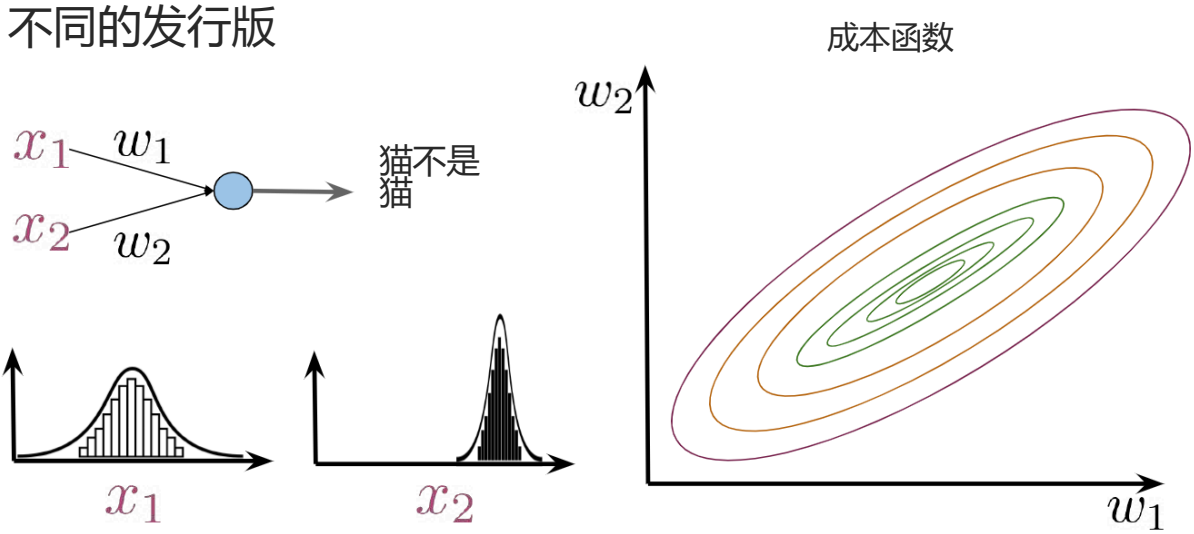
批量规范化（已解释）

大纲

- 规范化如何帮助模型
- 内部协变量偏移
- 批量规范化

不同的发行版



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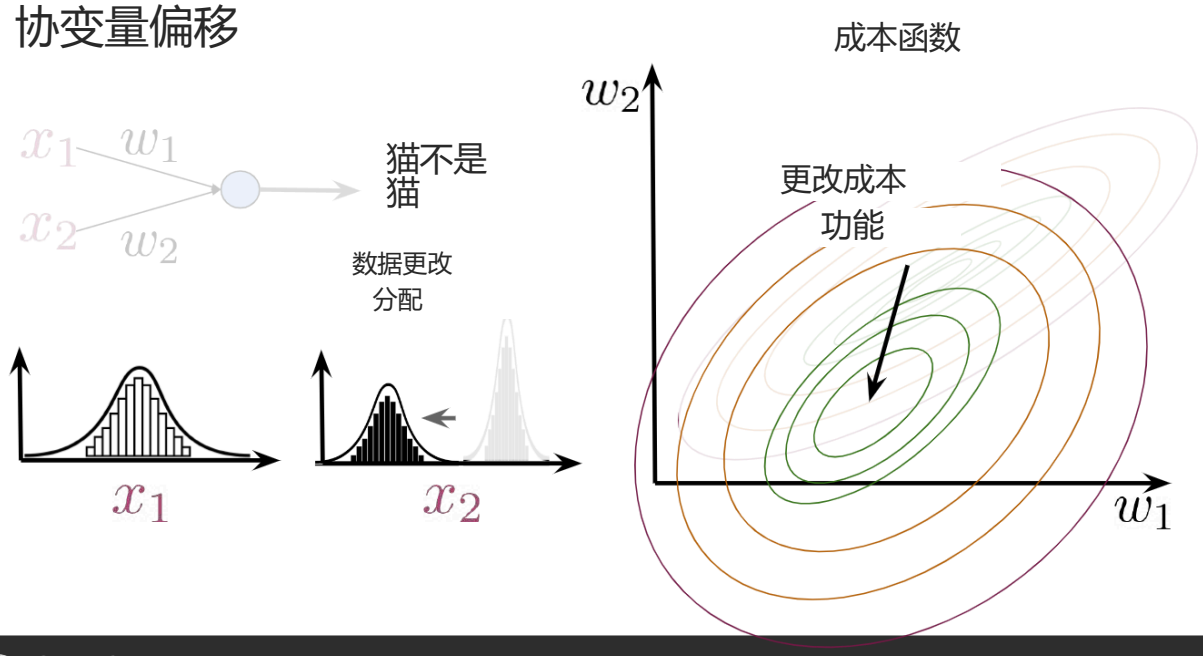
协变量偏移



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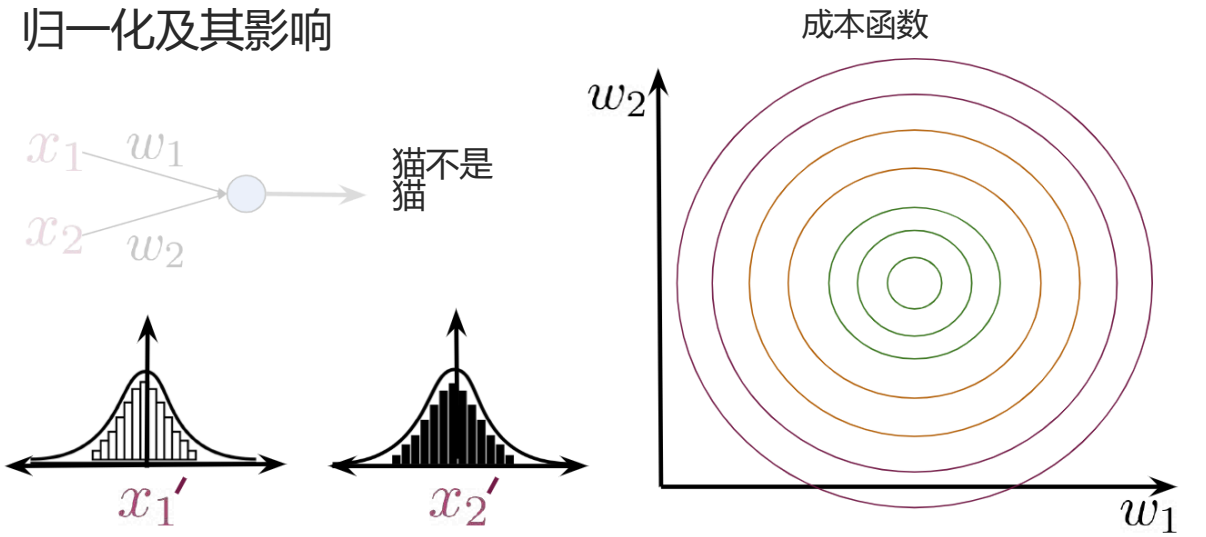
归一化及其影响



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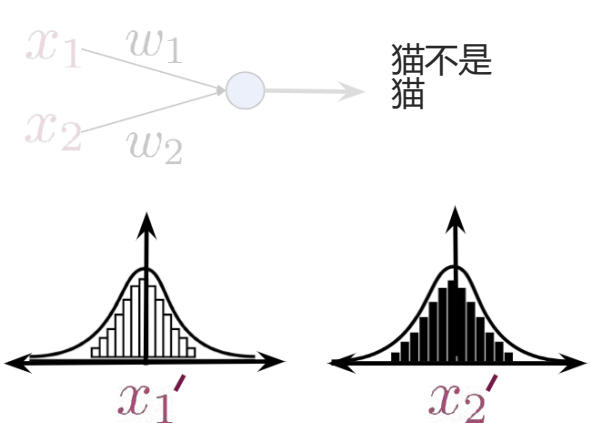
归一化及其影响



x_1' x_2'

在 0 处接近平均值，
在 1 处接近标准差

训练数据用途
批量统计

测试数据使用训练统计信息

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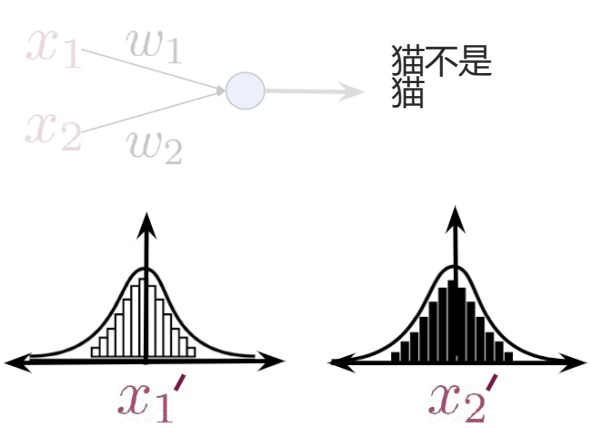
归一化及其影响



x_1' x_2'

在 0 处接近平均值，
在 1 处接近标准差

↓

减少协变量偏移

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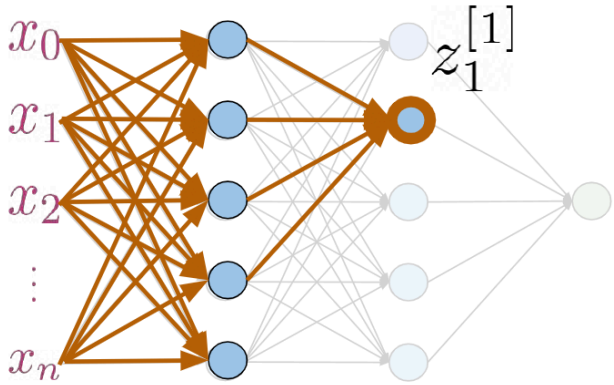
内部协变量偏移



更改
权重

↓

激活分布的
变化

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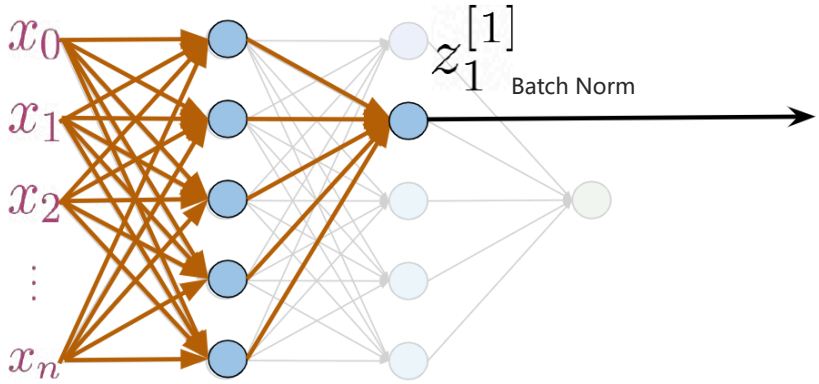
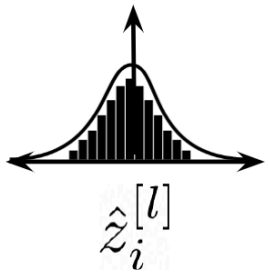
批量规范化



标准化每个神经
元的输入



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总结

- 批量规范化对成本函数进行平滑处理
- 批量归一化减少了内部协变量偏移
- 批量规范化加快了学习速度！

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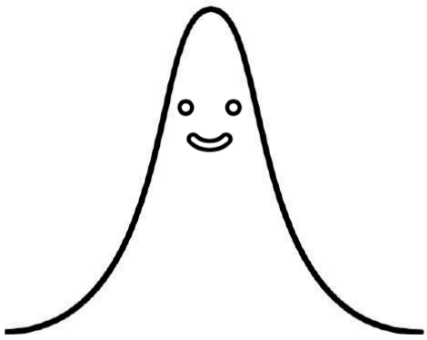
批量规范化（过程）

大纲

- 用于训练的 Batch 规范
- 用于测试的 Batch 规范



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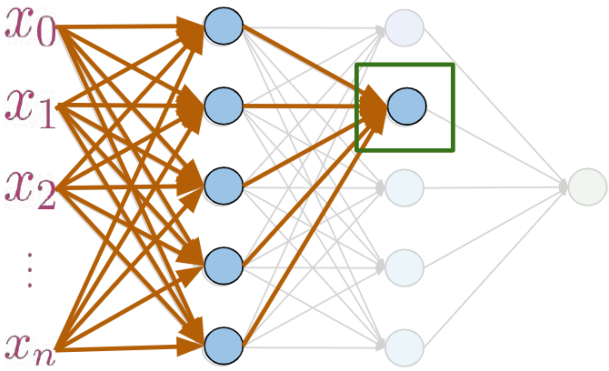
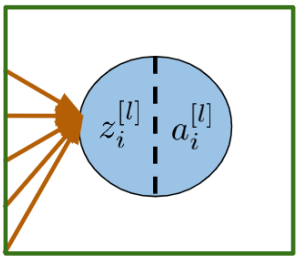
批量规范化：训练





$$z_i^{[l]} = \sum_{i=0} W_i^{[l]} a_i^{[l-1]}$$

对于批处理中的每个示例

$$\hat{z}_i^{[l]} = \frac{z_i^{[l]} - \mu_{z_i^{[l]}}}{\sqrt{\sigma^2_{z_i^{[l]}} + \epsilon}}$$

批次均值 $z_i^{[l]}$

批次标准 $z_i^{[l]}$

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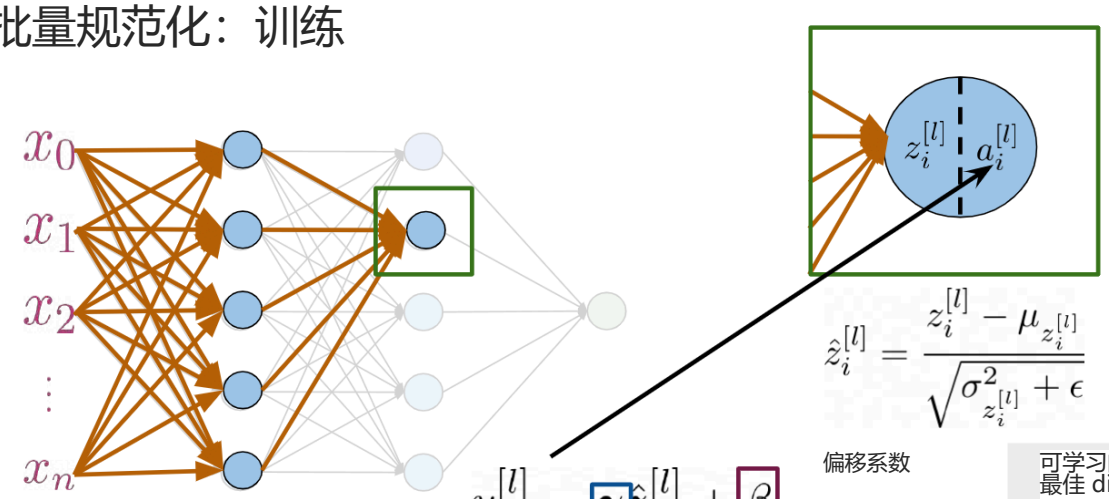
批量规范化：训练



$$\hat{z}_i^{[l]} = \frac{z_i^{[l]} - \mu_{z_i^{[l]}}}{\sqrt{\sigma^2_{z_i^{[l]}} + \epsilon}}$$

$$y_i^{[l]} = \boxed{\gamma}\hat{z}_i^{[l]} + \boxed{\beta}$$

偏移系数

比例因子

可学习的参数来获得最佳 dist。

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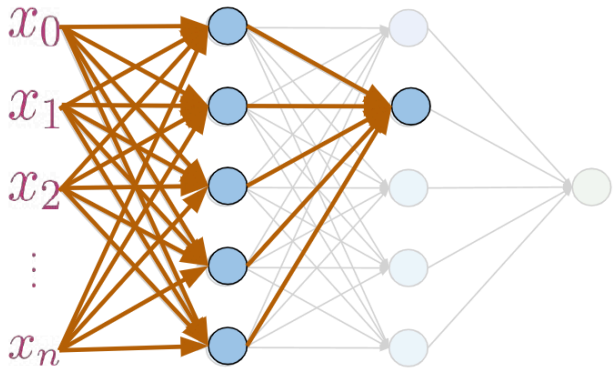
批量规范化：测试



$$\hat{z}_i^{[l]} = \frac{z_i^{[l]} - \boxed{\mathbf{E}(z_i^{[l]})}}{\boxed{\sqrt{\mathrm{Var}(z_i^{[l]}) + \epsilon}}}$$

Running mean 和 Running

来自训练的性病

Tensorflow 和 Pytorch 等框架会跟踪它们

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总结

- Batch Norm 引入了可学习的移位和比例因子
- 在测试期间，将使用训练的运行统计数据
- 框架负责整个过程

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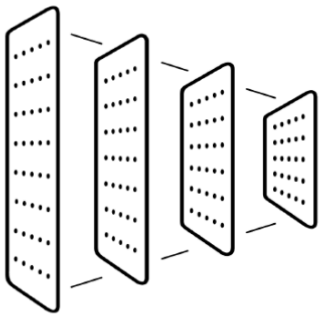
卷积回顾

大纲

- 什么是卷积
- 运作方式



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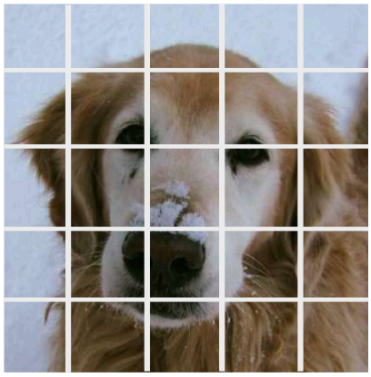
什么是卷积?



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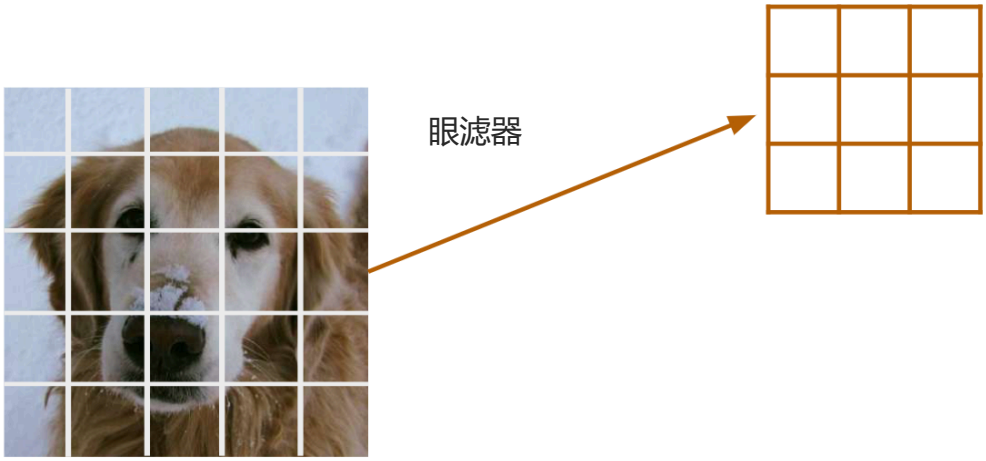
什么是卷积?



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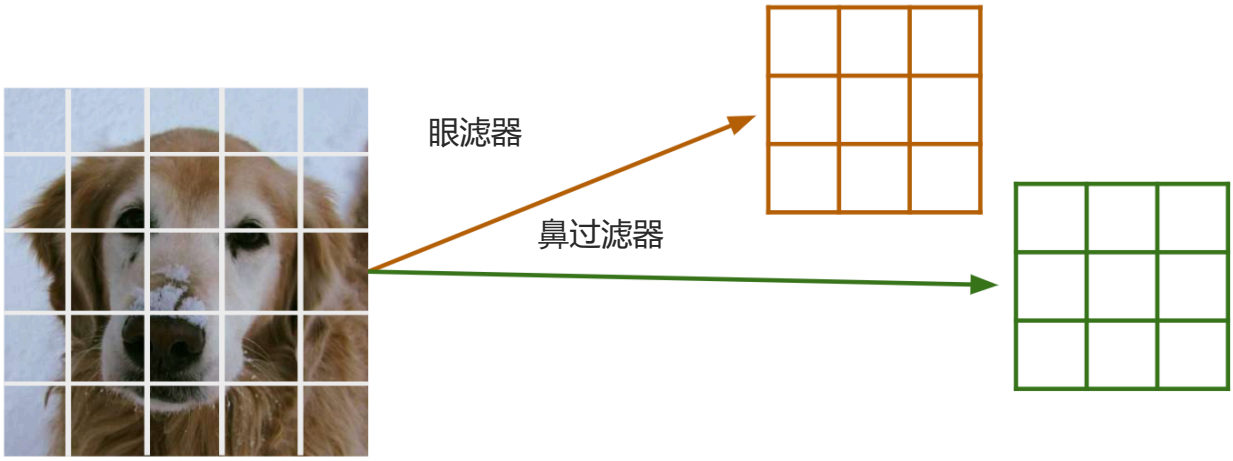
什么是卷积?



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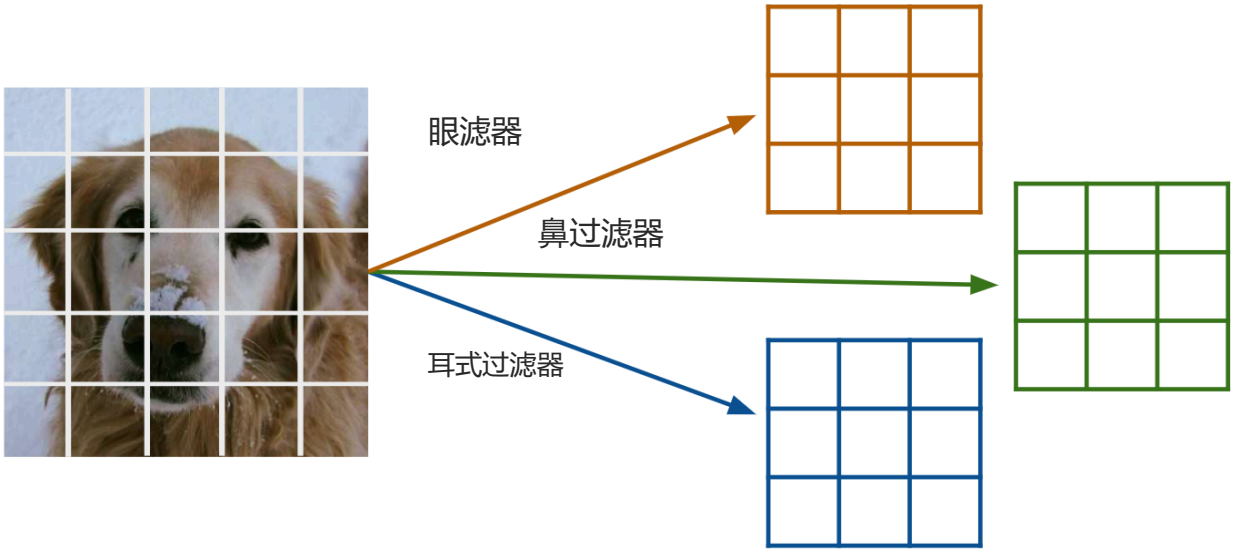
什么是卷积?



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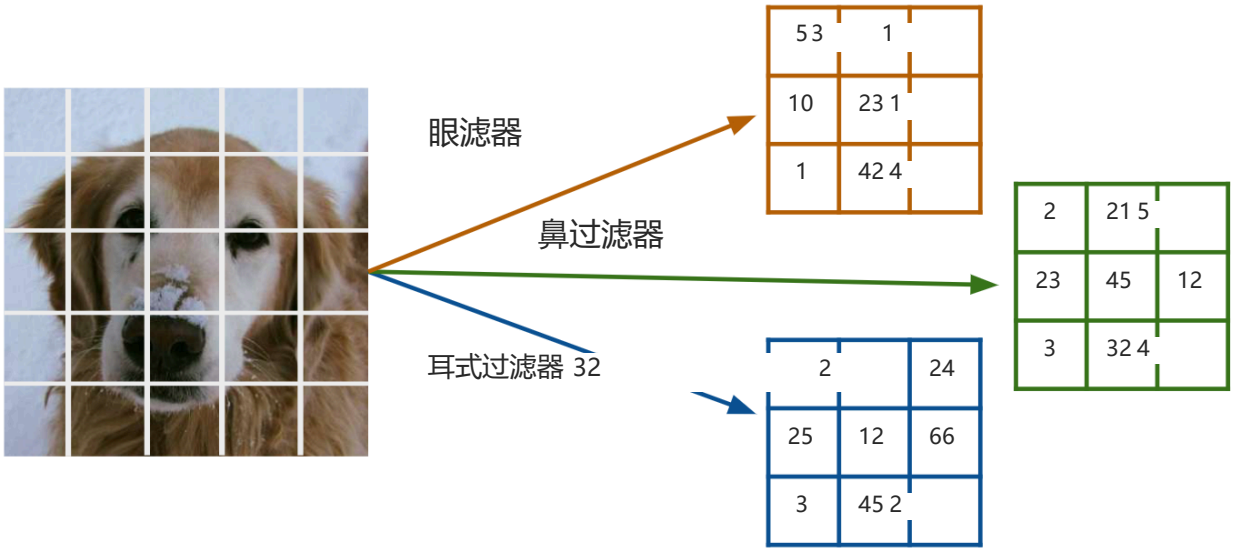
什么是卷积?



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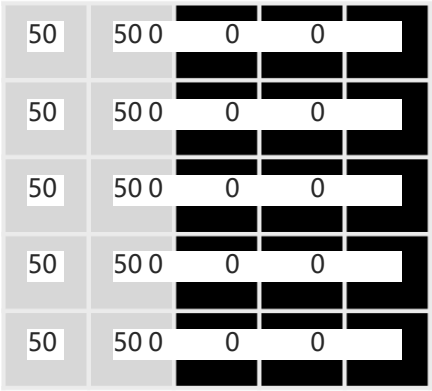
什么是卷积?



灰度图像

0（黑色）到 255（白色）

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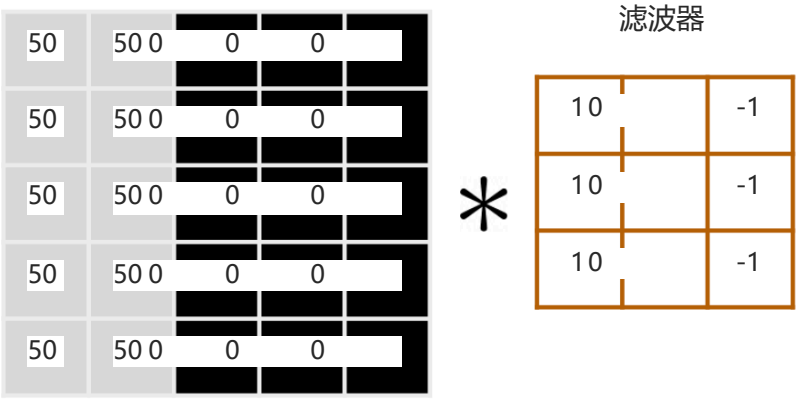
什么是卷积?



灰度图像

0（黑色）到 255（白色）

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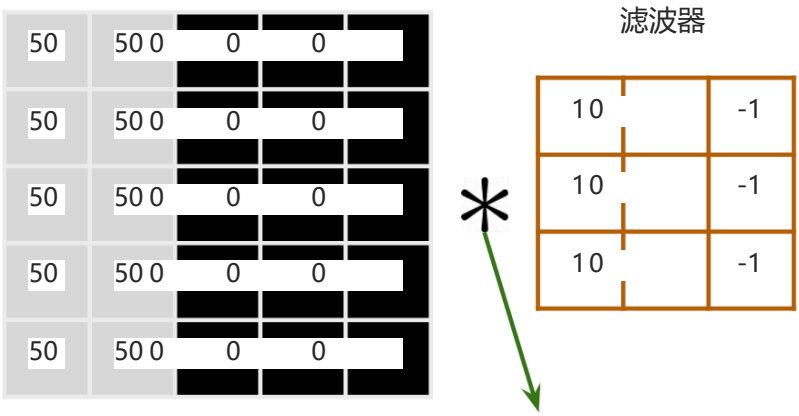
什么是卷积?



灰度图像 卷积 0（黑色）到 255（白色）

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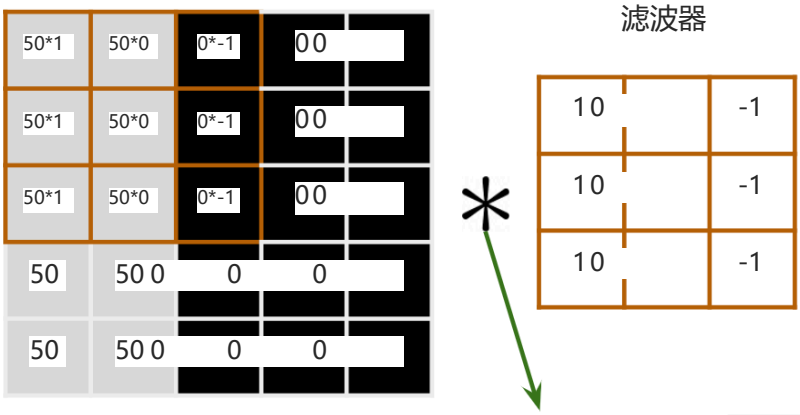
什么是卷积?



灰度图像 卷积 0（黑色）到 255（白色）

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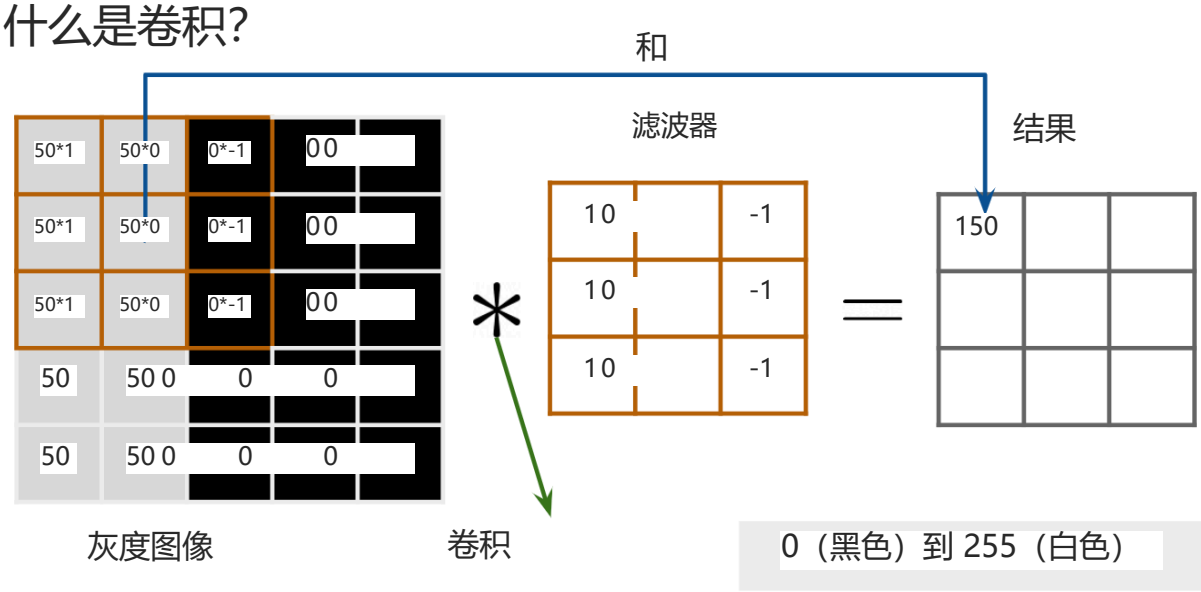
什么是卷积?



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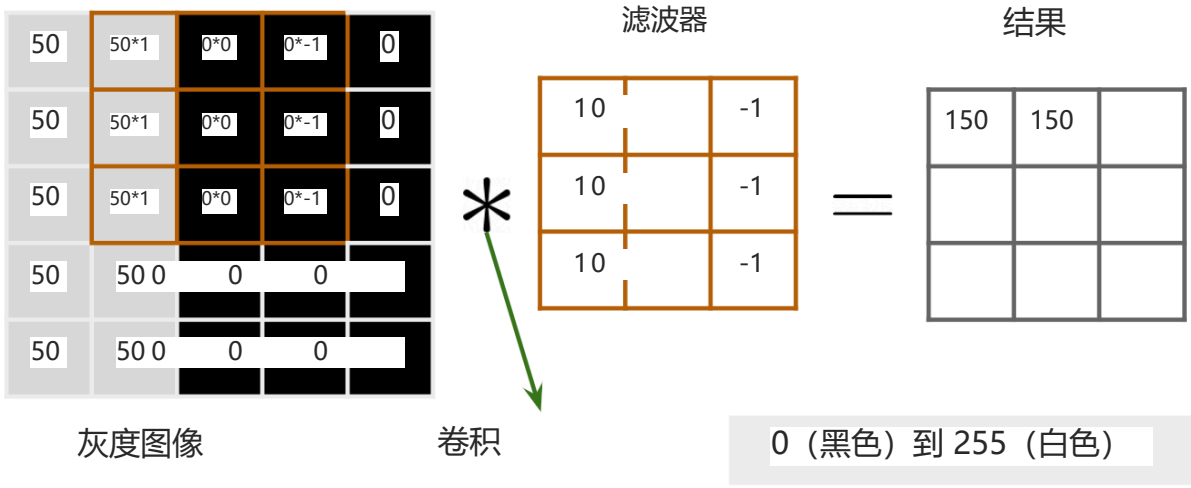
什么是卷积?



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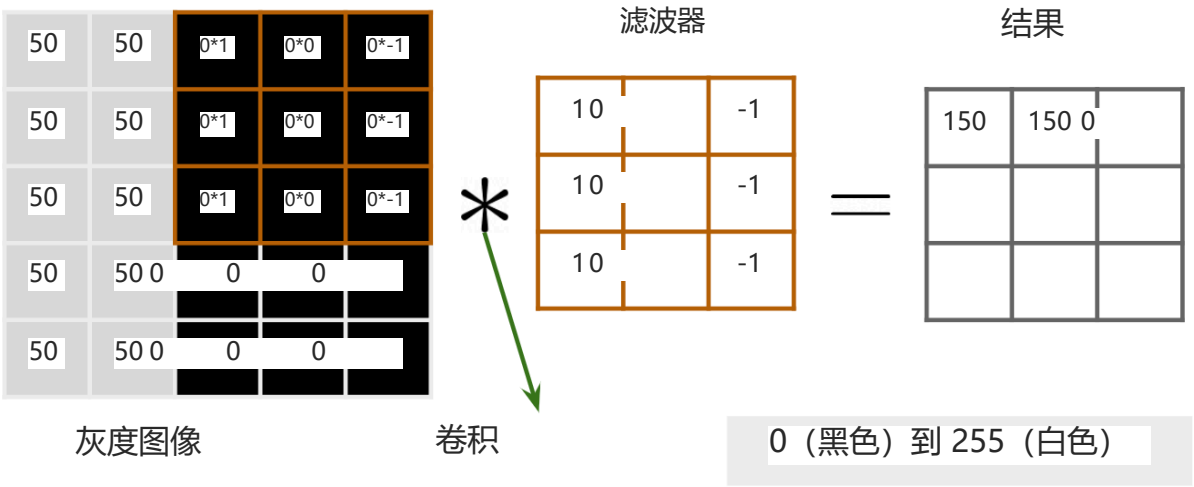
什么是卷积?



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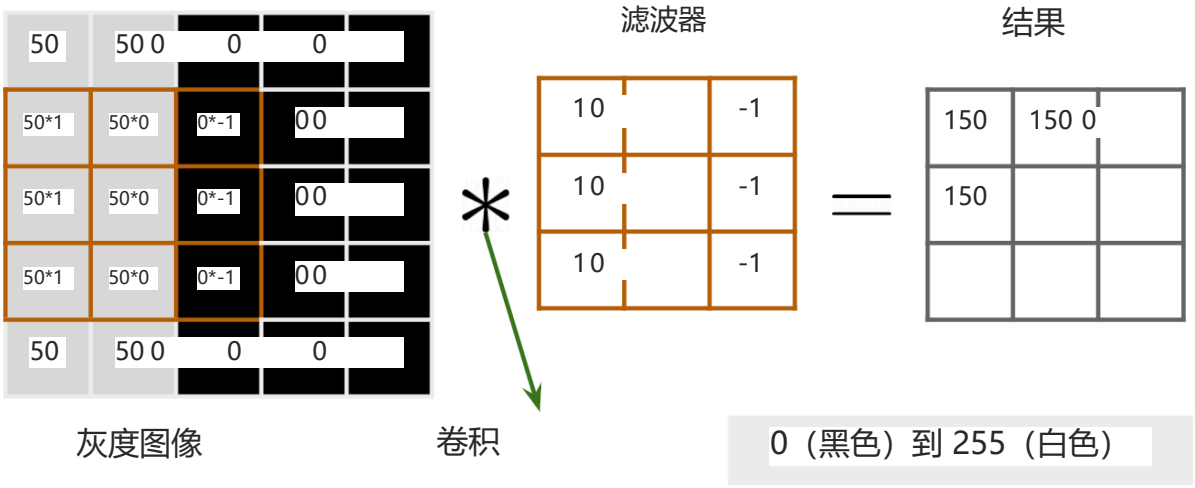
什么是卷积?



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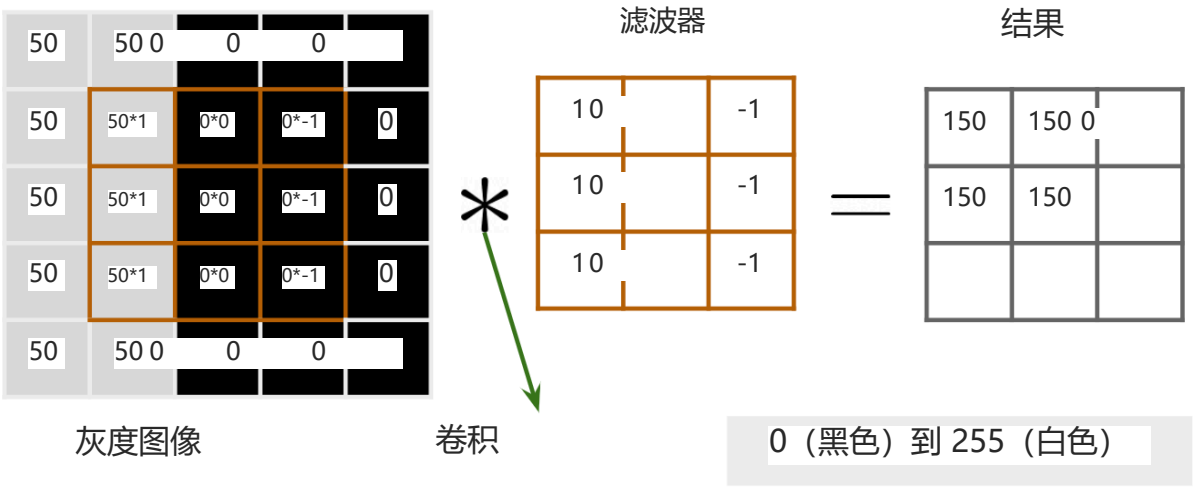
什么是卷积?



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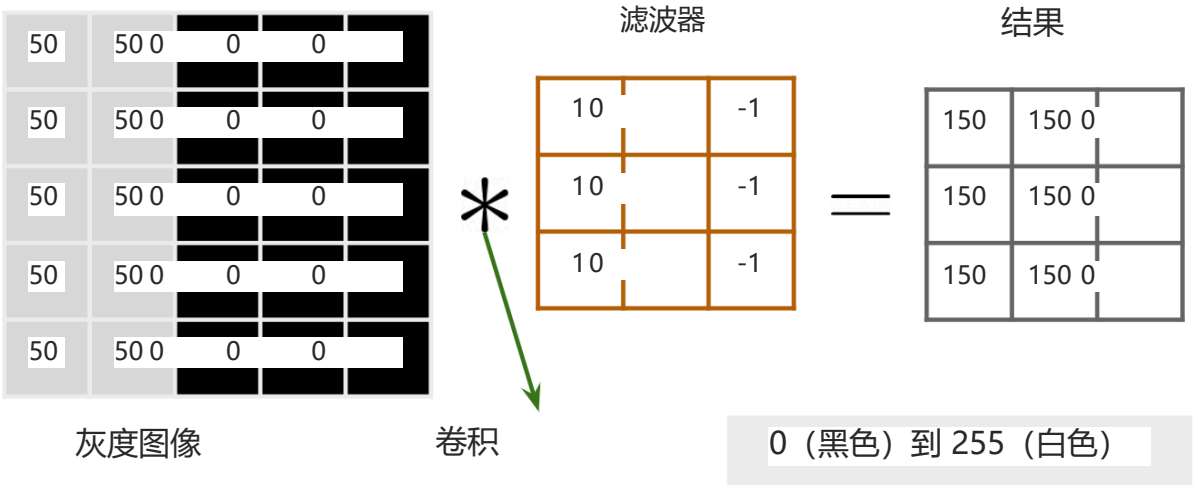
什么是卷积?



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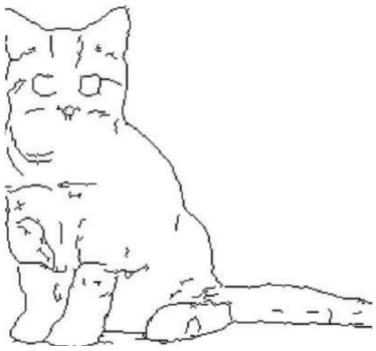
总结

- 卷积是处理图像的有用层
- 他们扫描图像以检测有用的特征
- 只是元素乘积和求和！



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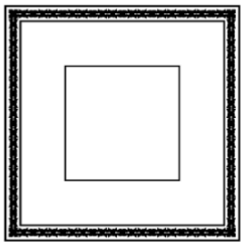
Padding 和跨

大纲

- 填充和步幅
- 填充背后的直觉



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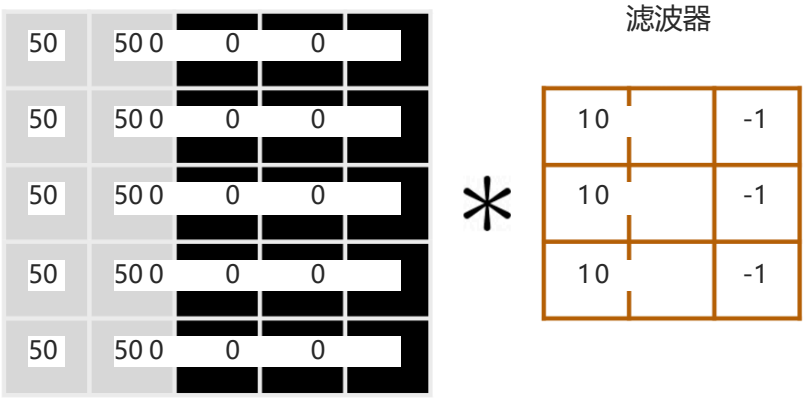
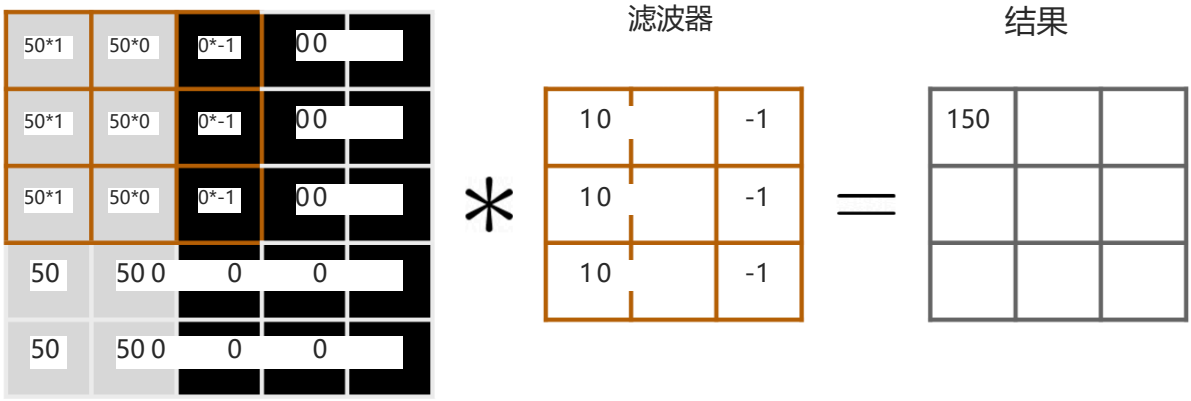
跨



灰度图像

deeplearning.ai

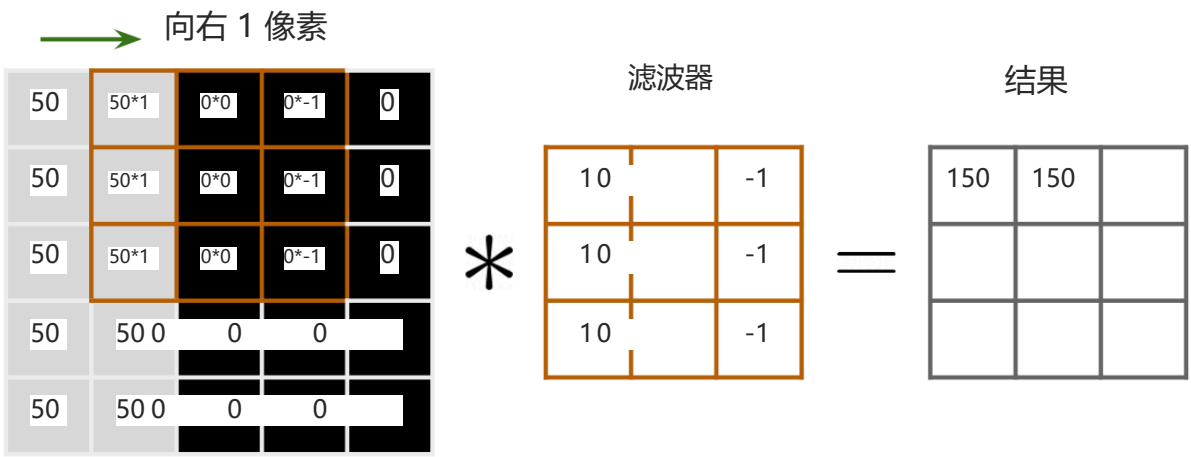
跨



灰度图像

deeplearning.ai

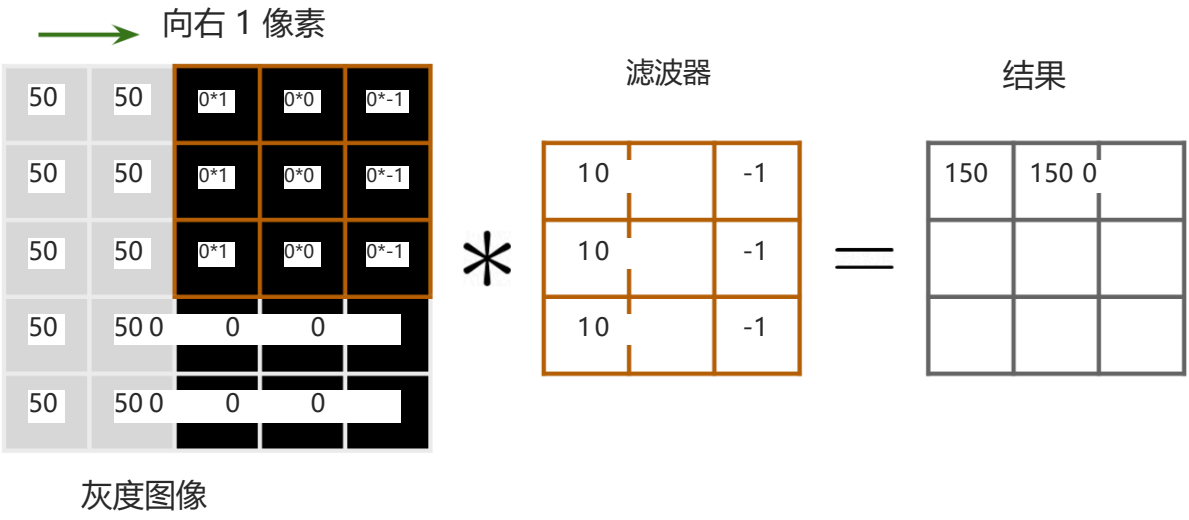
跨



灰度图像

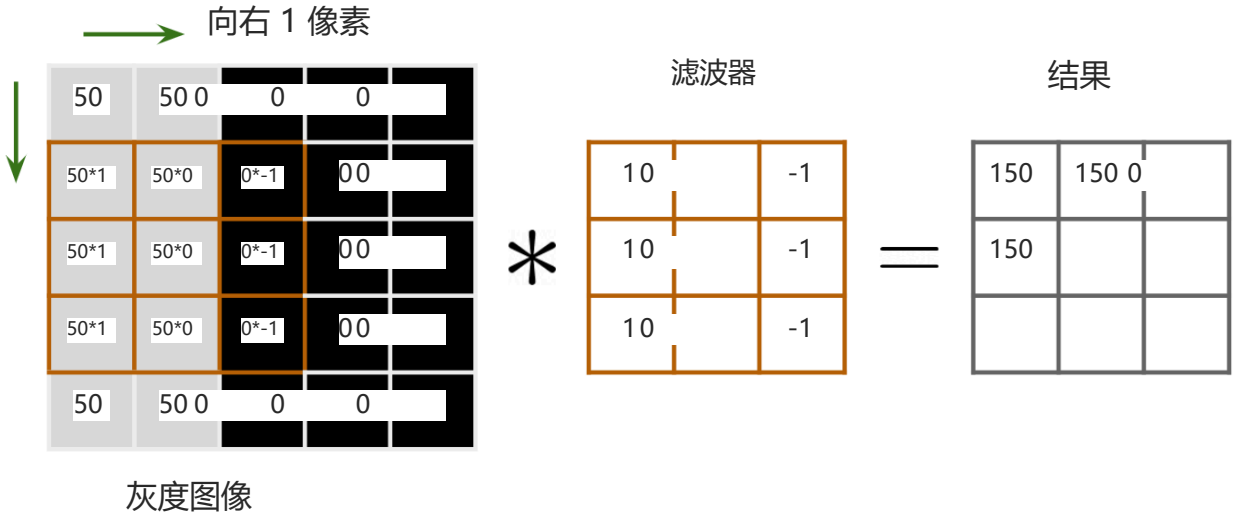
deeplearning.ai

跨



deeplearning.ai

跨



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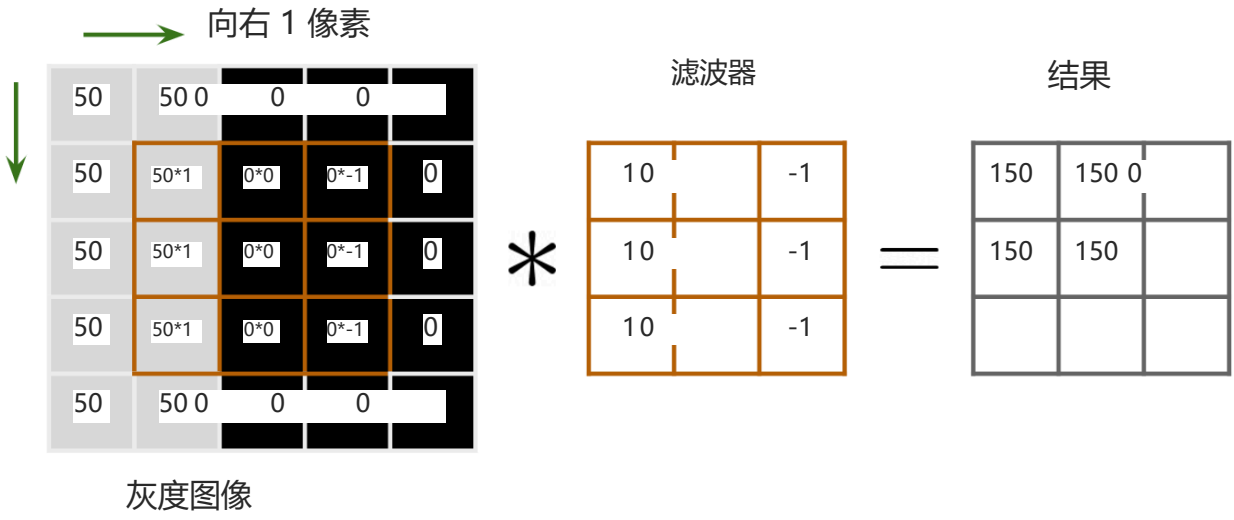
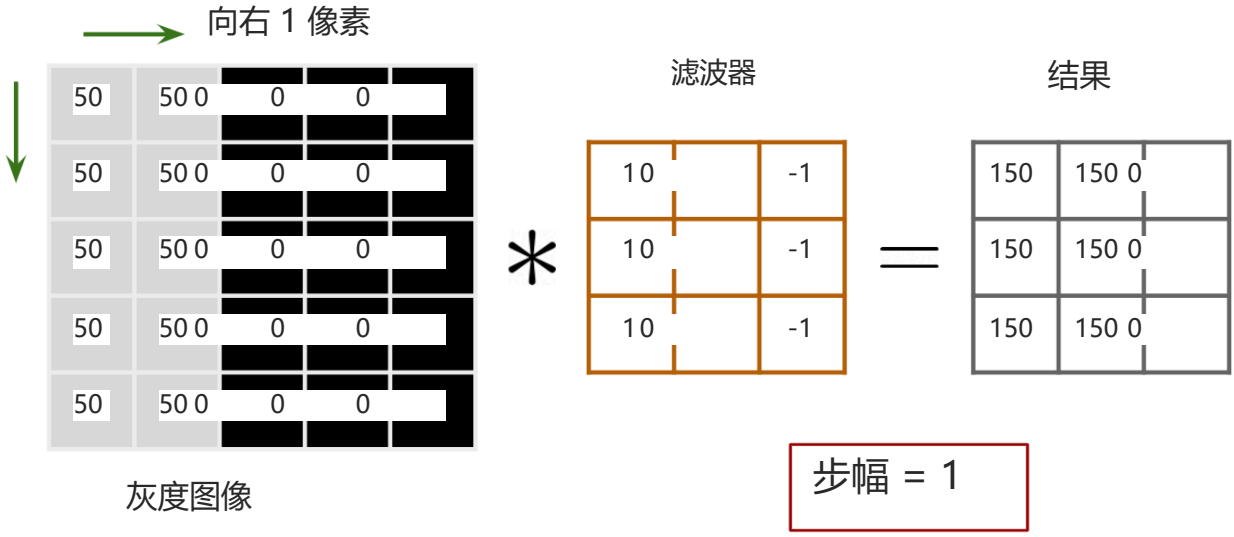
跨



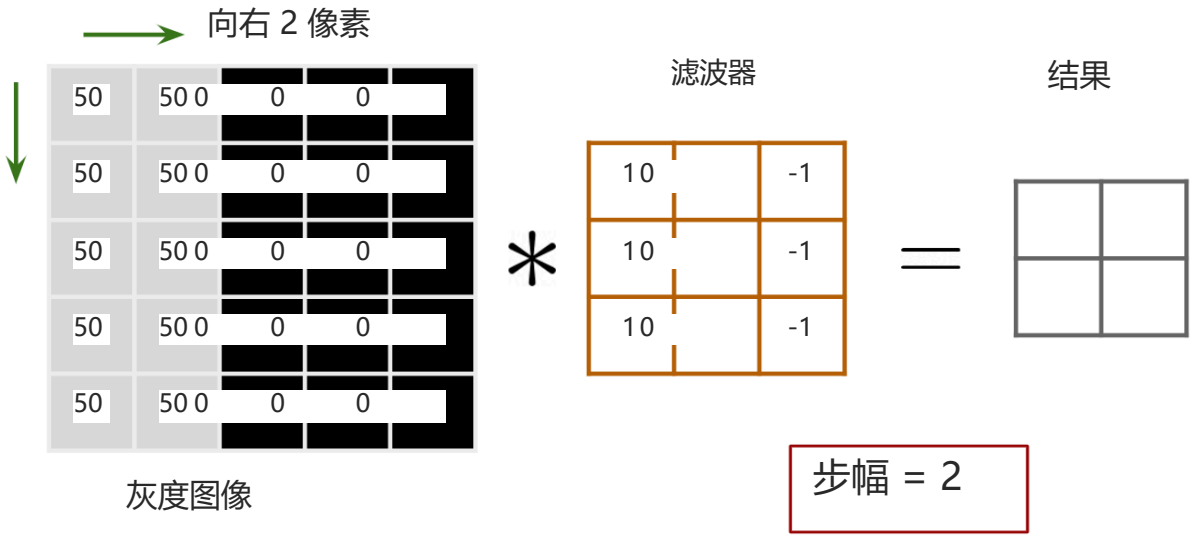
deeplearning.ai

跨



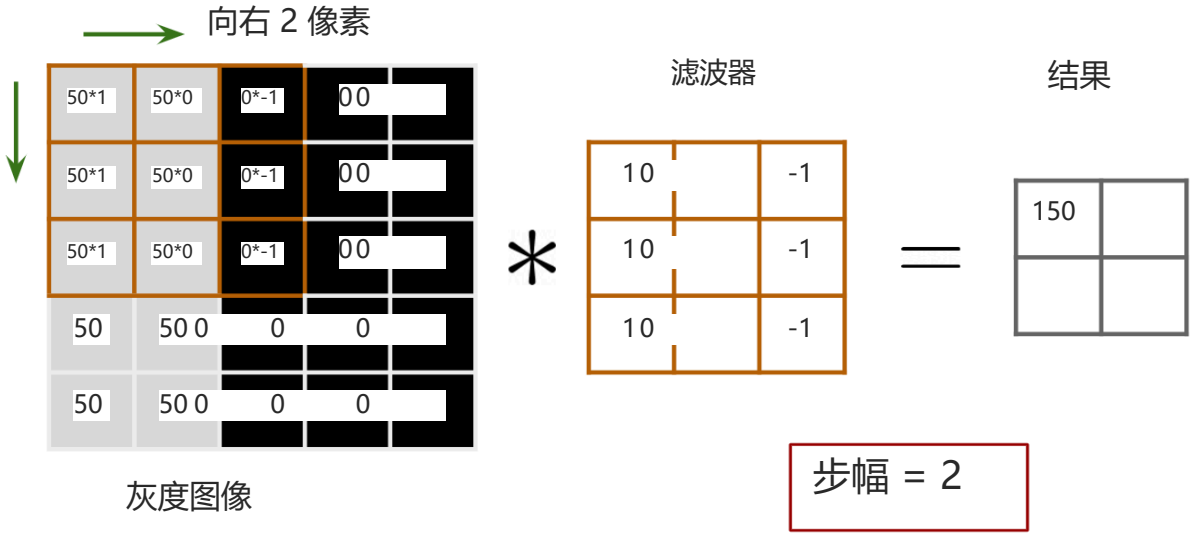
deeplearning.ai

跨



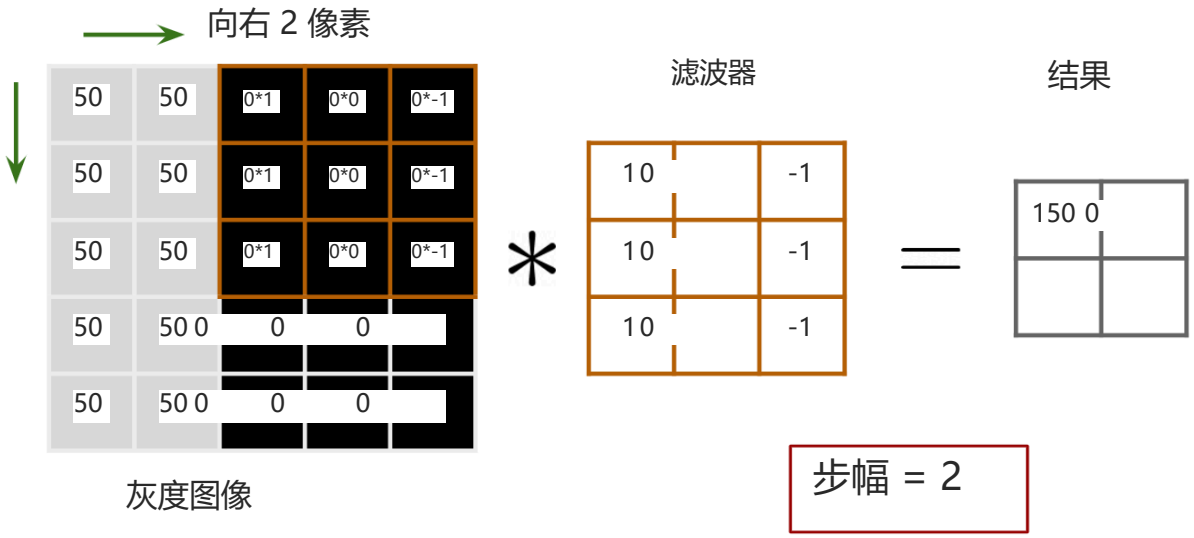
deeplearning.ai

跨



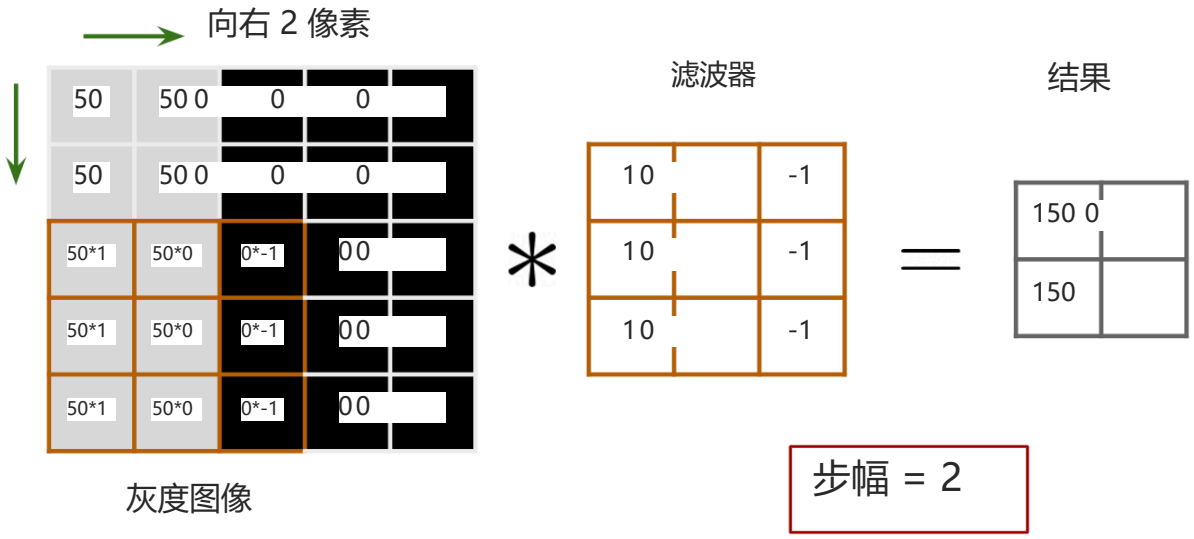
deeplearning.ai

跨



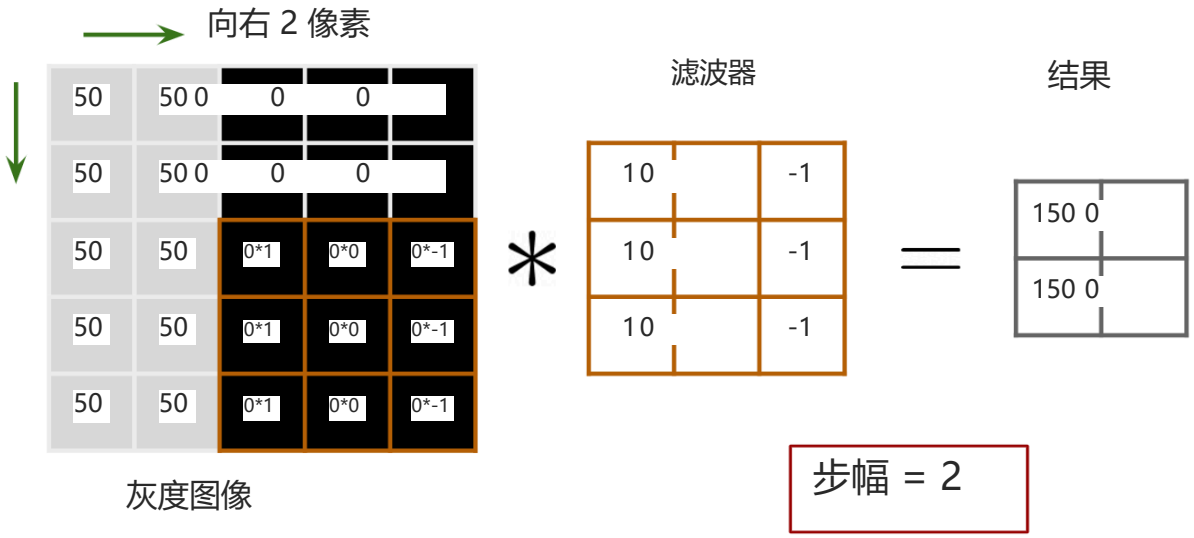
deeplearning.ai

跨



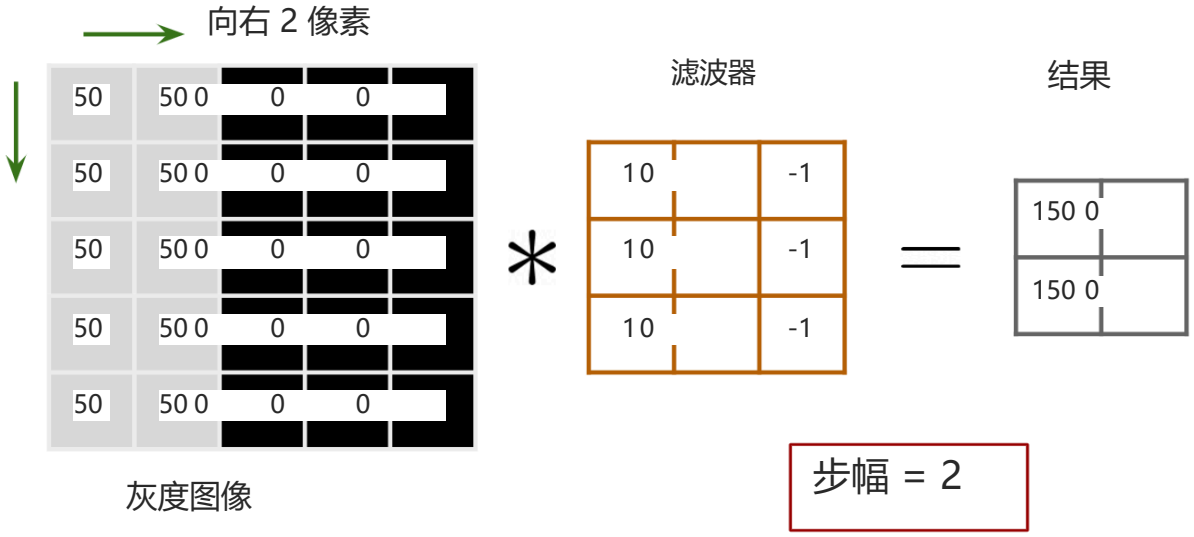
deeplearning.ai

跨



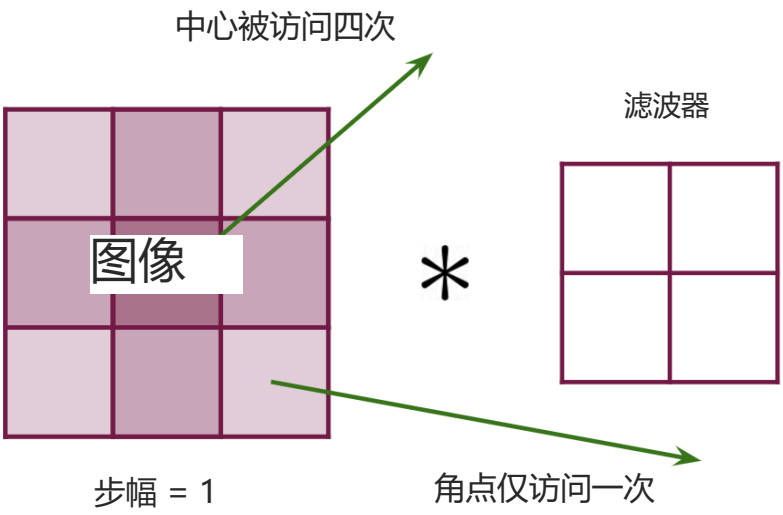
deeplearning.ai

跨



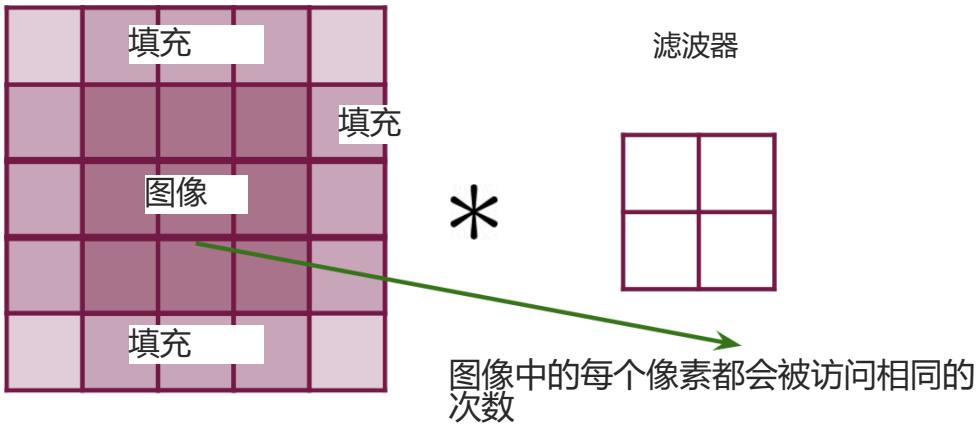
deeplearning.ai

填充



deeplearning.ai

填充



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总结

- 步幅确定滤镜扫描图像的方式
- 填充就像图像上的一个框架
- Padding 对 edges 和 center 给予类似的重要性

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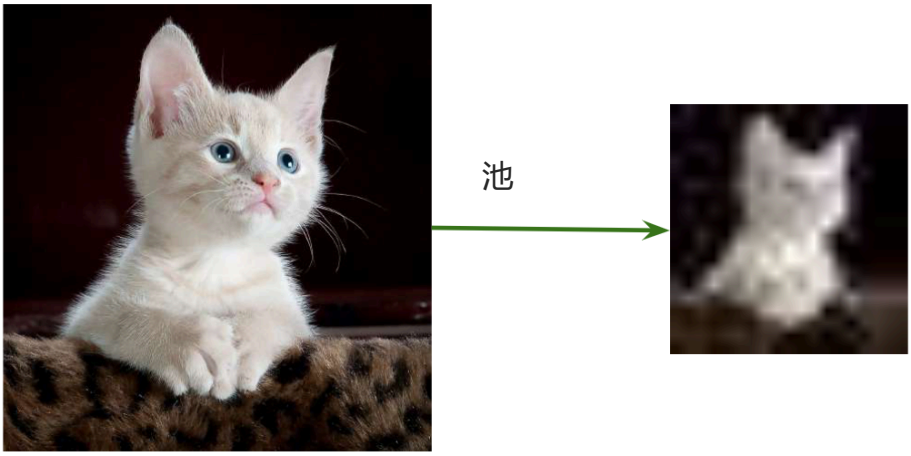
池化和上采样

大纲

- 池
- 上采样及其与池的关系

池



最大池化

4x4 输入到 2x2 输出

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最大池化

4x4 输入到 2x2 输出

deeplearning.ai

最大池化

4x4 输入到 2x2 输出

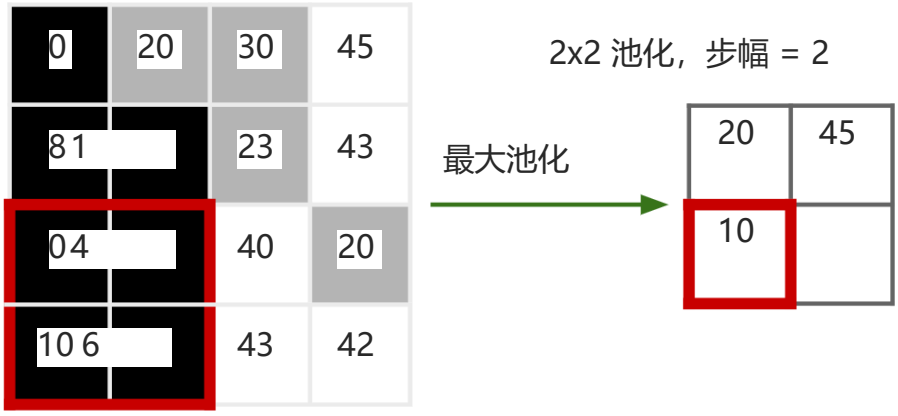
deeplearning.ai

最大池化

4x4 输入到 2x2 输出

deeplearning.ai

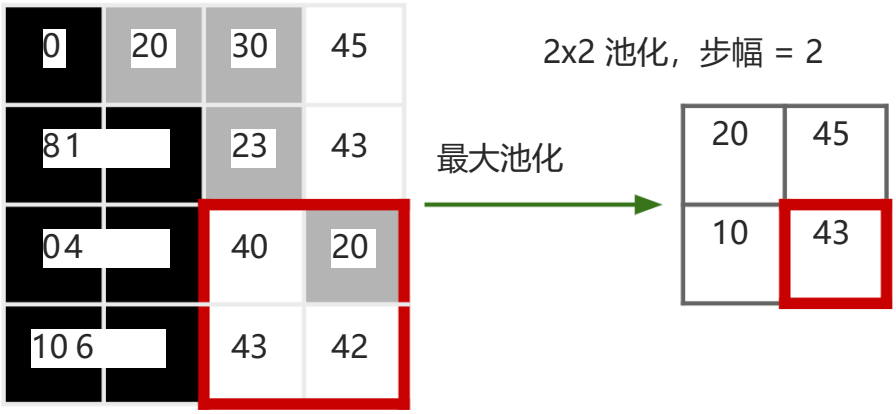
最大池化



4x4 输入到 2x2 输出

deeplearning.ai

最大池化



4x4 输入到 2x2 输出

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最大池化

0	20	30	45
81		23	43
04		40	20
10 6		43	42

4x4 输入到 2x2 输出

2x2 池化，步幅 = 2

最大池化 →

20	45
10	43

其他类型包括：1. 平均池化

2. 最小池化

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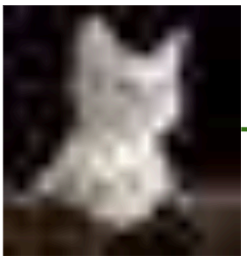
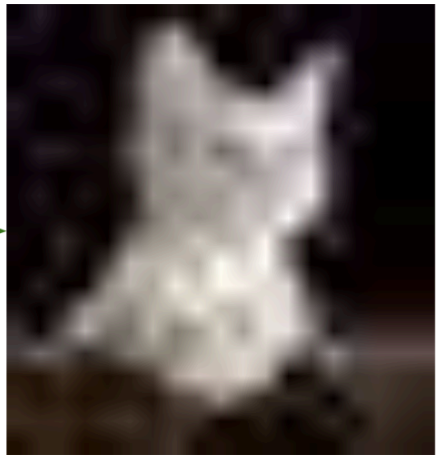
上采样



上采样 →



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Upsampling：最近邻

2x2 输入到 4x4 输出

20	45
10	43

上采样 →

20	20	45	45
20	20	45	45
10	10	43	43
10	10	43	43

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Upsampling：最近邻

2x2 输入到 4x4 输出

20	45
10	43

上采样 →

20	20	45	45
20	20	45	45
10	10	43	43
10	10	43	43

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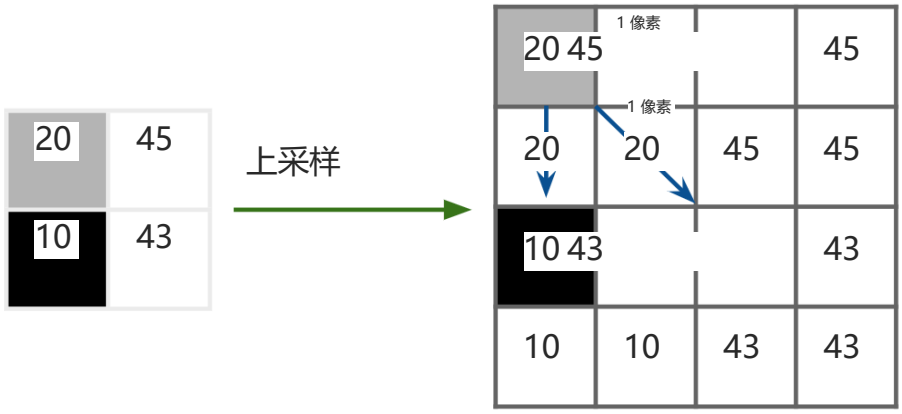
Upsampling：最近邻

2x2 输入到 4x4 输出



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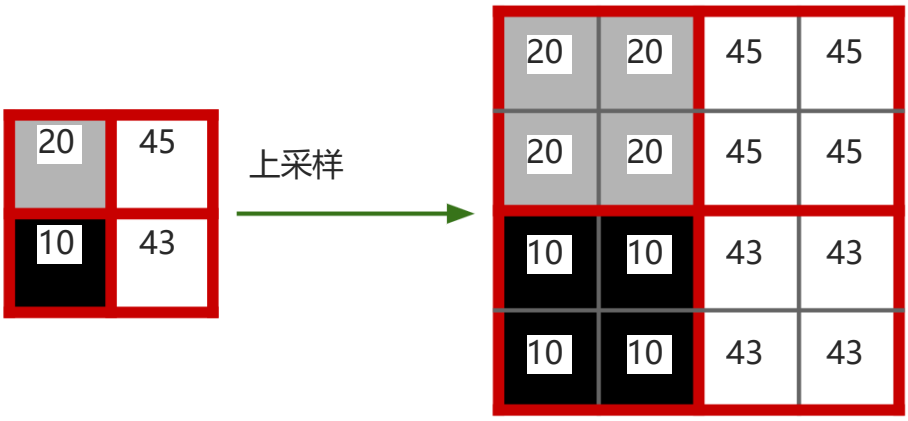
Upsampling：最近邻

2x2 输入到 4x4 输出



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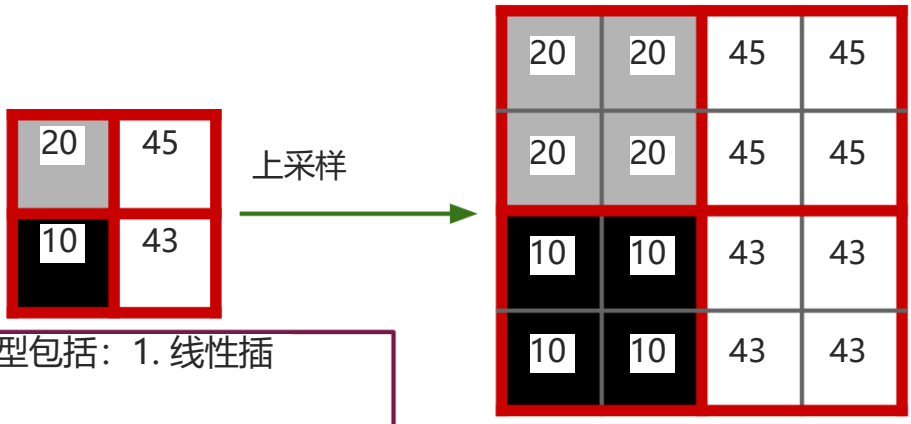
Upsampling：最近邻

2x2 输入到 4x4 输出



其他类型包括：1. 线性插值

2. 双线性插值

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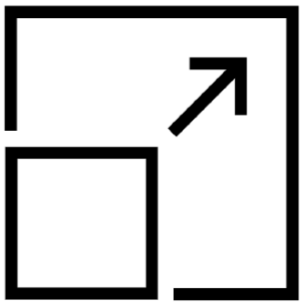
总结

- 池化可减小输入的大小
- 上采样会增加输入的大小
- 没有可学习的参数！



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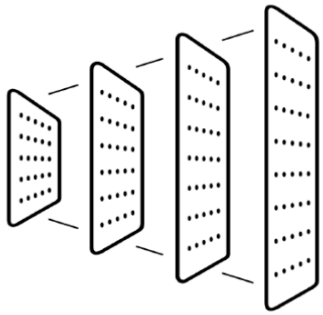
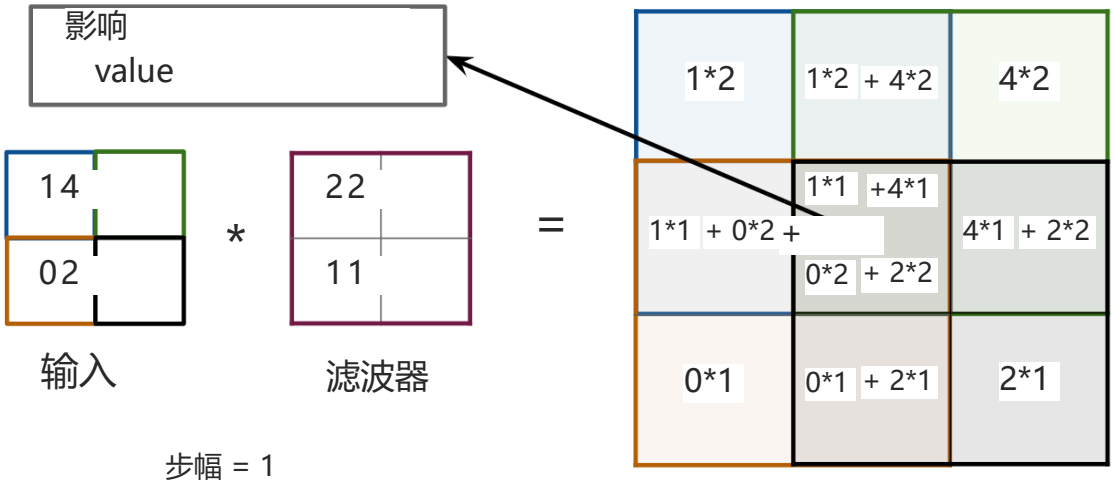
转置卷积

大纲

- 转置卷积作为上采样技术
- 转置卷积的问题



转置卷积



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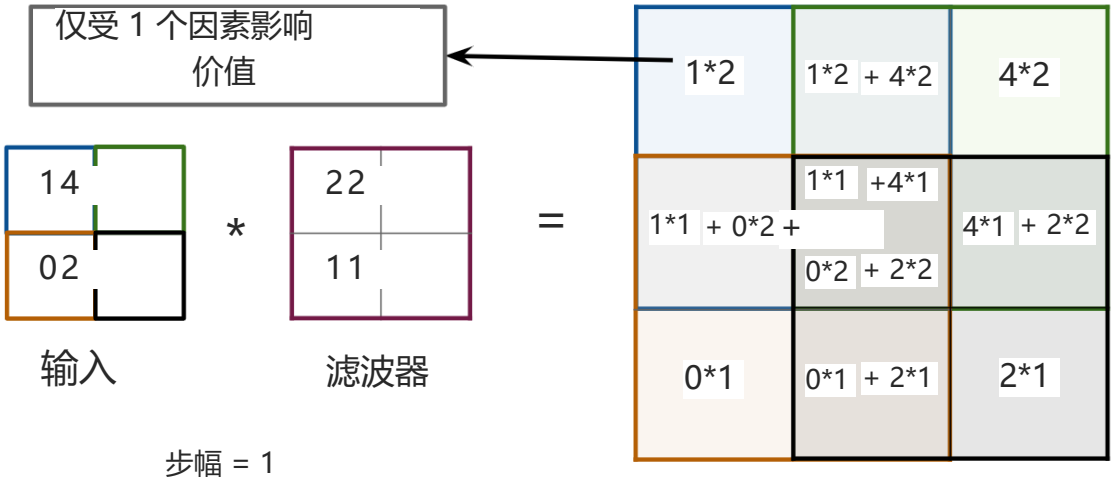
转置卷积



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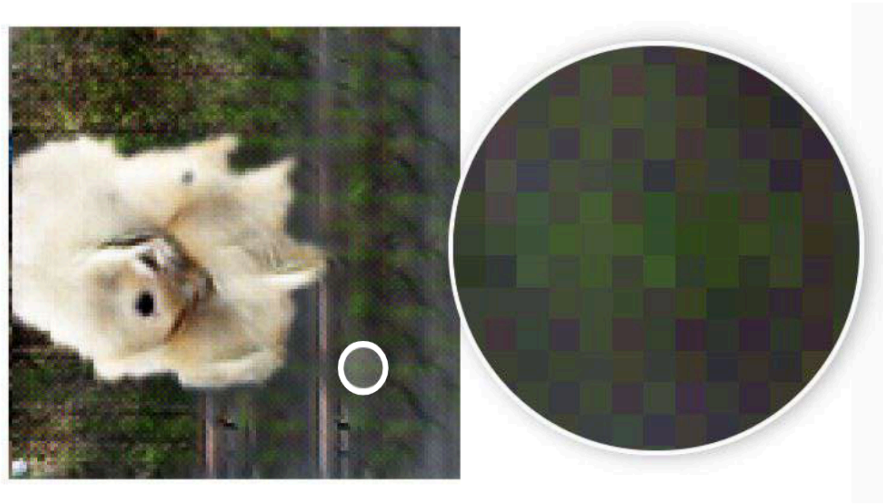
转置卷积的问题



棋盘
模式

可从： http://doi.org/10.23915/distill.00003

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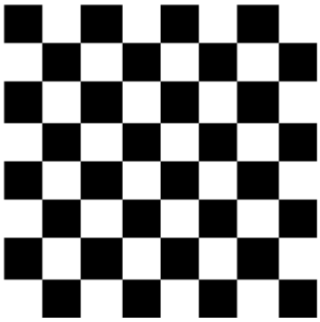
总结

- 转置卷积 upsample
- 它们具有可学习的参数
- 问题：结果具有棋盘格图案



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