INF-0618
Tópicos em Aprendizado de Máquina II

Aula 4 – Arquiteturas CNN

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2018

Instituto de Computação - Unicamp

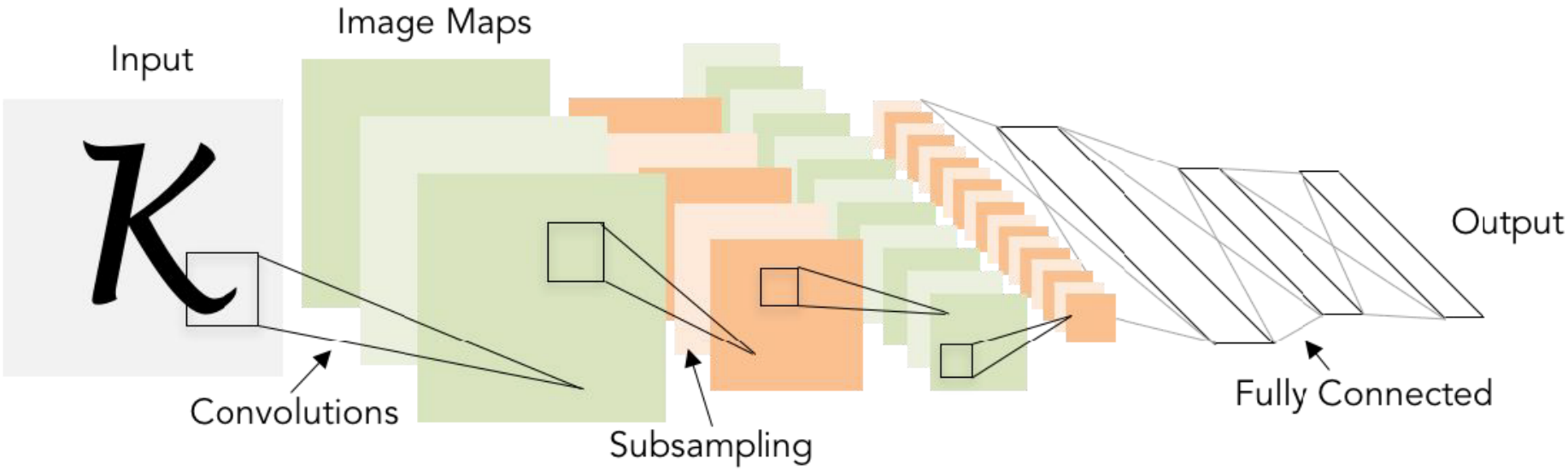
Arquiteturas CNN

Arquiteturas CNN

- LeNet
- AlexNet
- ZeNet
- VGGNet
- GoogLeNet (Inception-v1)
- ResNet
- SqueezeNet

LeNet-5

[LeCun et al., 1998]



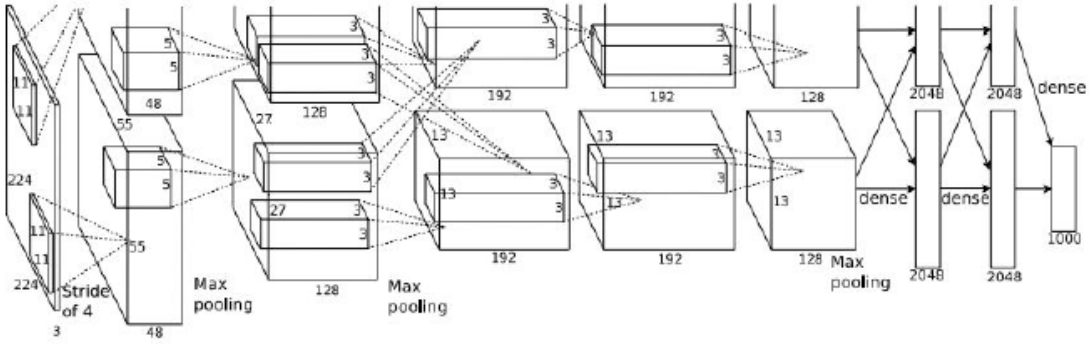
Conv filters: 5x5, stride 1
Pooling: 2x2, stride 2
Arquitetura: [CONV-POOL-CONV-POOL-FC-FC]

AlexNet

[Krizhevsky et al., 2012]

Arquitetura:

CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
Max POOL3
FC6
FC7
FC8



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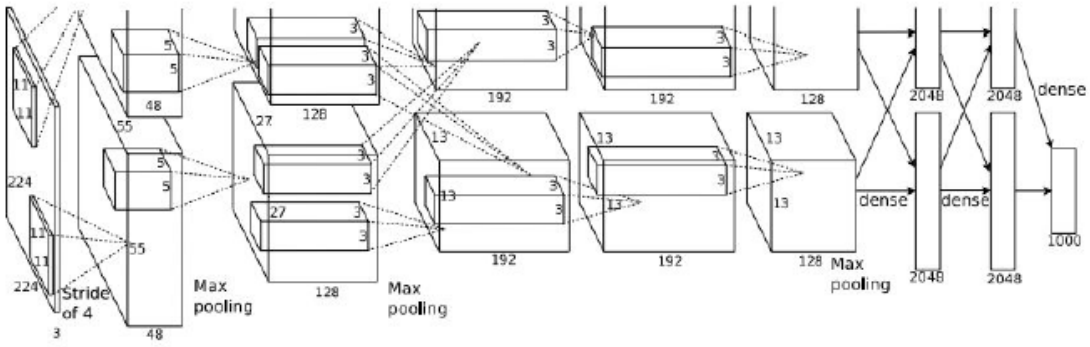
AlexNet

[Krizhevsky et al., 2012]



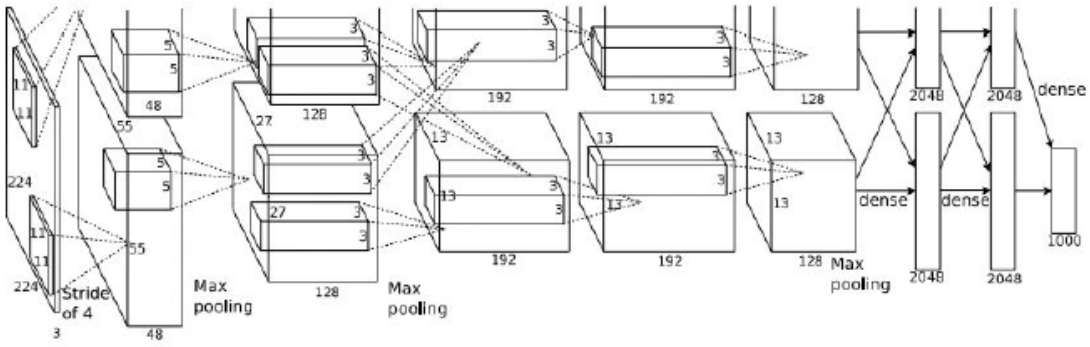
Input: imagens 227x227x3

Primeiro layer (CONV1): 96 filtros 11x11, com stride de 4.

=> Qual o tamanho do volume de saida? Dica: (227-11)/4+1 = 55

AlexNet

[Krizhevsky et al., 2012]



Input: imagens 227x227x3

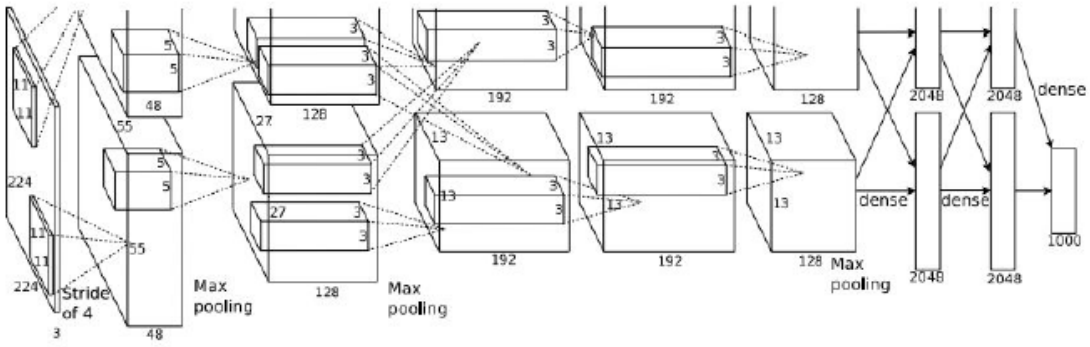
Primeiro layer (CONV1): 96 filtros 11x11, com stride de 4.

=> Volume de saída: [55x55x96]

=> Qual o total de parâmetros neste layer?

AlexNet

[Krizhevsky et al., 2012]



Input: imagens 227x227x3

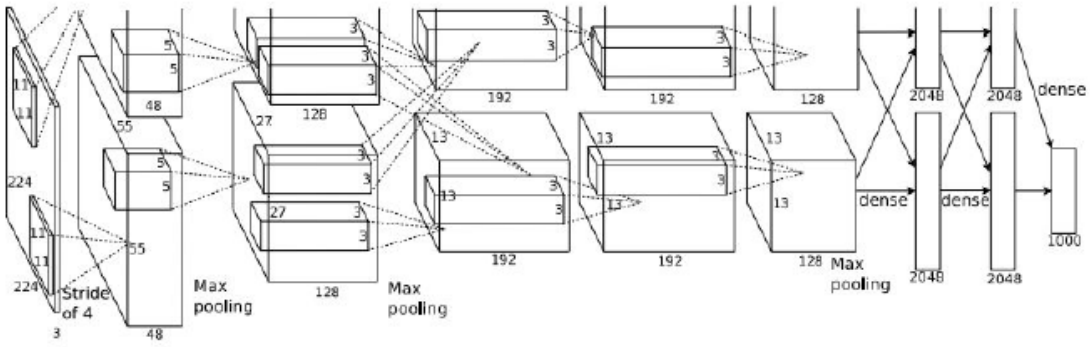
Primeiro layer (CONV1): 96 filtros 11x11, com stride de 4.

=> Volume de saída: [55x55x96]

=> Parâmetros: (11*11*3)*96 = 35K

AlexNet

[Krizhevsky et al., 2012]



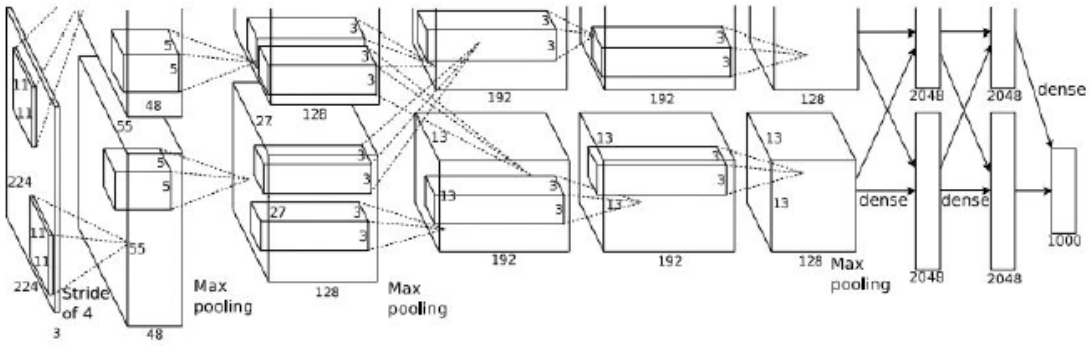
Input: imagens 227x227x3
Depois da CONV1: 55x55x96

Segundo layer (POOL1): filtros 3x3, com stride 2

=> Qual o tamanho do volume de saída? Dica: (55-3)/2+1 = 27

AlexNet

[Krizhevsky et al., 2012]



Input: imagens 227x227x3
Depois da CONV1: 55x55x96

Segundo layer (POOL1): filtros 3x3, com stride 2

=> Volume de saída: [27x27x96]

=> Qual o total de parâmetros neste layer?

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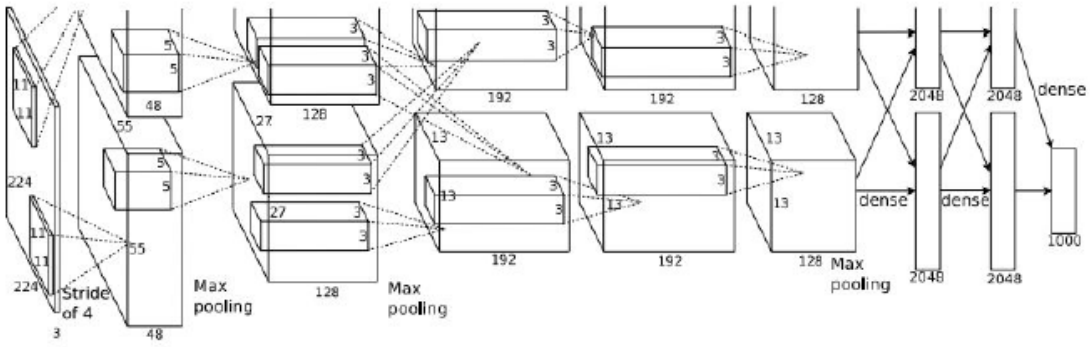
AlexNet

[Krizhevsky et al., 2012]



Input: imagens 227x227x3
Depois da CONV1: 55x55x96

Segundo layer (POOL1): filtros 3x3, com stride 2

=> Volume de saída: [27x27x96]

=> Parâmetros: 0

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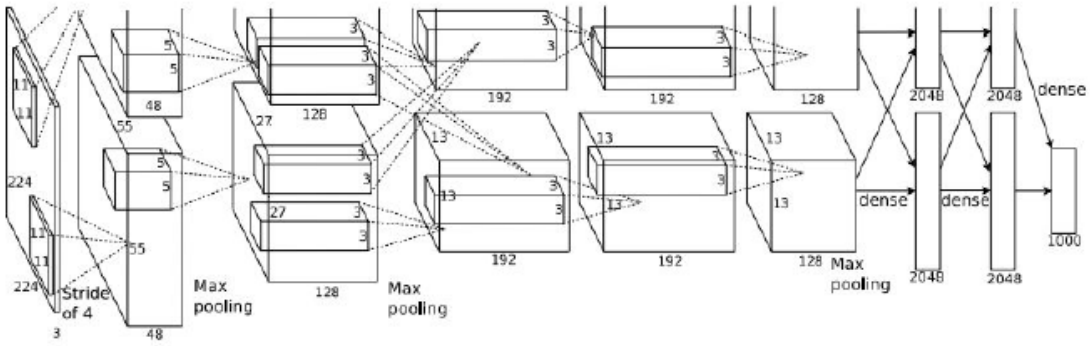
AlexNet

[Krizhevsky et al., 2012]



Input: imagens 227x227x3
Depois da CONV1: 55x55x96
Depois da POOL1: 27x27x96
...

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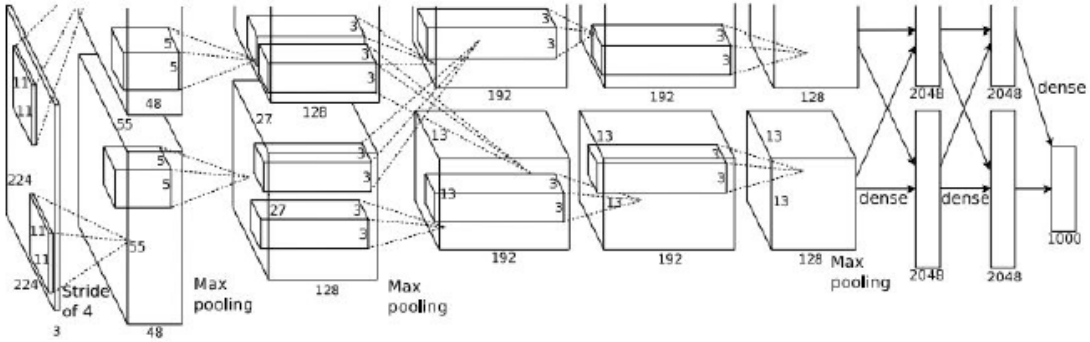
AlexNet

[Krizhevsky et al., 2012]

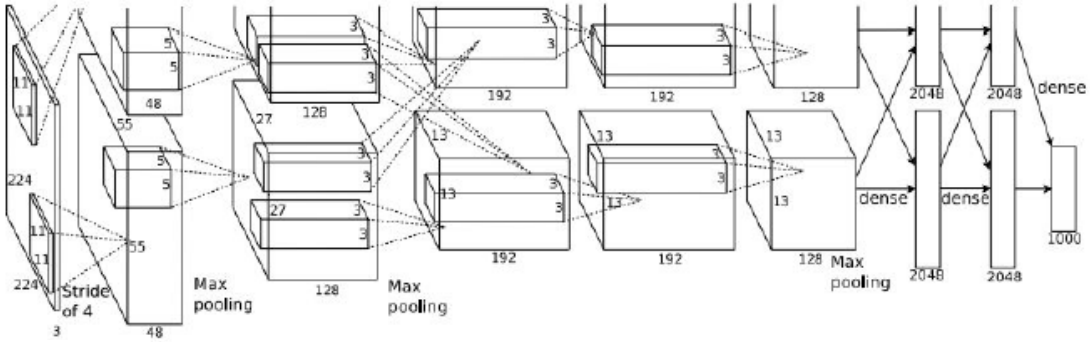


Arquitetura simplificada:

```
[227x227x3]     INPUT
[55x55x96]      CONV1: 96 filtros 11x11, stride 4, pad 0
[27x27x96]      MAX POOL1: filtros 3x3, stride 2
[27x27x96]      NORM1: layer de normalização
[27x27x256]     CONV2: 256 filtros 5x5, stride 1, pad 2
[13x13x256]     MAX POOL2: filtros 3x3, stride 2
[13x13x256]     NORM2: layer de normalização
[13x13x384]     CONV3: 384 filtros 3x3, stride 1, pad 1
[13x13x384]     CONV4: 384 filtros 3x3, stride 1, pad 1
[13x13x256]     CONV5: 256 filtros 3x3, stride 1, pad 1
[6x6x256]       MAX POOL3: filtros 3x3, stride 2
[4096]          FC6: 4096 neurônios
[4096]          FC7: 4096 neurônios
[1000]          FC8: 1000 neurônios (classes)
```

AlexNet

[Krizhevsky et al., 2012]



Arquitetura simplificada:

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[227x227x3]    INPUT
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[27x27x96]     NORM1: layer de normalização
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[13x13x256]    MAX POOL2: filtros 3x3, stride 2
[13x13x256]    NORM2: layer de normalização
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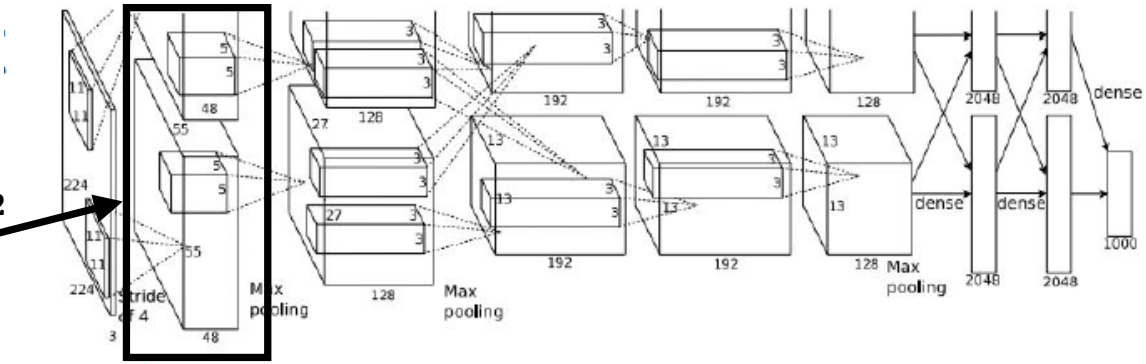
[13x13x384]    CONV4: 384 filtros 3x3, stride 1, pad 1
[13x13x256]    CONV5: 256 filtros 3x3, stride 1, pad 1
[6x6x256]      MAX POOL3: filtros 3x3, stride 2
[4096]         FC6: 4096 neurônios
[4096]         FC7: 4096 neurônios
[1000]         FC8: 1000 neurônios (classes)
```

Detalhes:

- primeiro uso de ReLU
- layers de norm: não são mais usados
- data augmentation pesado
- dropout 0.5
- batch 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduzido por 10 sempre que a acurácia de validação ficava em um plateau
- L2 weight decay 5e-4
- Ensemble de 7 CNNs: 18.2% -> 15.4%

AlexNet

[Krizhevsky et al., 2012]



Arquitetura simplificada:

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[4096]         FC6: 4096 neurônios
[4096]         FC7: 4096 neurônios
[1000]         FC8: 1000 neurônios (classes)
```

- Treinada em 2 GPUs com apenas 3GB
- Metade dos neurônios (mapas de ativação) em cada

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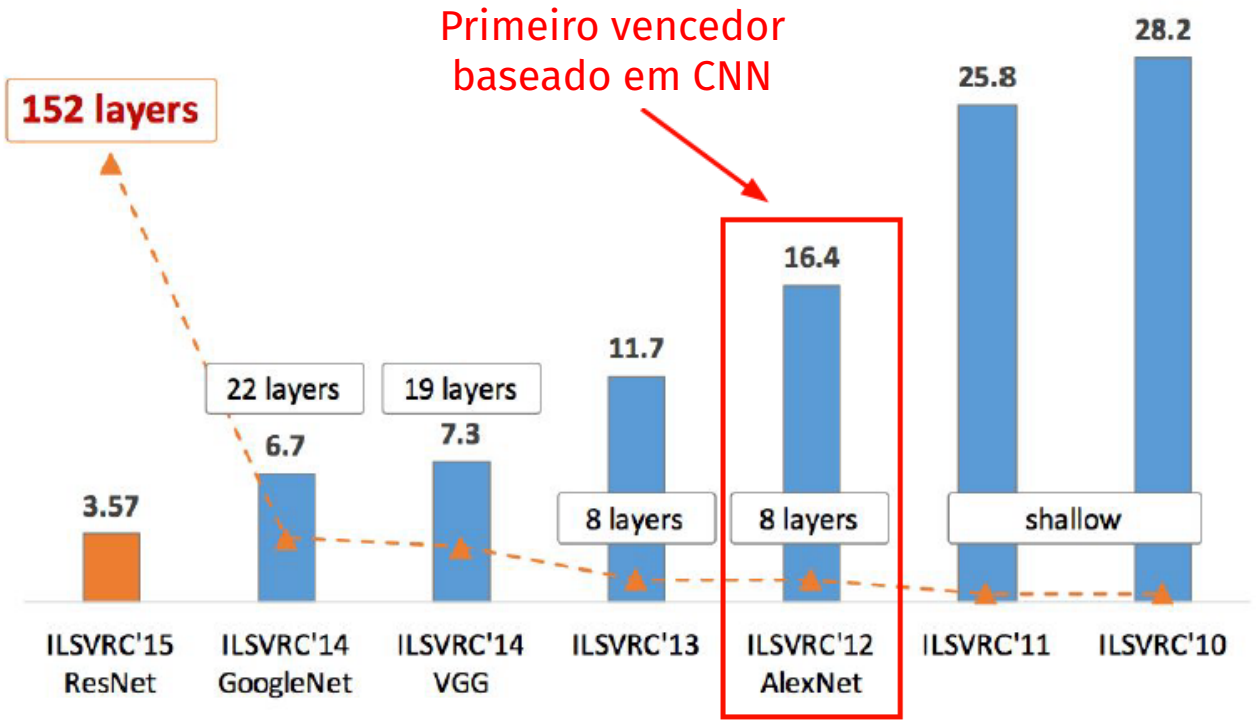
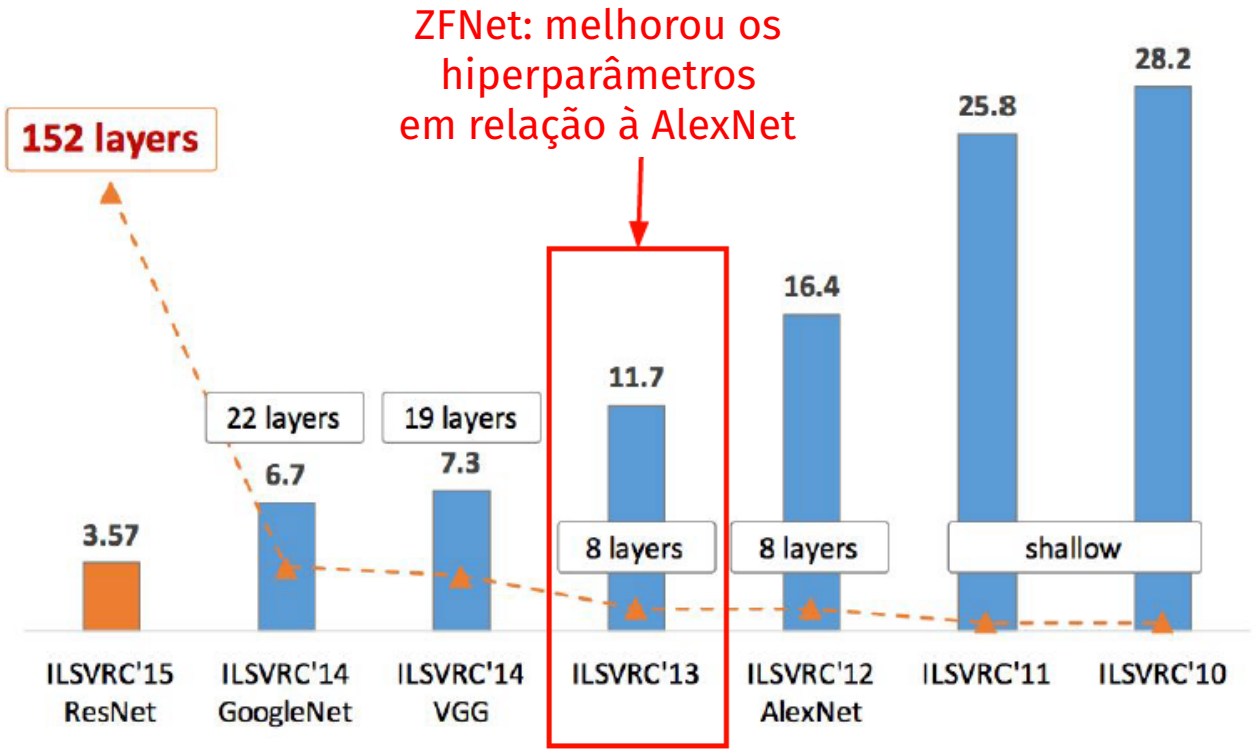
Vencedores do ImageNet Large Scale Visual Recognition Challenge (ILSVRC)

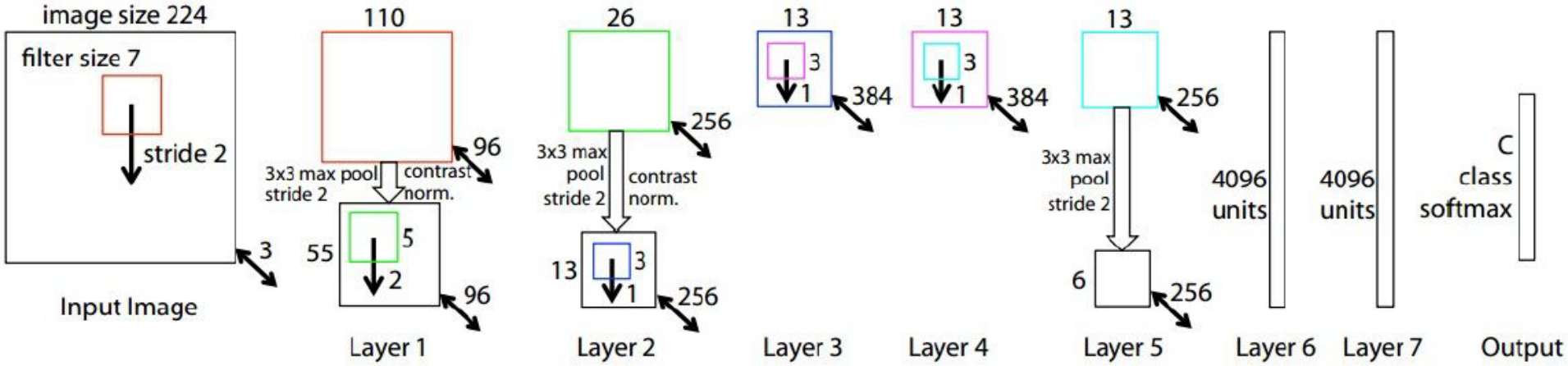


Vencedores do ImageNet Large Scale Visual Recognition Challenge (ILSVRC)



ZeNet

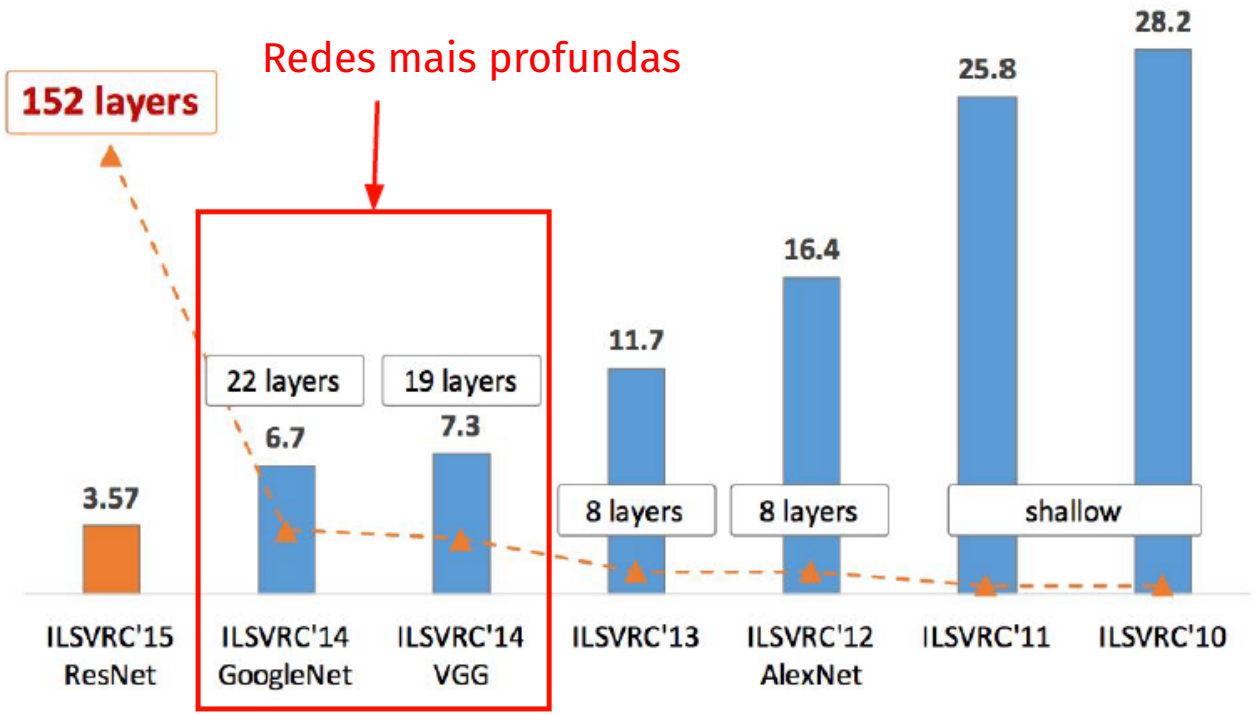
[Zeiler e Fergus, 2013]



AlexNet, porém:
CONV1: muda de (11x11, stride 4) para (7x7 stride 2)
CONV3,4,5: ao invés de 384, 384 e 356 filtros, muda para 512, 1024, 512

ImageNet top error: 16.4% -> 11.7%

Vencedores do ImageNet Large Scale Visual Recognition Challenge (ILSVRC)



VGGNet

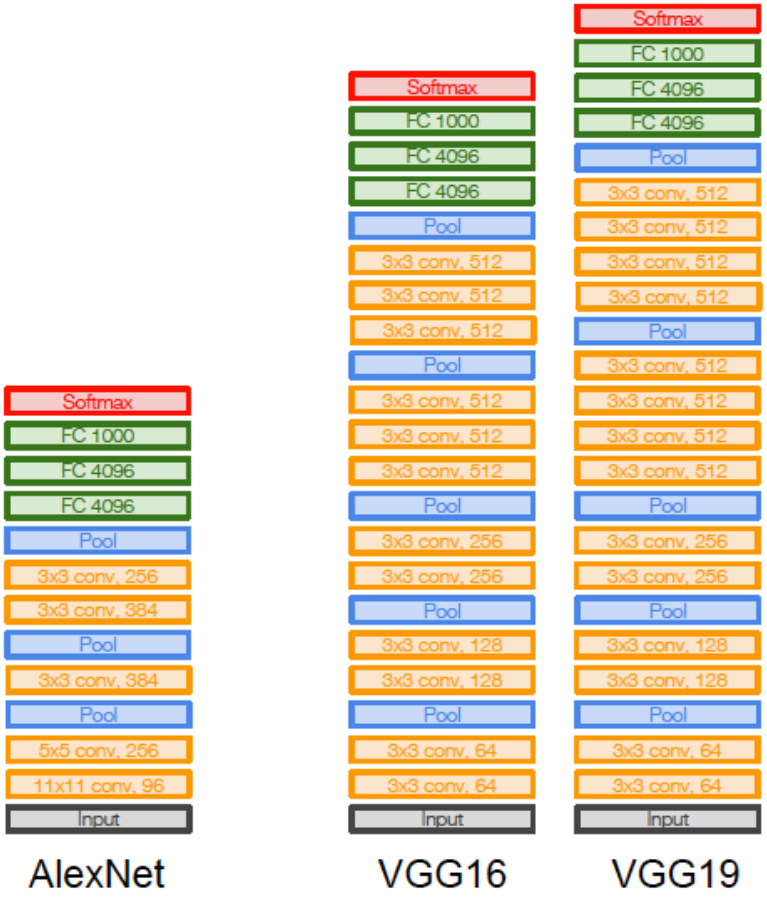
[Simonyan and Zisserman, 2014]

Filtros menores, rede mais profunda

AlexNet 8 layers -> VGGNet 16 a 19 layers

Apenas 3x3 CONV, stride 1, pad 1
e 2x2 MAX POOL, stride 2

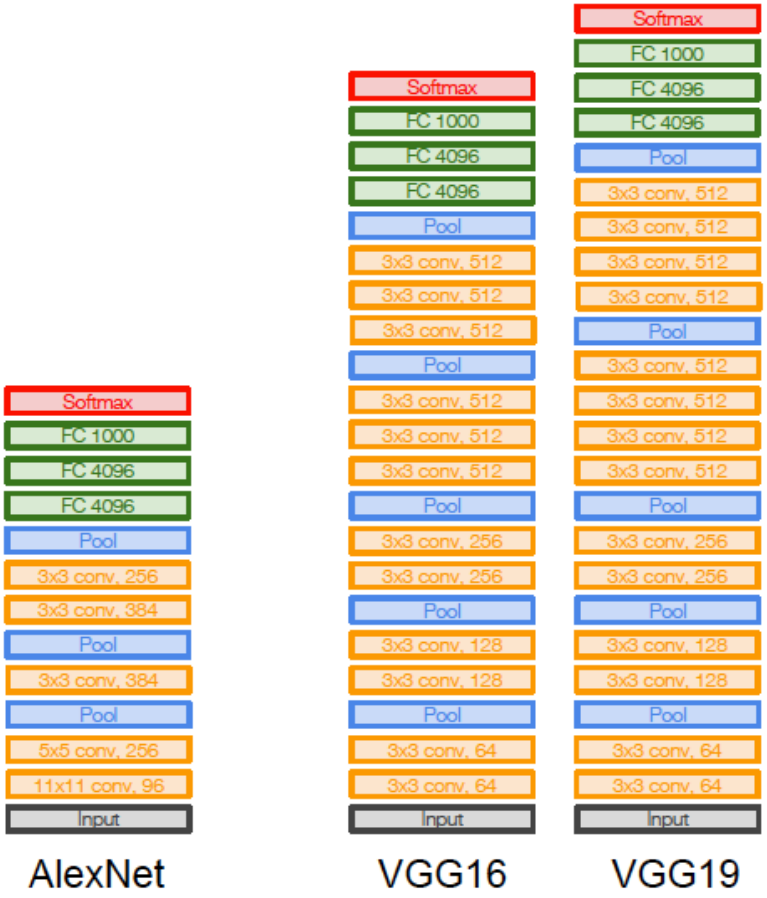
ZFNet 11.7% top error (2013) ->
VGGNet 7.3% top error (2014)



VGGNet

[Simonyan and Zisserman, 2014]

=> Por que usar filtros menores e rede mais profunda?



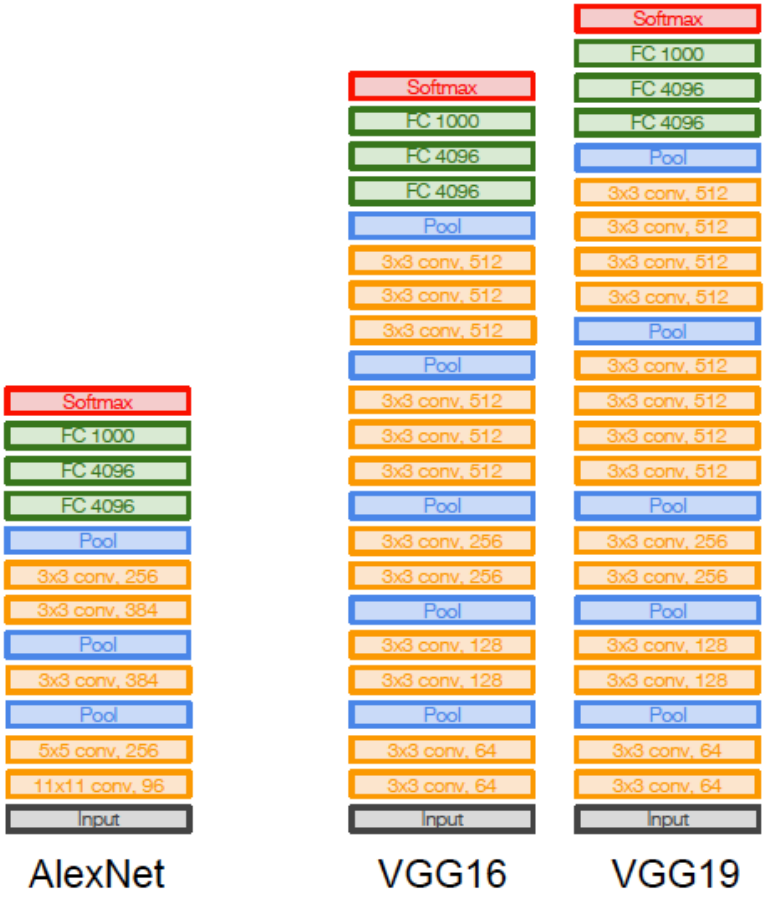
VGGNet

[Simonyan and Zisserman, 2014]

=> Por que usar filtros menores e rede mais profunda?

Mais profunda: mais não-linearidade

Filtros menores: menos parâmetros



VGGNet

[Simonyan and Zisserman, 2014]

não contando o bias

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
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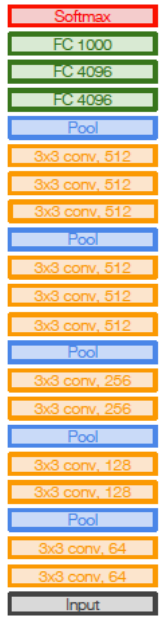
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000



VGG16

VGGNet

[Simonyan and Zisserman, 2014]

não contando o bias

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
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POOL2: [28x28x256] memory: 28*28*256=200K params: 0
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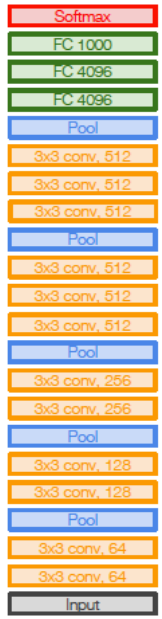
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

Memória total: 24M * 4 bytes ~= 96MB / image
Parâmetros totais: 138M



VGG16

VGGNet

[Simonyan and Zisserman, 2014]

não contando o bias

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POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = **102,760,448**
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

Maioria da memória está nas CONV anteriores

Maioria dos parâmetros está nas camadas fully-connected

Memória total: 24M * 4 bytes ~= 96MB / image
Parâmetros totais: 138M

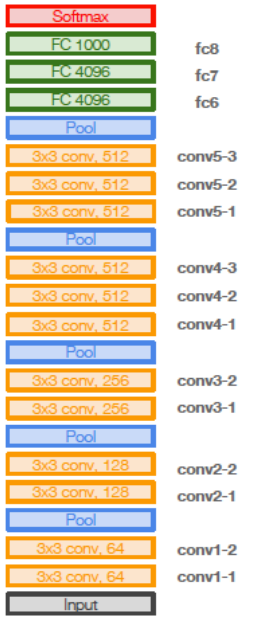
VGGNet

[Simonyan and Zisserman, 2014]

não contando o bias

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

Memória total: 24M * 4 bytes ~= 96MB / image
Parâmetros totais: 138M



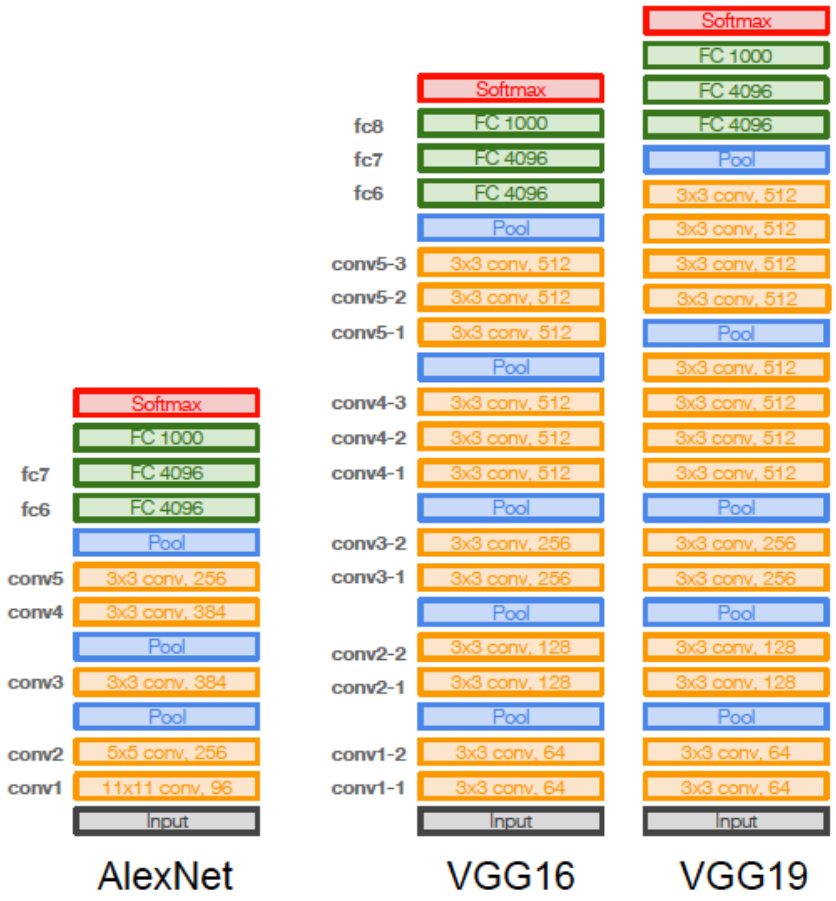
VGG16

nomes comuns

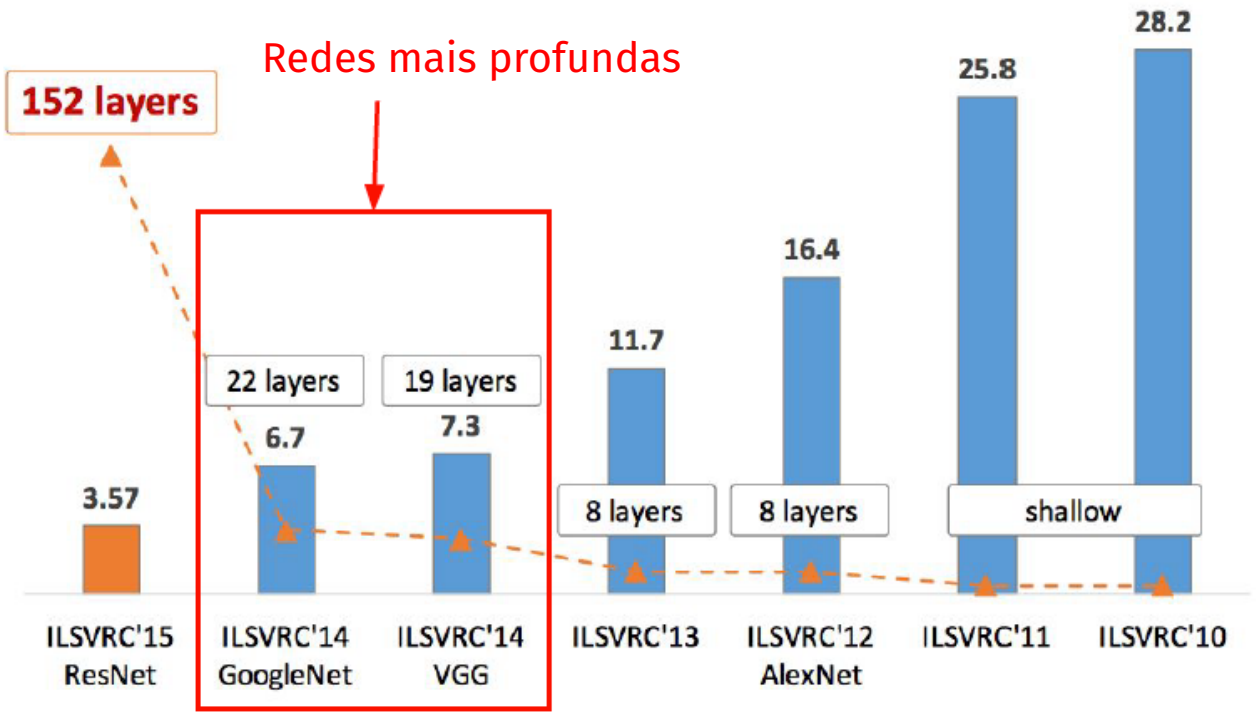
VGGNet

[Simonyan and Zisserman, 2014]

- ILSVRC ’14: 2º lugar em classificação, 1º lugar em localização
- Treinamento similar à AlexNet
- Features geradas pela FC7 generalizam bem para outras tarefas



Vencedores do ImageNet Large Scale Visual Recognition Challenge (ILSVRC)



GoogLeNet

[Szegedy et al., 2014]

Rede mais profunda, com eficiência computacional

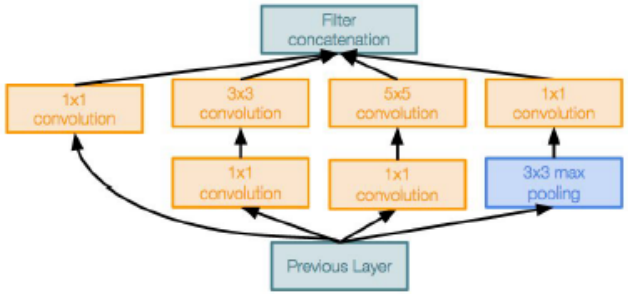
22 layers

Módulo Inception

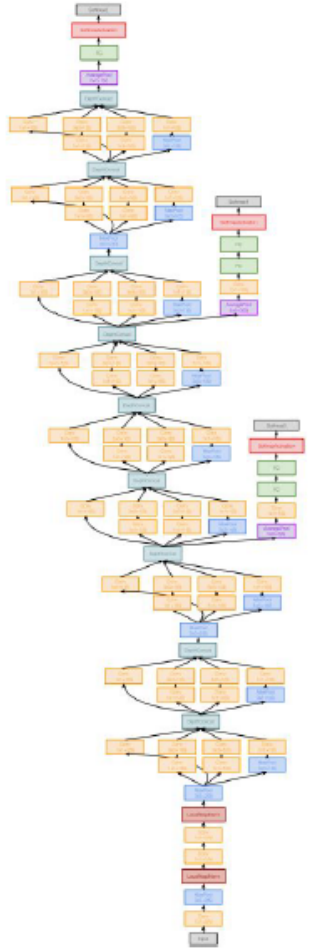
Sem layers FC

Apenas 5 milhões de parâmetros (12x menos que a AlexNet)

Campeão na tarefa de classificação na ILSVRC ’14: 6.7% top error



Inception module

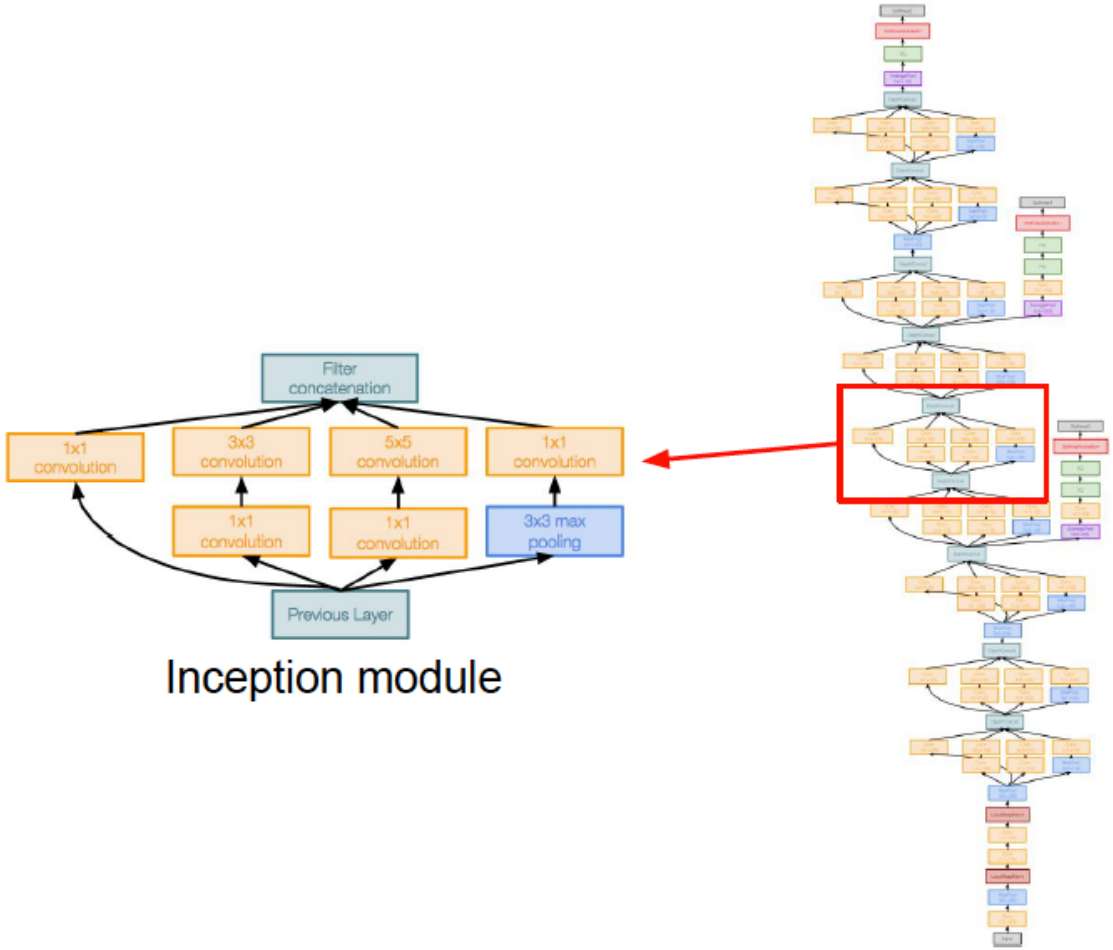


GoogLeNet

[Szegedy et al., 2014]

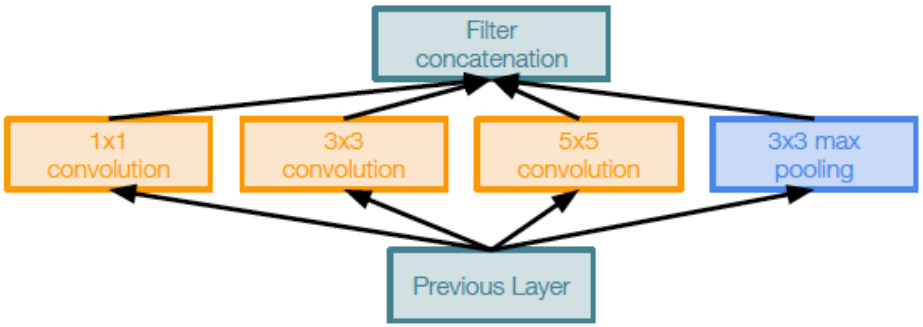
Módulo **inception**:

criar uma topologia de rede local (rede dentro de uma rede) e empilhar os módulos.



GoogLeNet

[Szegedy et al., 2014]



Módulo inception “ingênuo"

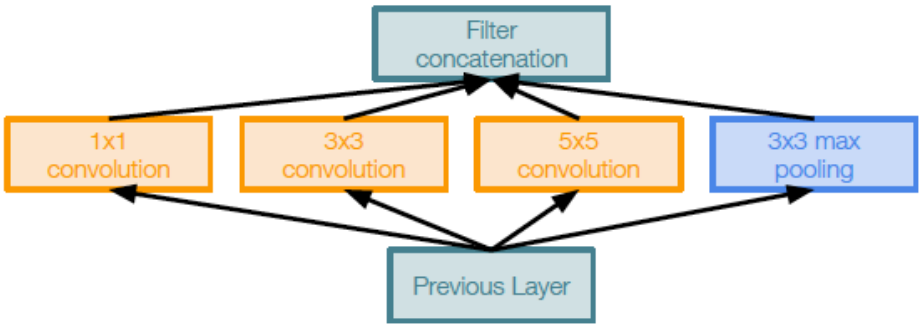
Aplicar filtros paralelos ao input da camada anterior:

- Múltiplos campos receptivos para convolução
  - 1x1
  - 3x3
  - 5x5
- Operações de pooling 3x3

Concatenar todos os outputs dos filtros (nos canais)

GoogLeNet

[Szegedy et al., 2014]



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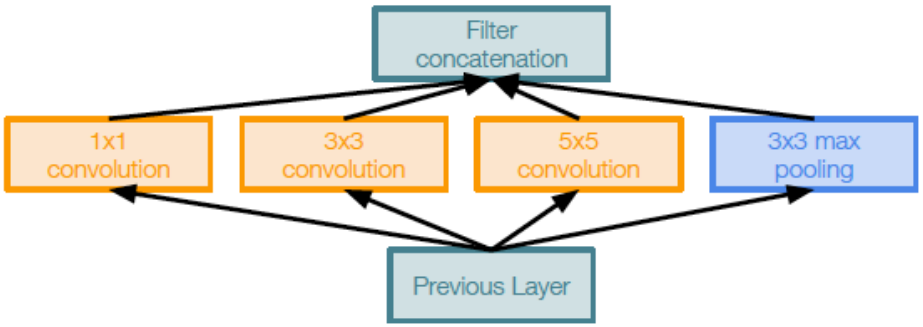
- Múltiplos campos receptivos para convolução
  - 1x1
  - 3x3
  - 5x5
- Operações de pooling 3x3

Concatenar todos os outputs dos filtros (nos canais)

=> Qual o problema com essa abordagem?

GoogLeNet

[Szegedy et al., 2014]



Módulo inception “ingênuo"

Aplicar filtros paralelos ao input da camada anterior:

- Múltiplos campos receptivos para convolução
  - 1x1
  - 3x3
  - 5x5
- Operações de pooling 3x3

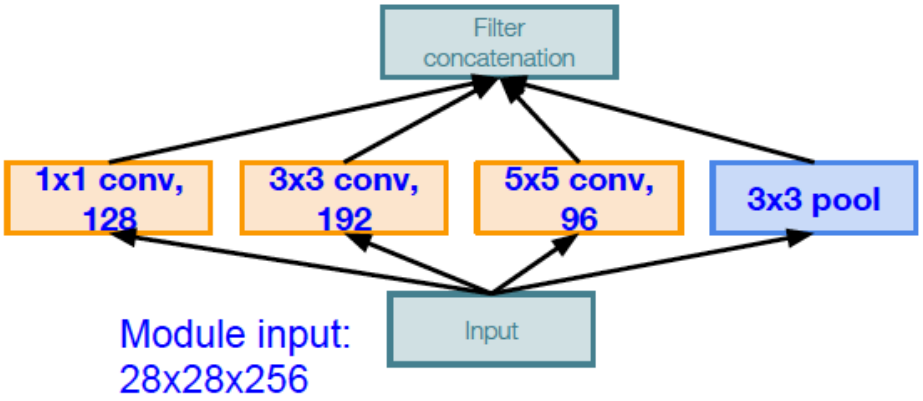
Concatenar todos os outputs dos filtros (nos canais)

=> Complexidade computacional!

GoogLeNet

[Szegedy et al., 2014]

Exemplo:



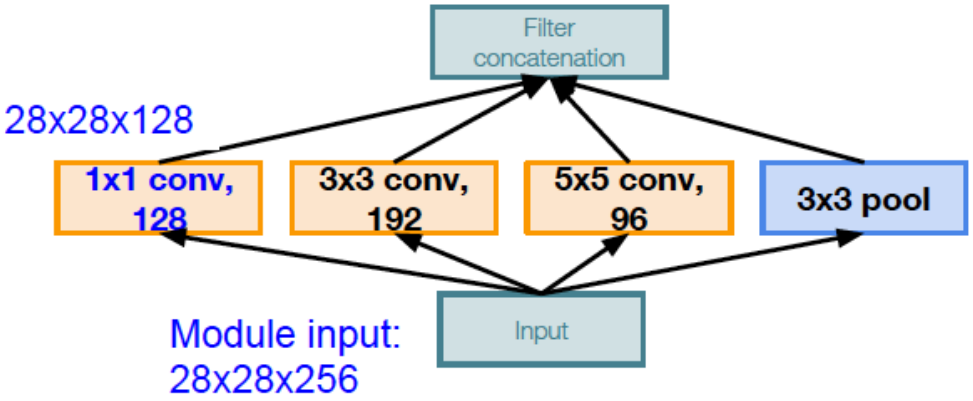
Módulo inception “ingênuo"

=> Qual o tamanho do output da CONV 1x1, com 128 filtros?

GoogLeNet

[Szegedy et al., 2014]

Exemplo:



Módulo inception “ingênuo"

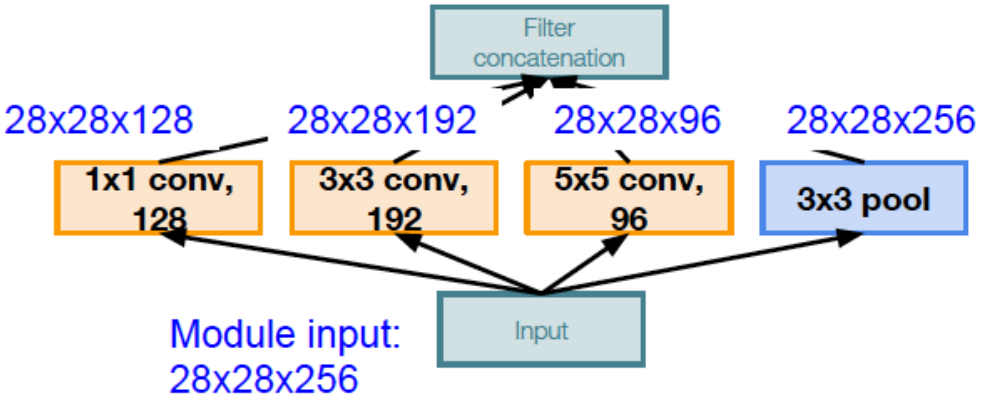
=> Qual o tamanho do output da CONV 1x1, com 128 filtros?

=> Qual o tamanho do output das outras operações?

GoogLeNet

[Szegedy et al., 2014]

Exemplo:



Módulo inception “ingênuo"

=> Qual o tamanho do output da CONV 1x1, com 128 filtros?

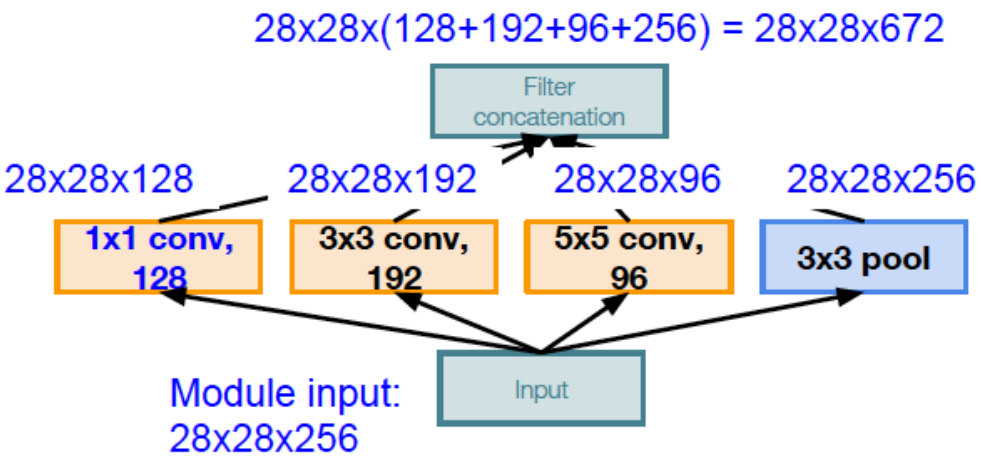
=> Qual o tamanho do output das outras operações?

=> Qual o tamanho do output depois da concatenação?

GoogLeNet

[Szegedy et al., 2014]

Exemplo:



Módulo inception “ingênuo"

=> Qual o tamanho do output da CONV 1x1, com 128 filtros?

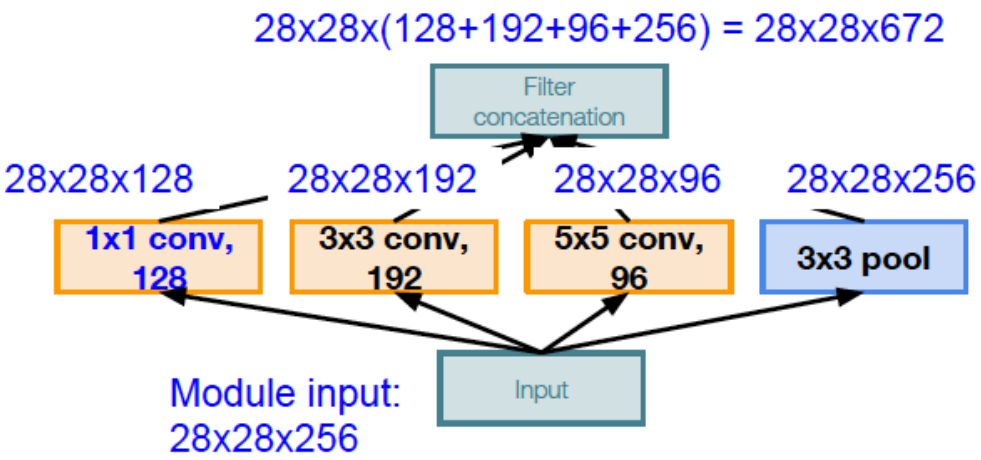
=> Qual o tamanho do output das outras operações?

=> Qual o tamanho do output depois da concatenação?

GoogLeNet

[Szegedy et al., 2014]

Exemplo:



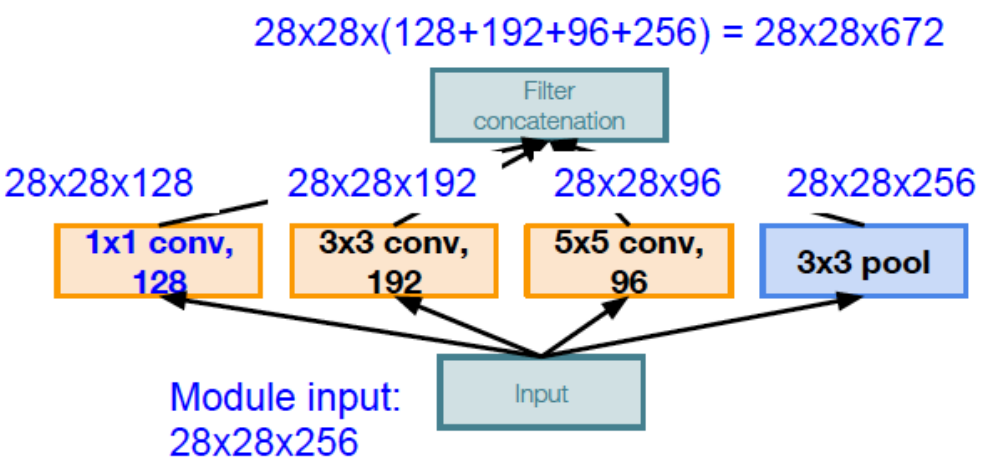
Módulo inception “ingênuo"

Conv Ops:
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x256
[5x5 conv, 96] 28x28x96x5x5x256
Total: 854M ops

GoogLeNet

[Szegedy et al., 2014]

Exemplo:



Módulo inception “ingênuo"

Conv Ops:
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x256
[5x5 conv, 96] 28x28x96x5x5x256
Total: 854M ops

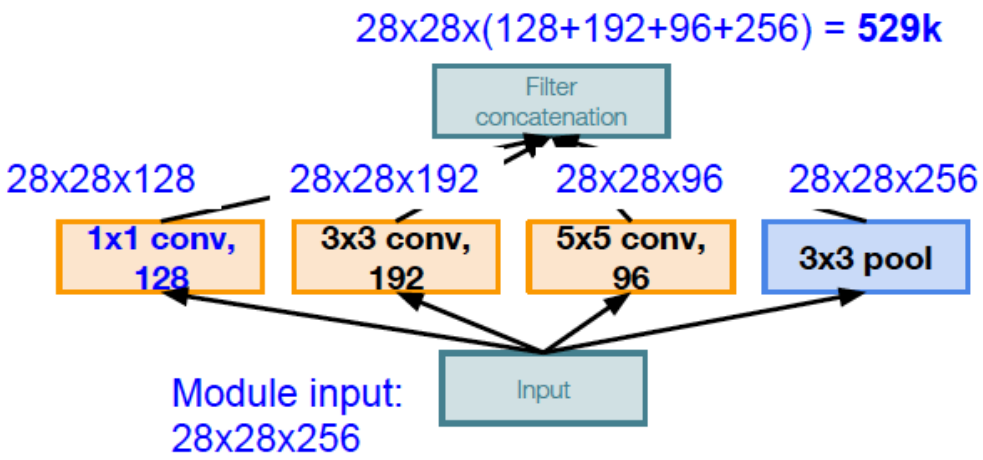
Muito caro computacionalmente!

O pooling preserva a profundidade e, assim, a profundidade após a concatenação apenas cresce a cada layer!

GoogLeNet

[Szegedy et al., 2014]

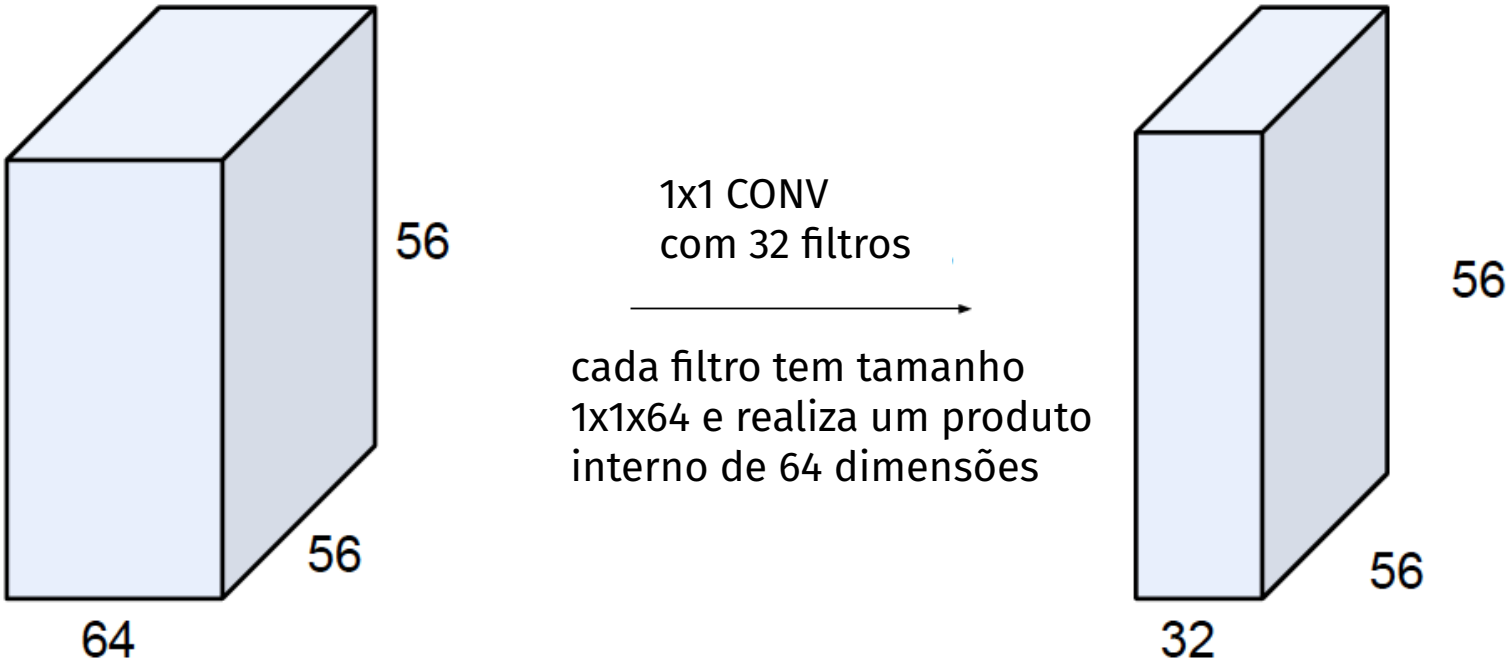
Exemplo:



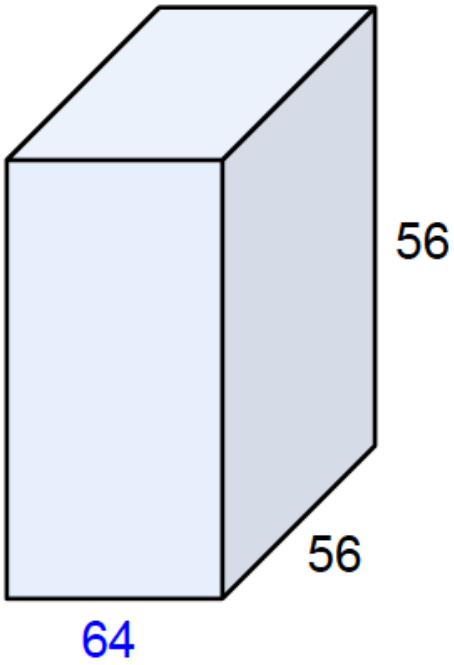
Módulo inception “ingênuo"

Solução: camadas de “gargalo"
que usam convoluções 1x1
para reduzir a profundidade
das features

Lembrete: convoluções 1x1



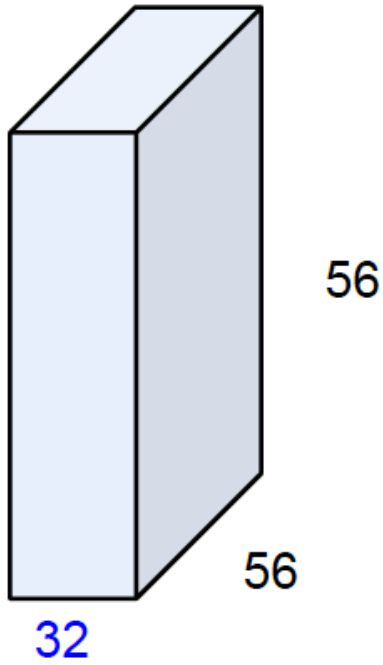
Lembrete: convoluções 1x1



1x1 CONV
com 32 filtros

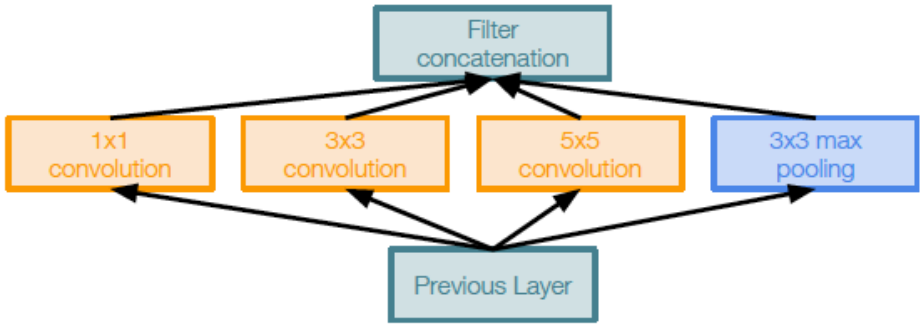
cada filtro tem tamanho
1x1x64 e realiza um produto
interno de 64 dimensões

projeta a profundidade
para dimensões menores
(combinação de mapas
de ativação)

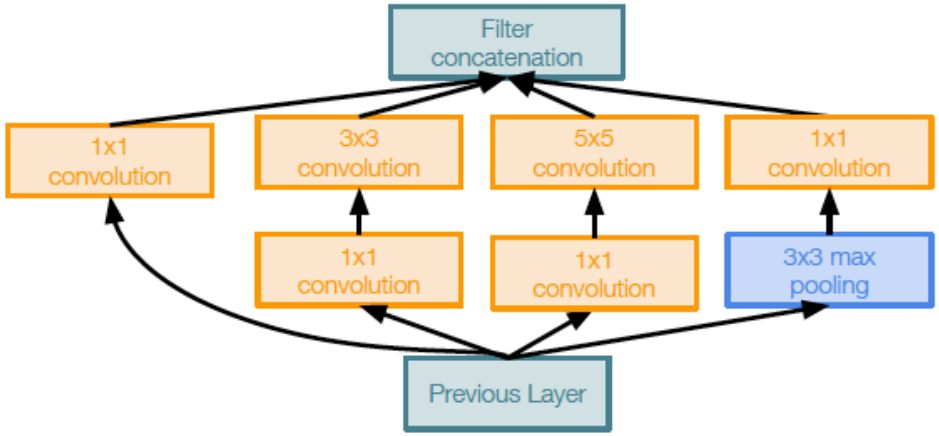


GoogLeNet

[Szegedy et al., 2014]



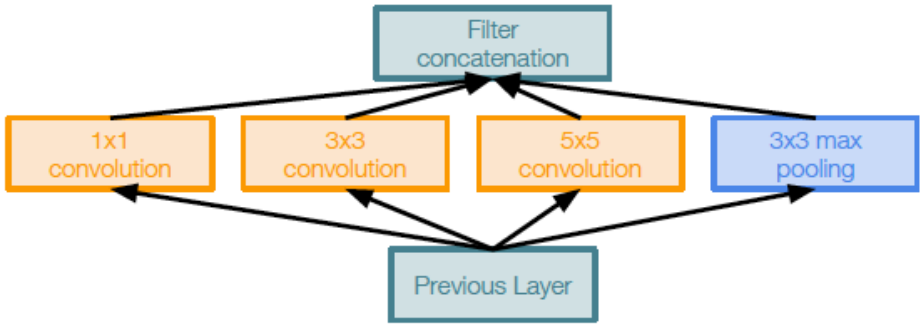
Módulo inception “ingênuo"



Módulo inception com
redução de dimensionalidade

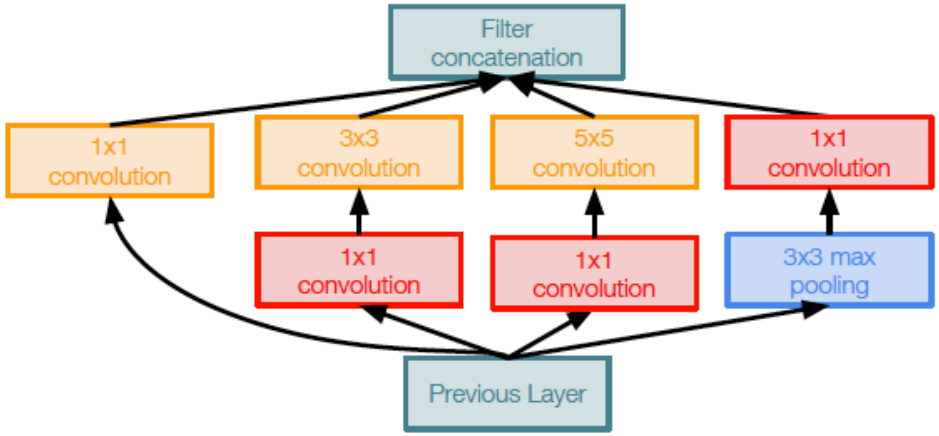
GoogLeNet

[Szegedy et al., 2014]



Módulo inception “ingênuo"

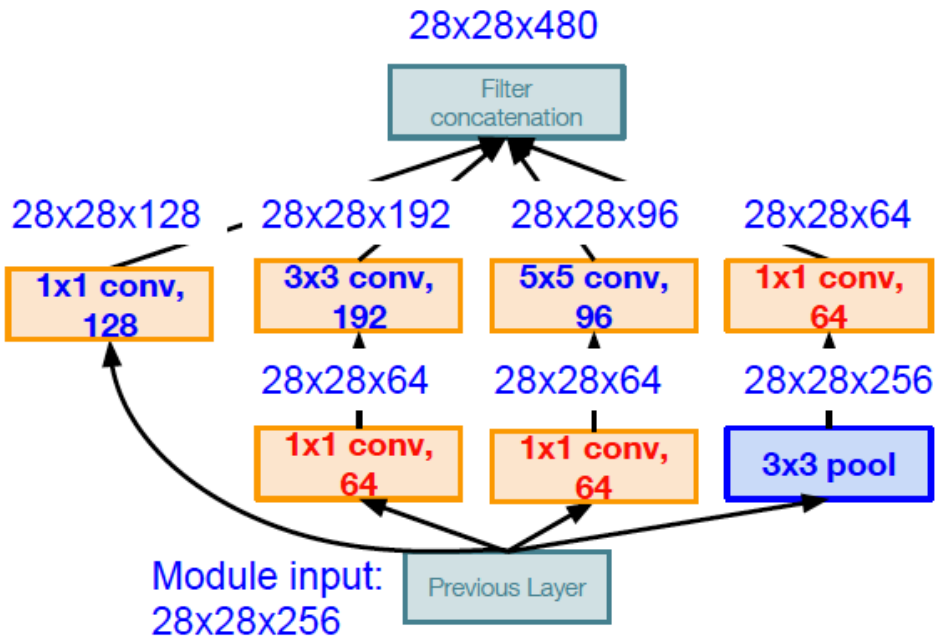
1x1 conv “bottleneck” layers



Módulo inception com redução de dimensionalidade

GoogLeNet

[Szegedy et al., 2014]



Módulo inception com redução de dimensionalidade

Utilizar os mesmos layers paralelos do exemplo “ingênuo” e adicionar conv 1x1, 64 filtros “gargalo”:

Conv Ops:
[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x64
[5x5 conv, 96] 28x28x96x5x5x64
[1x1 conv, 64] 28x28x64x1x1x256
Total: 358M ops

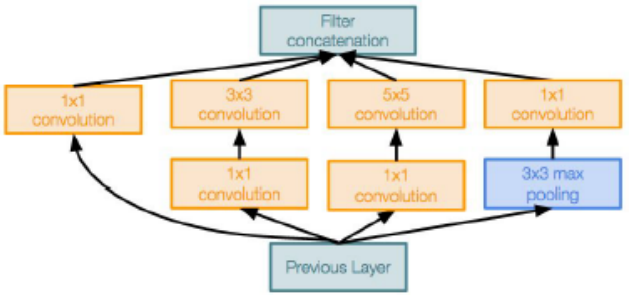
Comparado aos 854M de operações da versão “ingênua”

O “gargalo" também diminui os canais depois do pooling

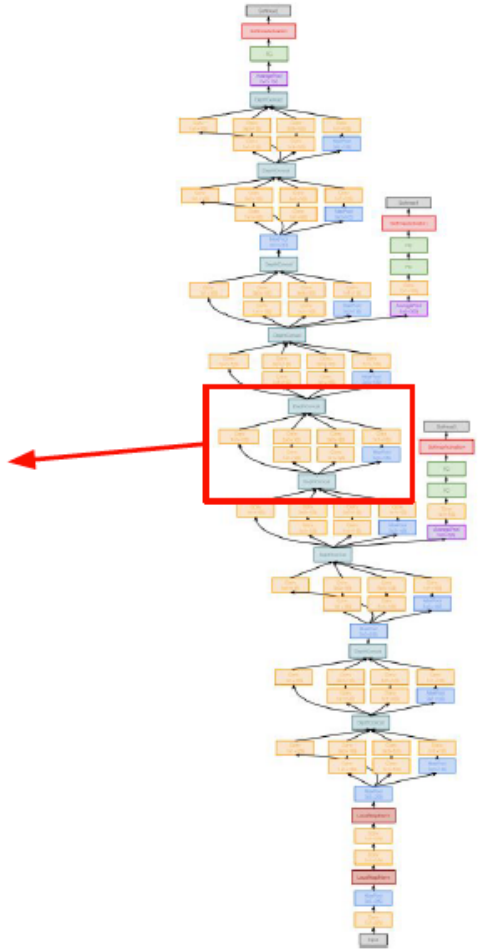
GoogLeNet

[Szegedy et al., 2014]

Empilhar módulos inception
com redução de dimensionalidade



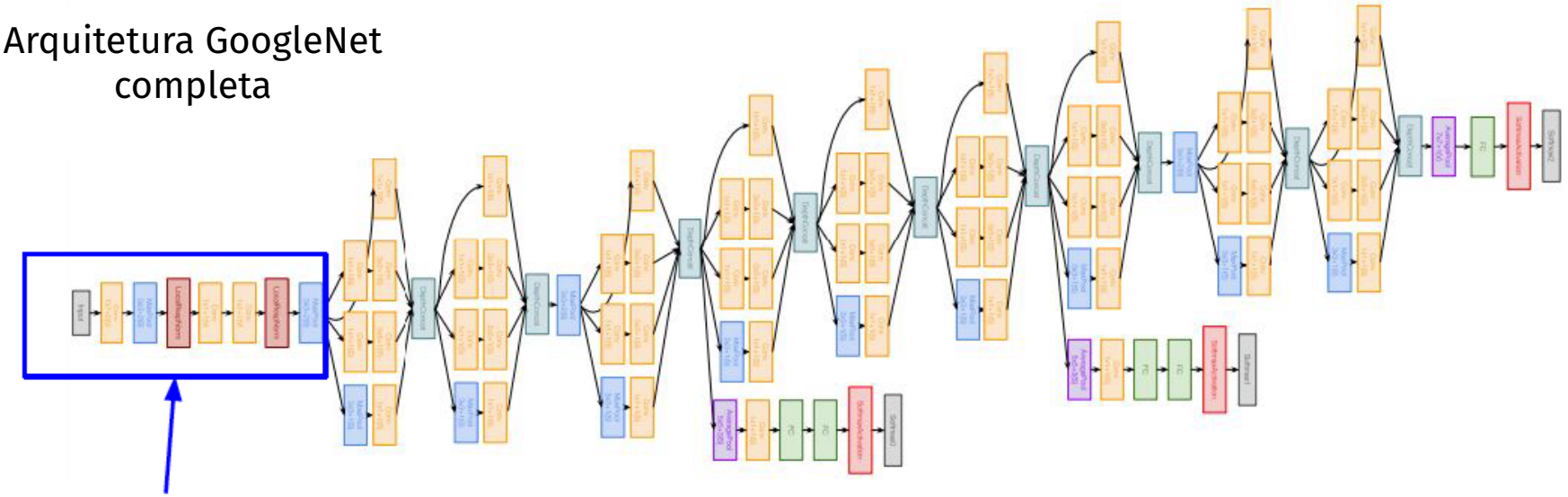
Inception module



GoogLeNet

[Szegedy et al., 2014]

Arquitetura GoogleNet completa

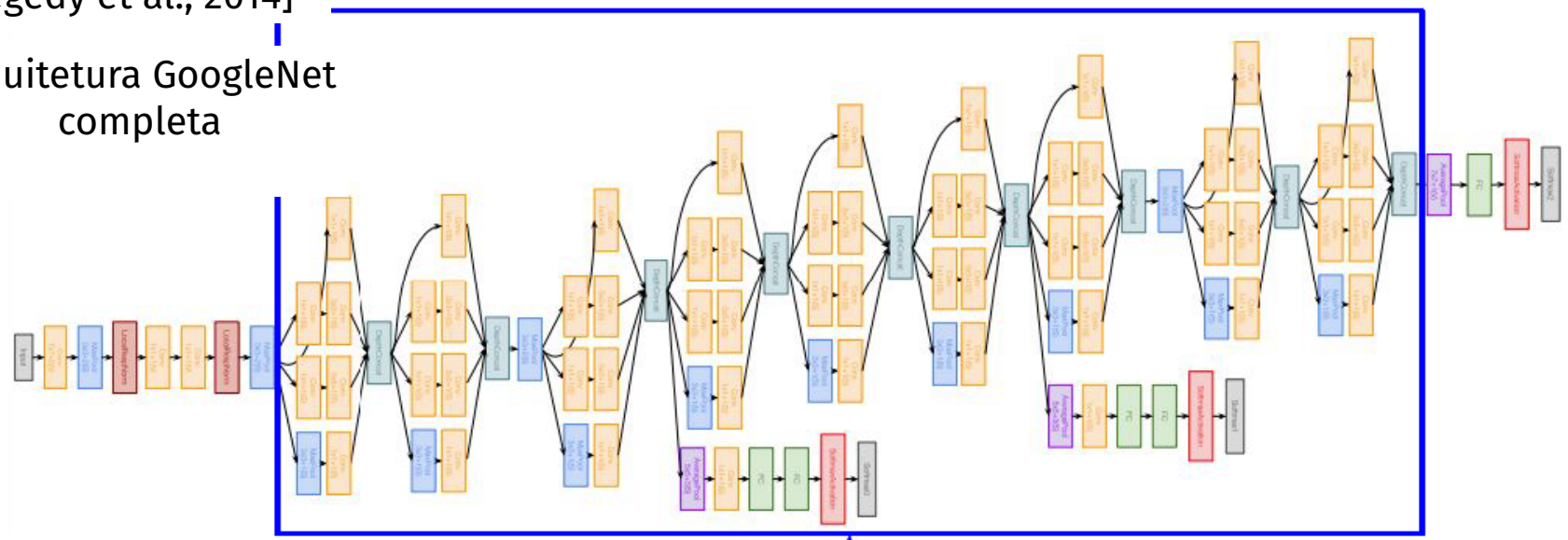


Rede inicial:
CONV-POOL-2x CONV-POOL

GoogLeNet

[Szegedy et al., 2014]

Arquitetura GoogleNet completa

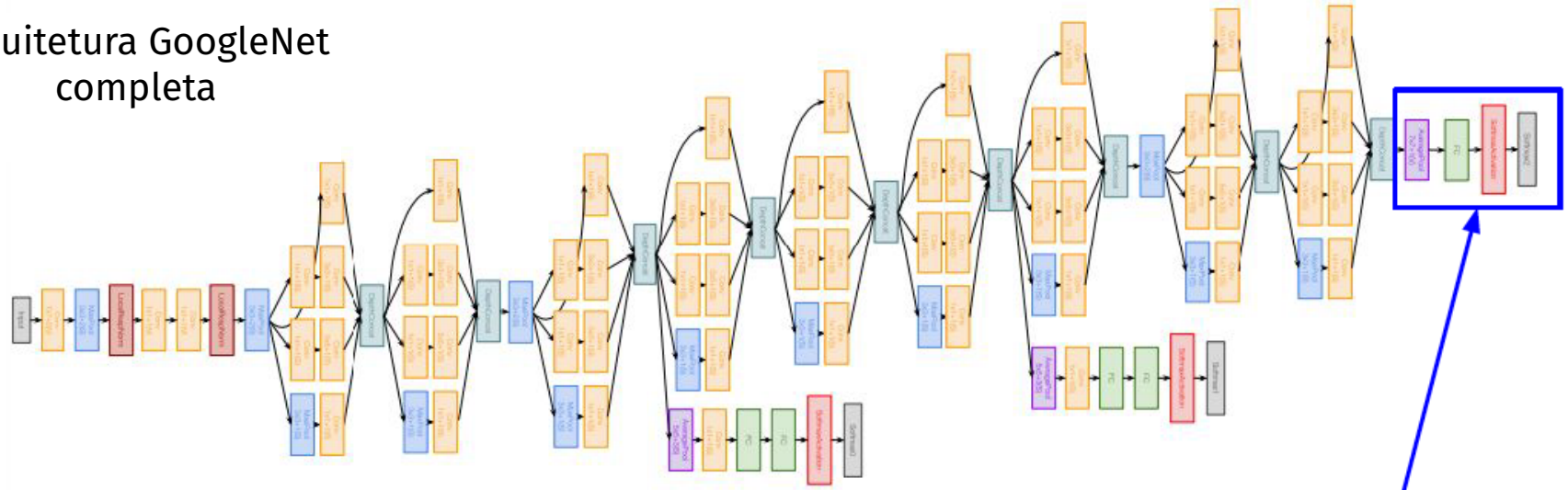


Módulos inception empilhados

GoogLeNet

[Szegedy et al., 2014]

Arquitetura GoogleNet completa

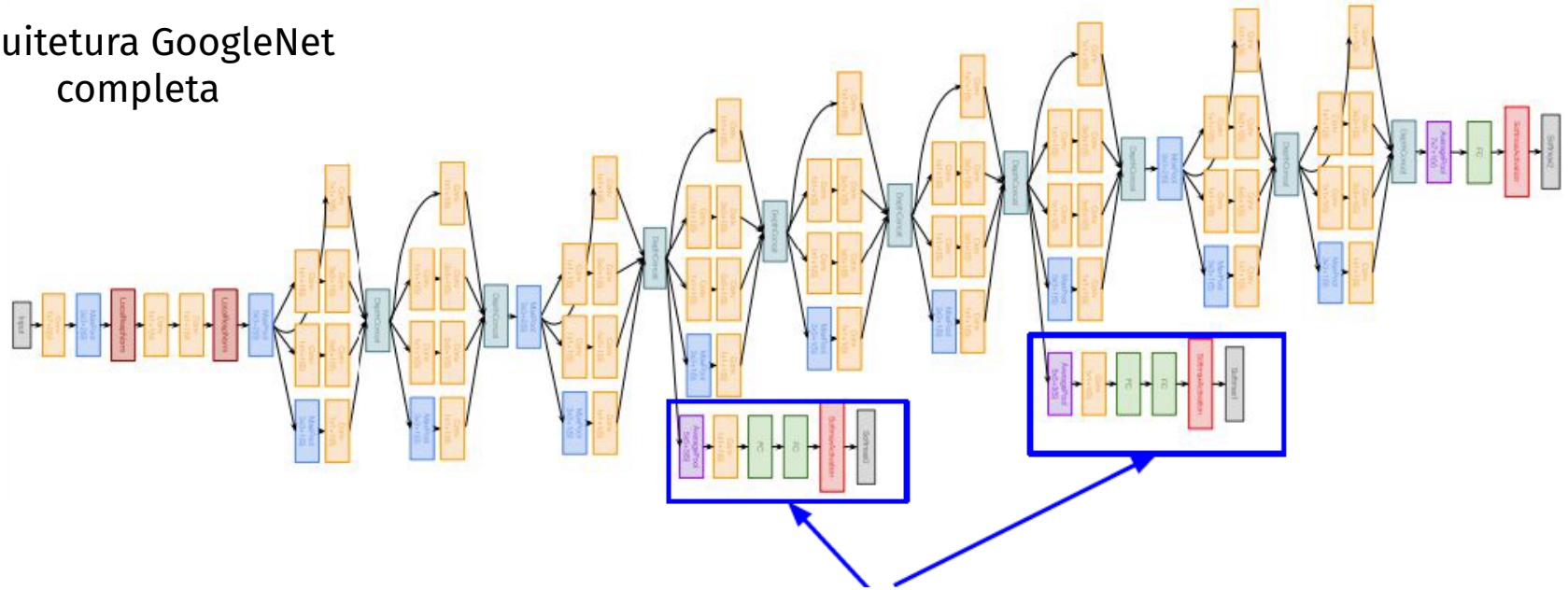


Layers de classificação (remoção dos FCs caros)

GoogLeNet

[Szegedy et al., 2014]

Arquitetura GoogleNet completa

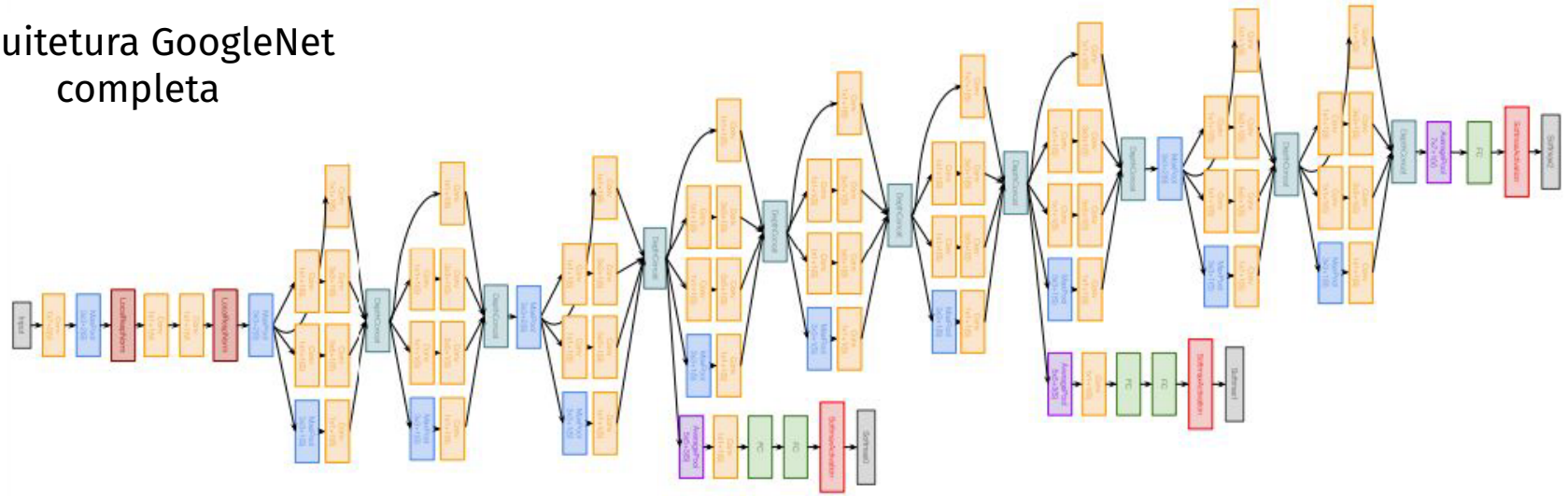


Camadas auxiliares de classificação para injetar gradientes adicionais em camadas mais cedo na rede (AvgPool-1x1 CONV-FC-FC-Softmax)

GoogLeNet

[Szegedy et al., 2014]

Arquitetura GoogleNet completa



Total de 22 layers com pesos (incluindo cada layer paralelo no módulo inception)

GoogLeNet

[Szegedy et al., 2014]

Rede mais profunda, com eficiência computacional

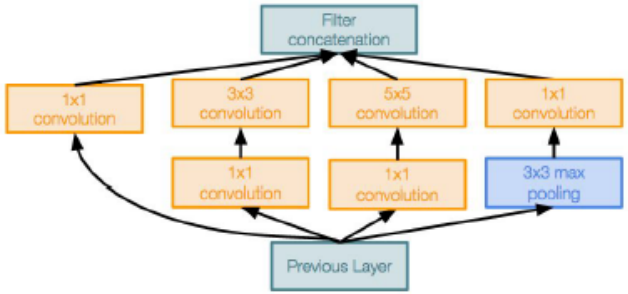
22 layers

Módulo Inception

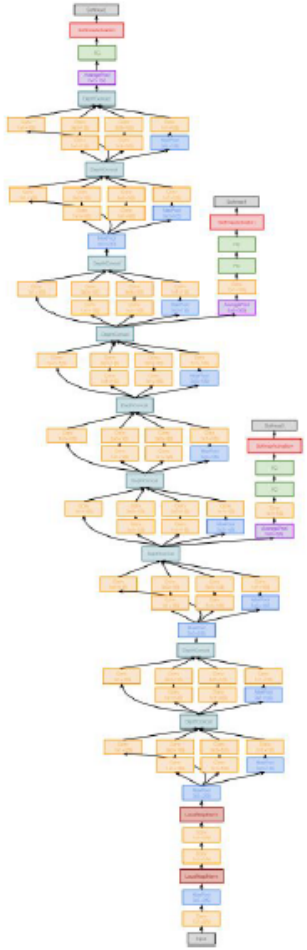
Sem layers FC

Apenas 5 milhões de parâmetros (12x menos que a AlexNet)

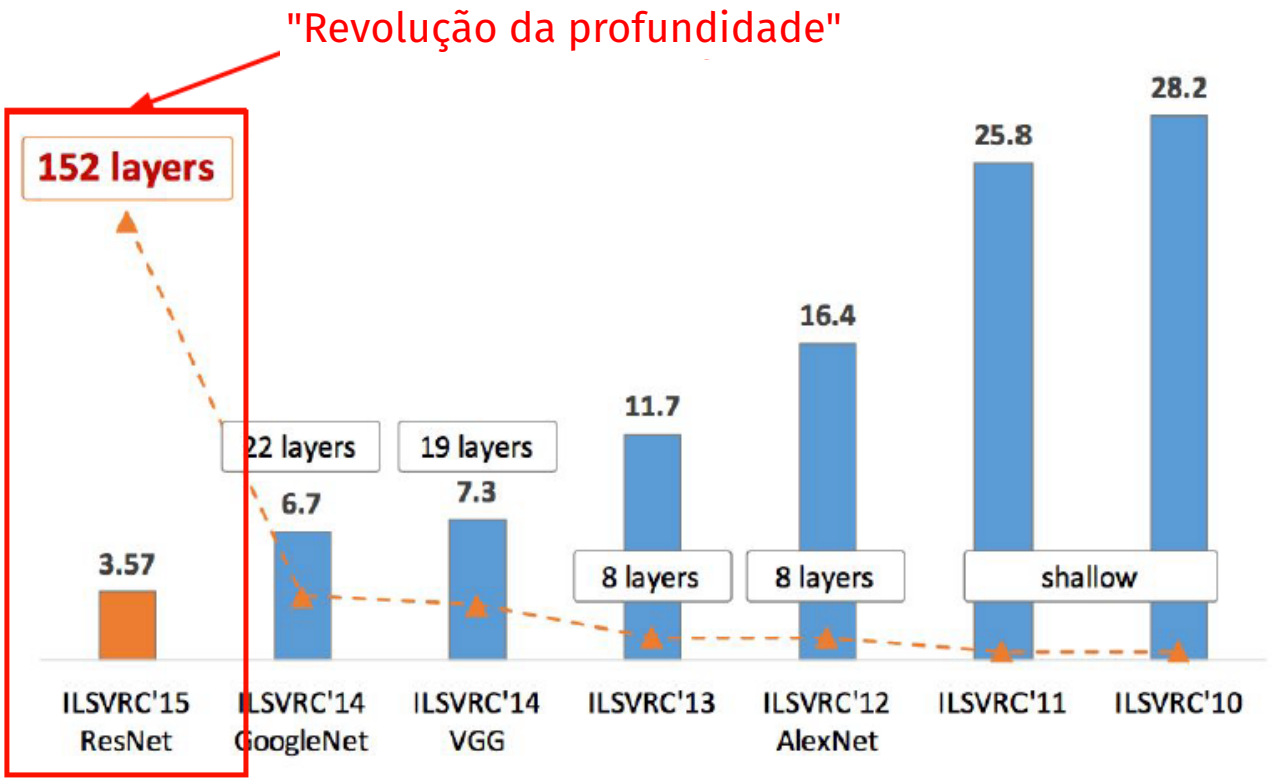
Campeão na tarefa de classificação na ILSVRC ’14: 6.7% top error



Inception module



Vencedores do ImageNet Large Scale Visual Recognition Challenge (ILSVRC)



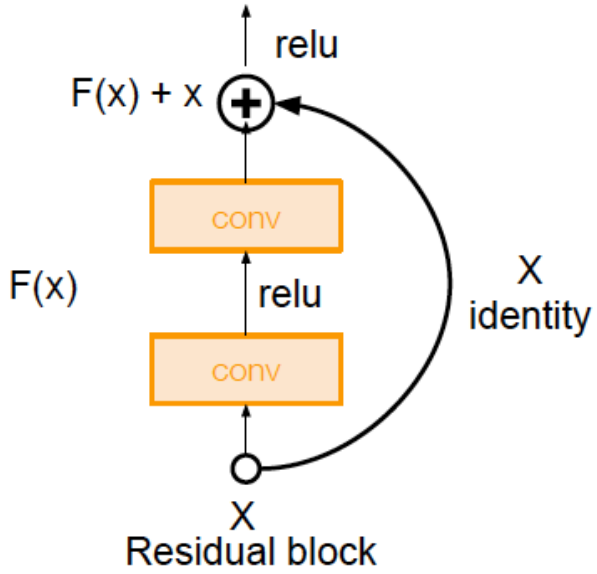
ResNet

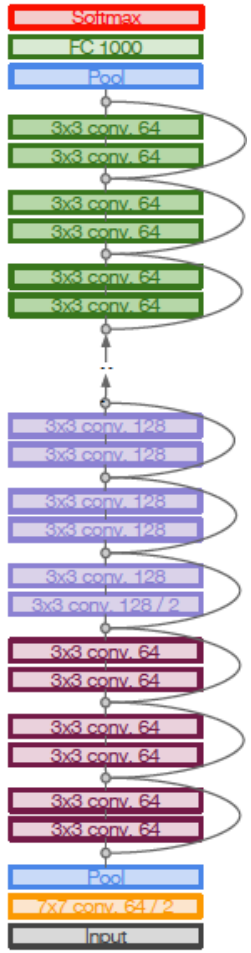
[He et al., 2015]

Rede muito profunda usando conexões residuais

152 layers

Campeão em todas as terefas na ILSVRC ’15: 3.57% top 5 error na classificação





ResNet

[He et al., 2015]

=> O que ocorre se continuarmos empilhando camadas em uma rede neural “comum"?

ResNet

[He et al., 2015]

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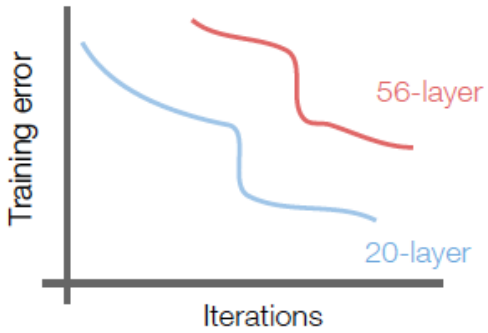
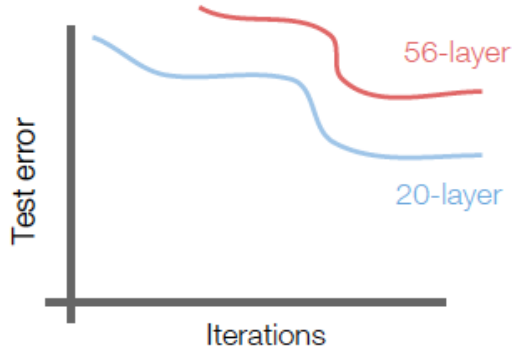


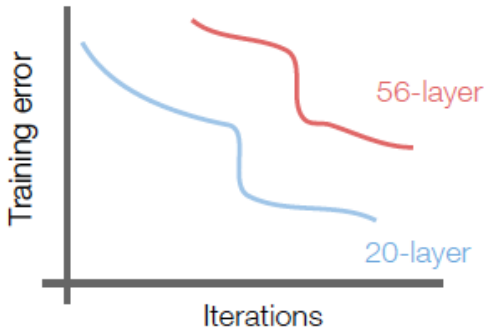


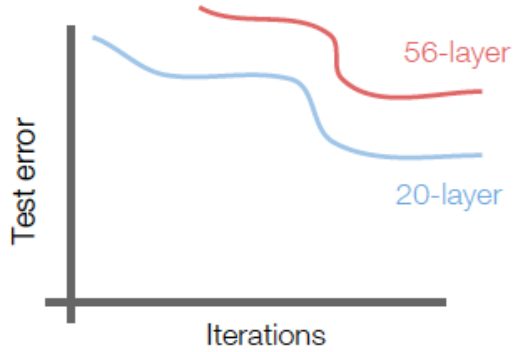
=> O que está estranho nestas curvas de treinamento e teste?

ResNet

[He et al., 2015]

=> O que ocorre se continuarmos empilhando camadas em uma rede neural “comum"?





=> O que está estranho nestas curvas de treinamento e teste?
O modelo de 56 camadas é pior em ambos os casos! Não é overfitting!

ResNet

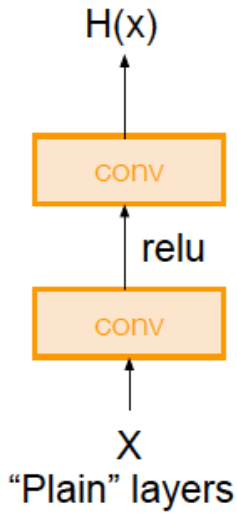
[He et al., 2015]

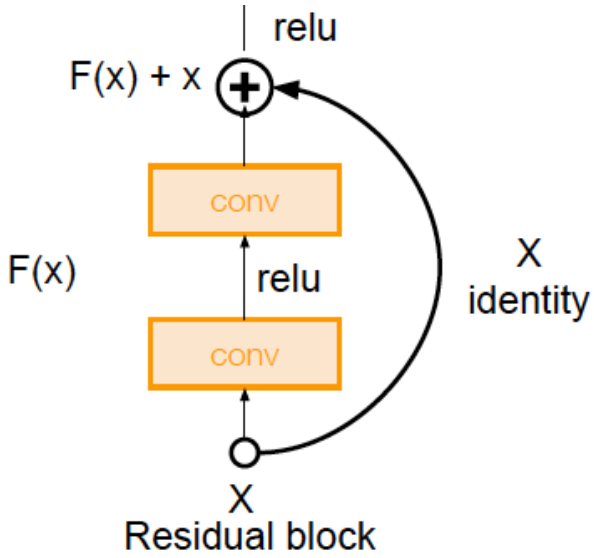
Hipótese: modelos mais profundos são mais difíceis de otimizar.

ResNet

[He et al., 2015]

Solução: Use os layers da rede para calcular um mapa residual, ao invés de calcular o mapa adjacente desejável





ResNet

[He et al., 2015]

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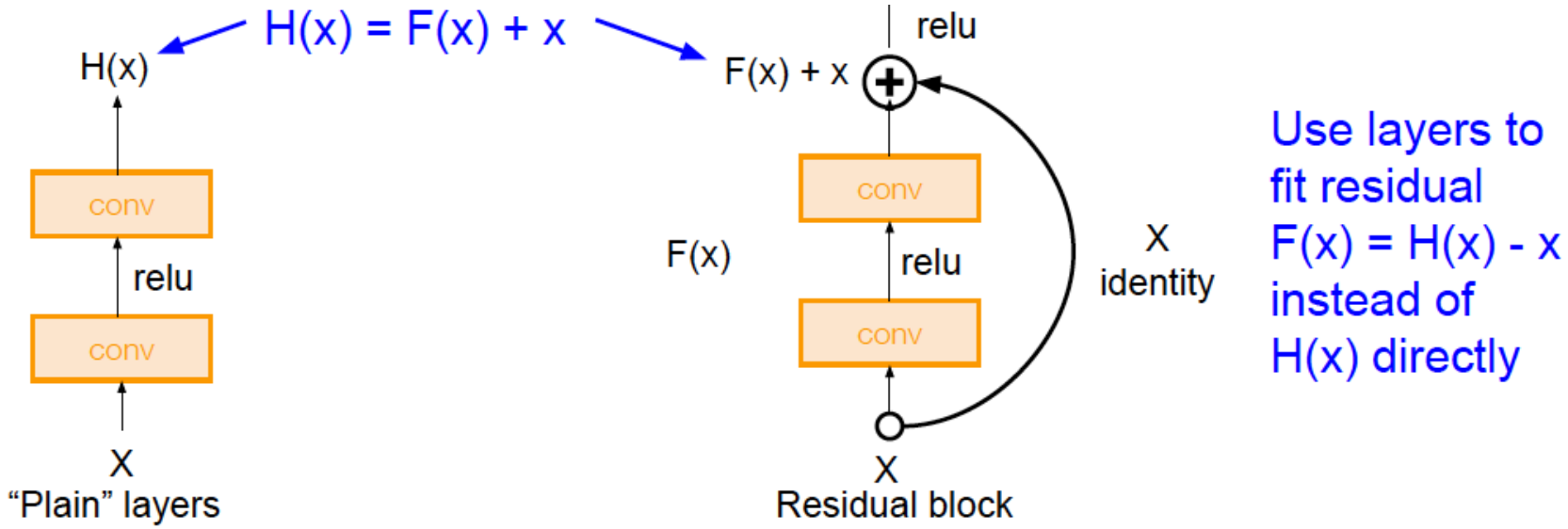
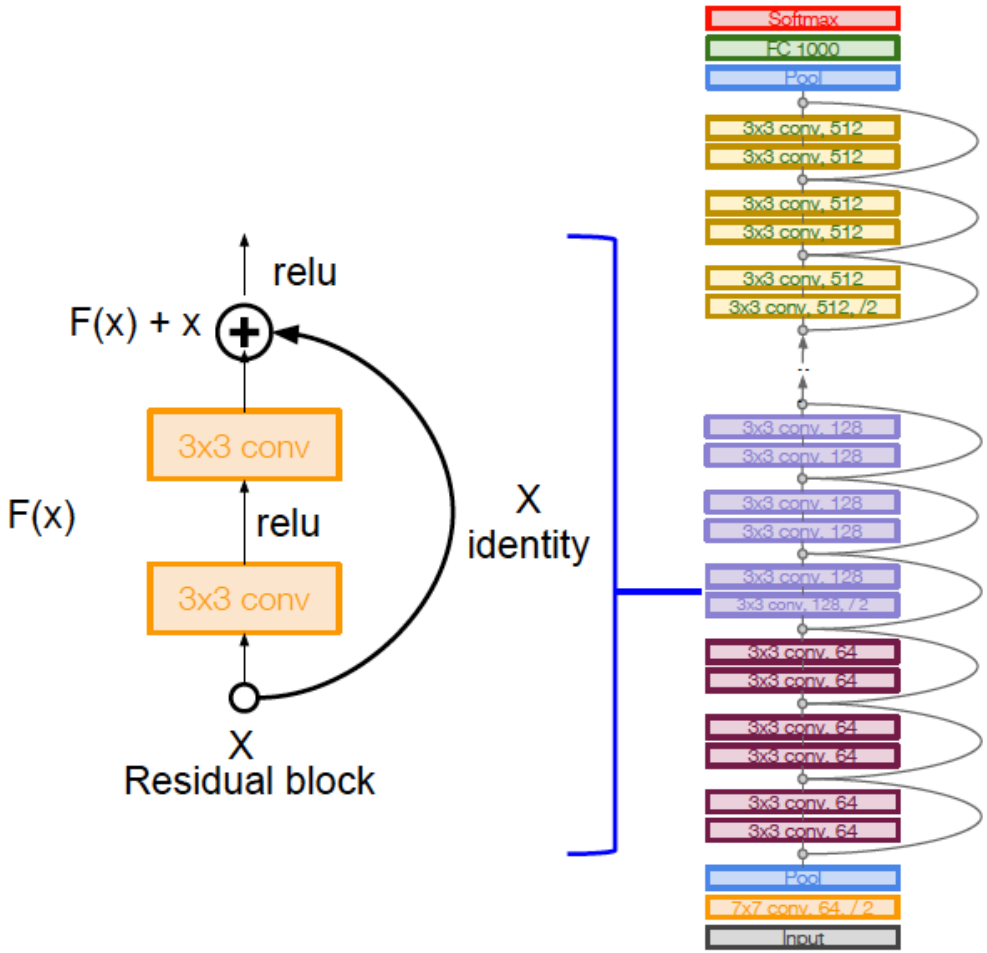


ResNet

[He et al., 2015]

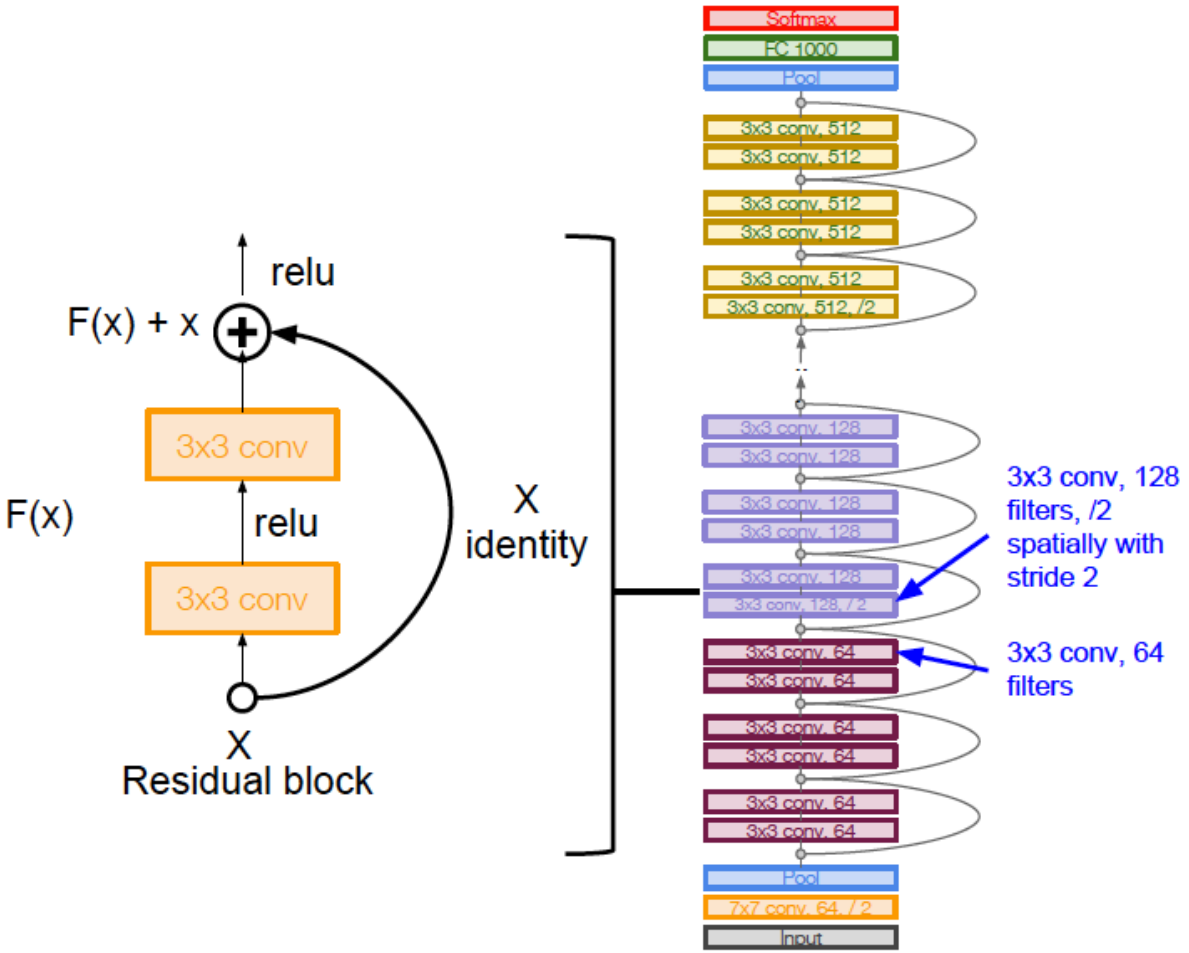
- Empilhe blocos residuais
- Cada bloco tem dois layers CONV 3x3



ResNet

[He et al., 2015]

- Empilhe blocos residuais
- Cada bloco tem dois layers CONV 3x3
- Periodicamente dobre o número de filtros e reduza espacialmente com stride 2



ResNet

[He et al., 2015]

- Empilhe blocos residuais
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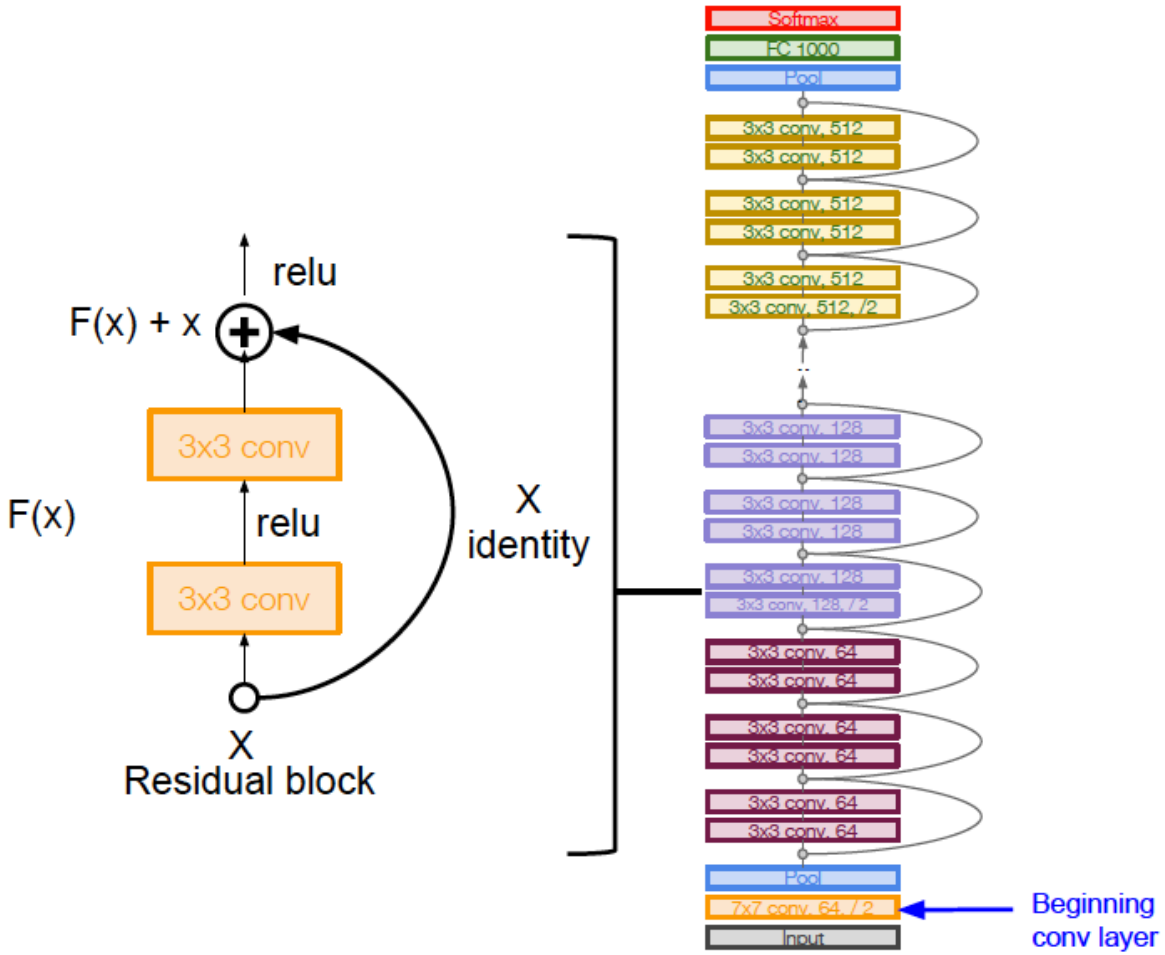
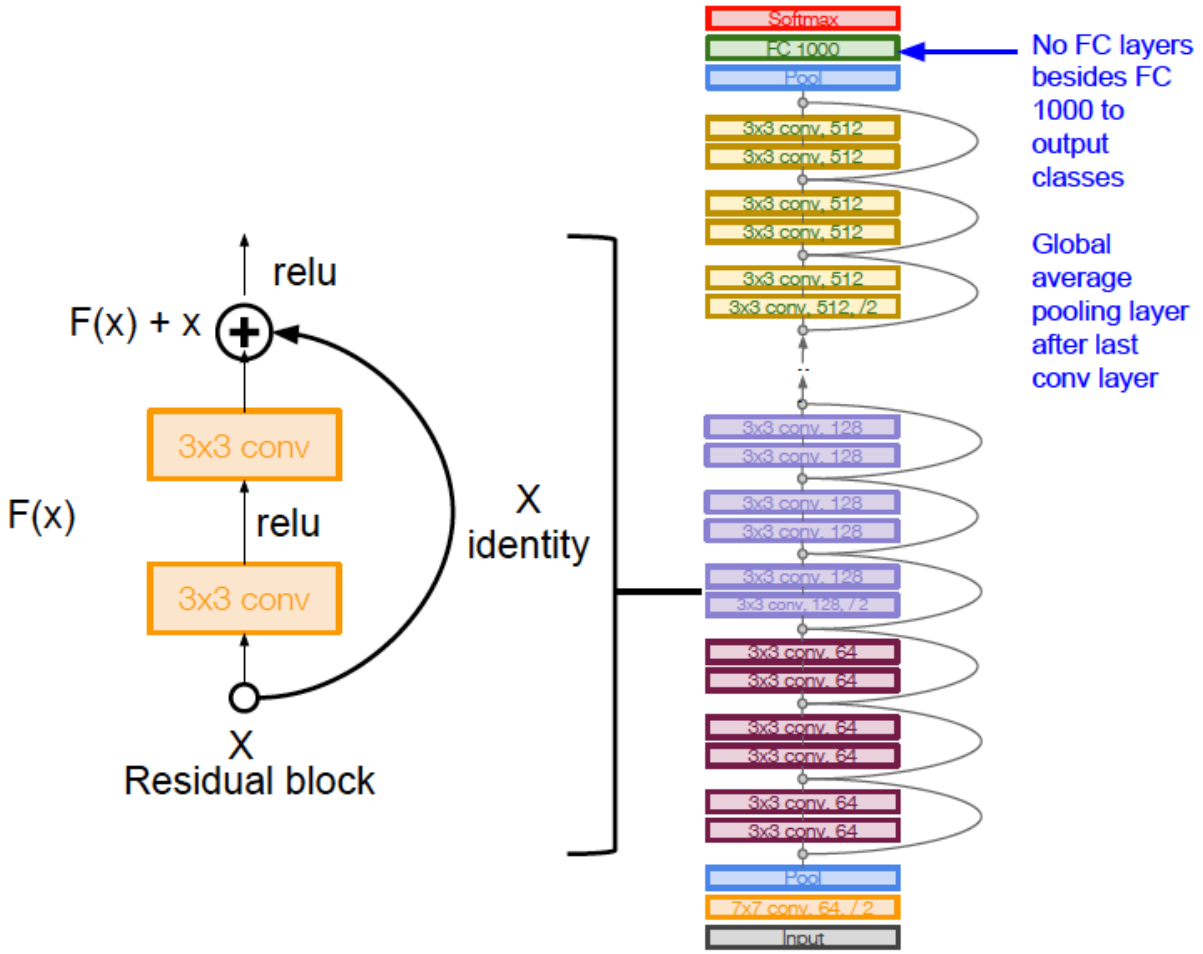


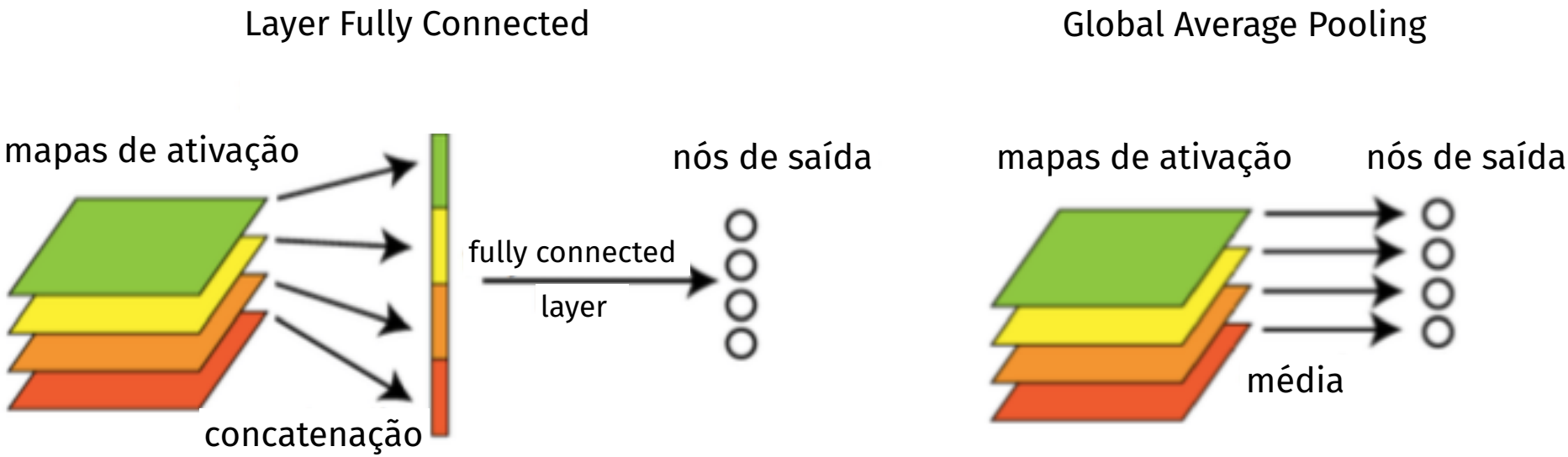
ResNet

[He et al., 2015]

- Empilhe blocos residuais
- Cada bloco tem dois layers CONV 3x3
- Periodicamente dobre o número de filtros e reduza espacialmente com stride 2
- Layer CONV adicional no início
- Apenas um layer FC ao final para o output das classes



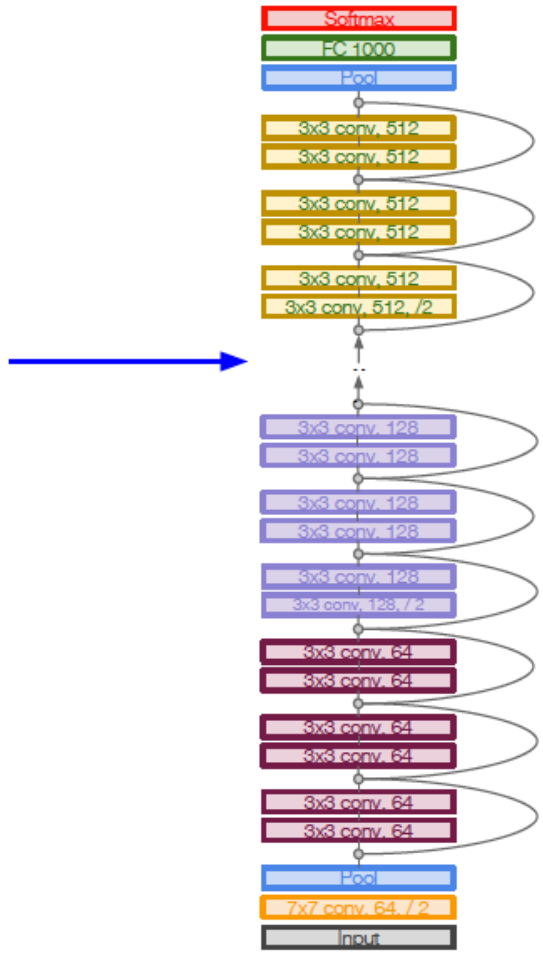
Global Average Pooling



ResNet

[He et al., 2015]

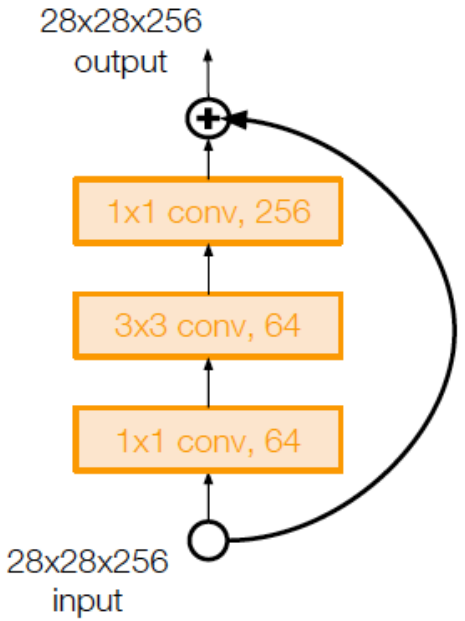
Profundidade: 34, 50, 101, ou 152 layers para a ImageNet



ResNet

[He et al., 2015]

Para redes mais profundas (ResNet-50+): utiliza camada de "gargalo" para eficiência (similar à GoogLeNet)



ResNet

[He et al., 2015]

Treinando a ResNet:

- Batch normalization após cada layer CONV
- Inicialização Xavier
- SGD + Momentum 0.9
- Learning rate: 0.1, dividido por 10 quando a validação fica em um plateau
- Mini-batch de 256
- Weight decay de 1e-5
- Não utiliza dropout

SqueezeNet

[Iandola et al., 2017]

- Módulos fire formados por:
  - uma camada “squeeze" com filtros 1x1
  - uma camada “expand" com filtros 1x1 e 3x3
- Acurácia equivalente à AlexNet na ImageNet, com 50x menos parâmetros
- Modelo 510x menor do que a AlexNet (0.5MB)

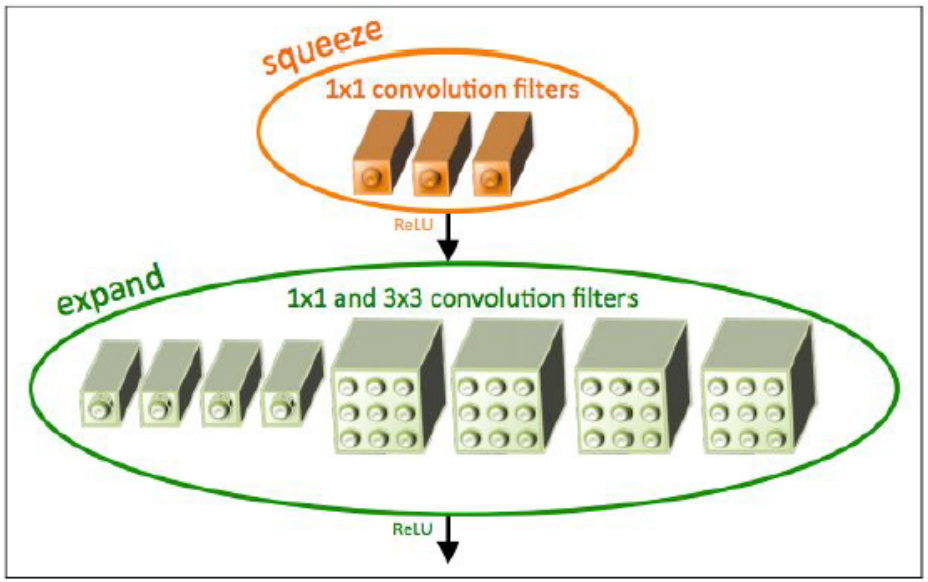
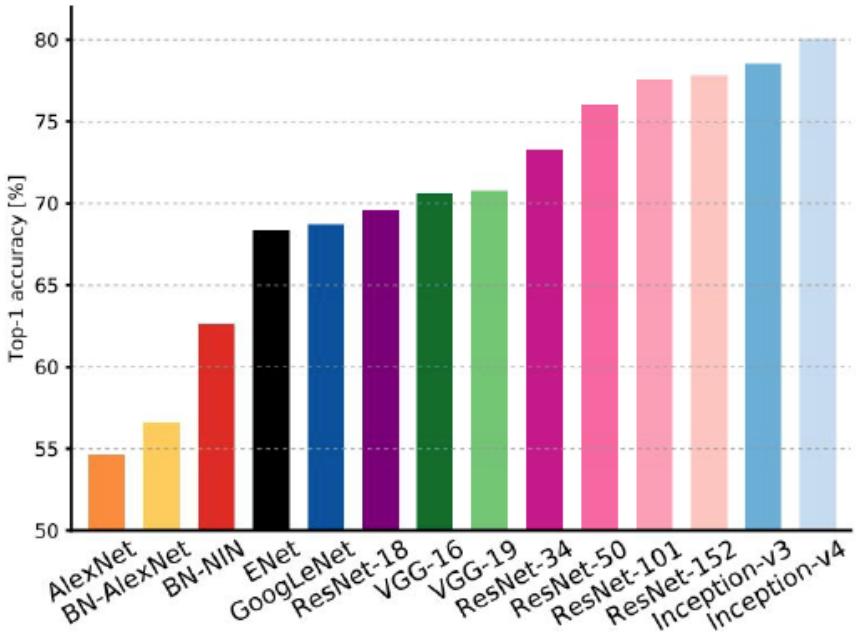
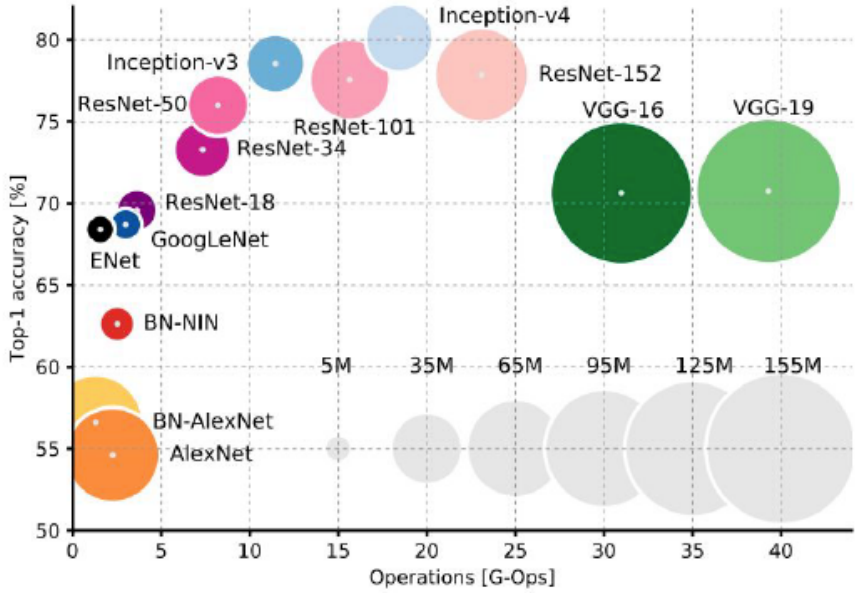


Figure copyright Iandola, Han, Moskewicz, Ashraf, Dally, Keutzer, 2017. Reproduced with permission.

Comparando a complexidade



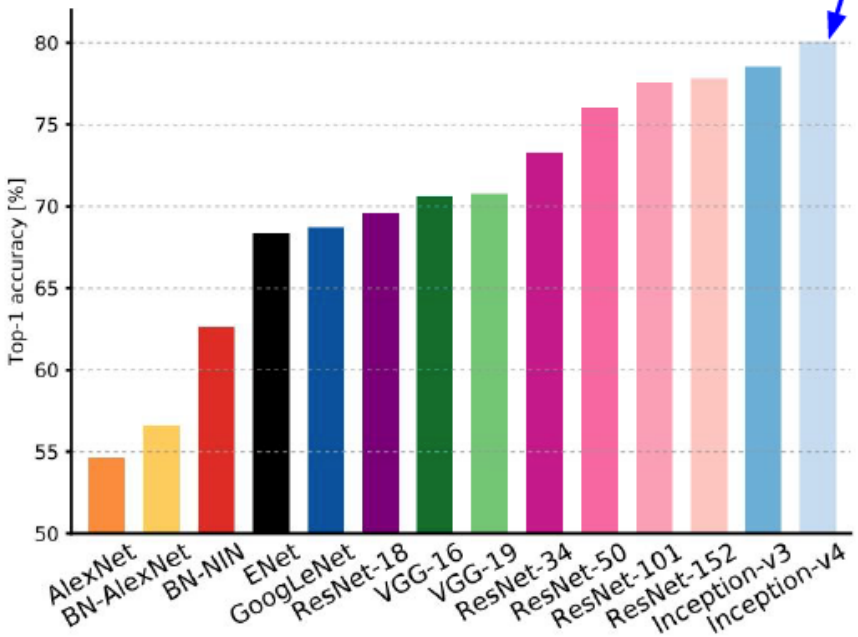


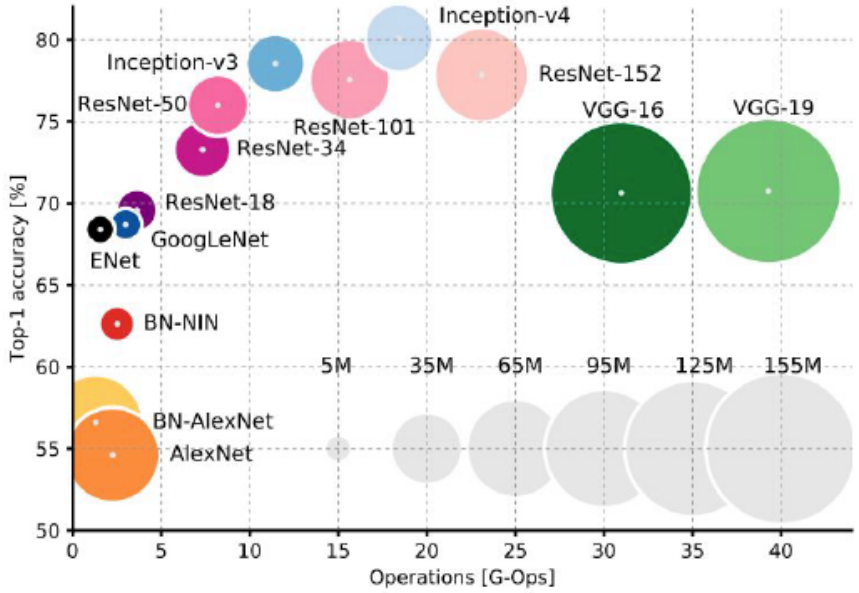
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Arquiteturas CNN

Comparando a complexidade

Inception-v4: ResNet + Inception





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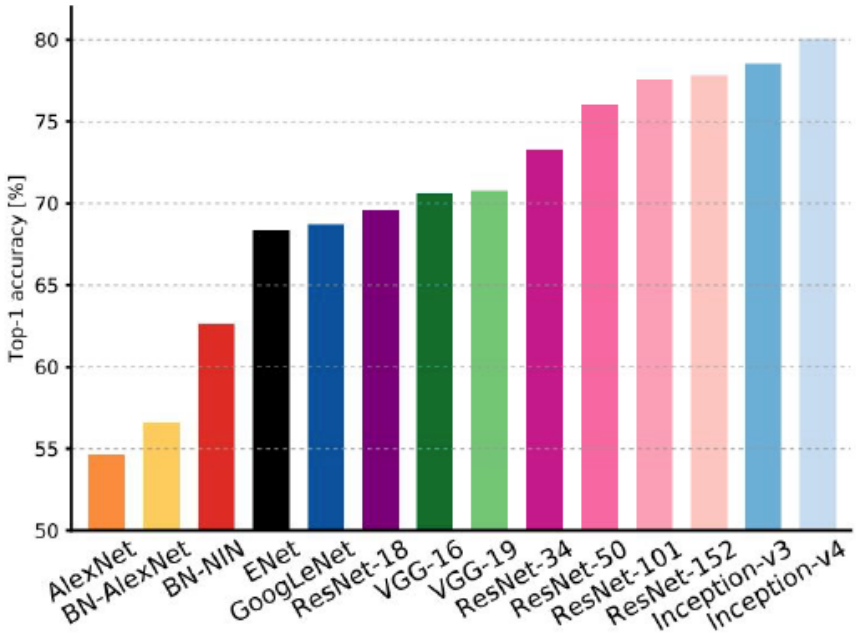
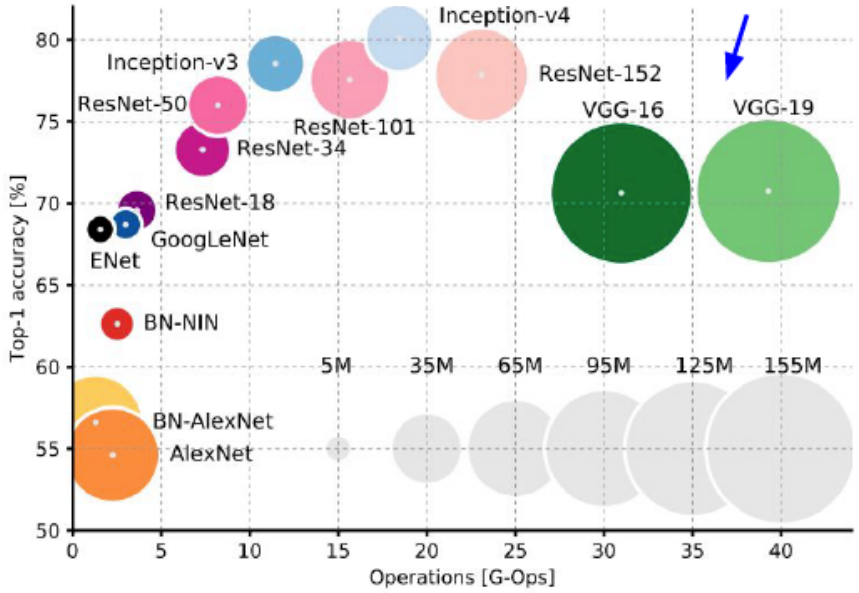
Arquiteturas CNN

Comparando a complexidade

VGG: maior modelo,
maior número de operações



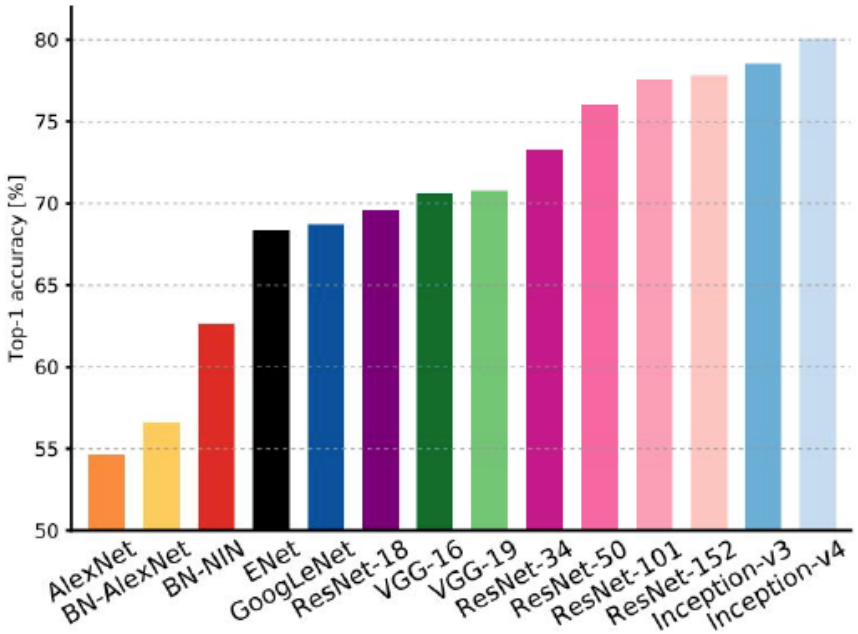


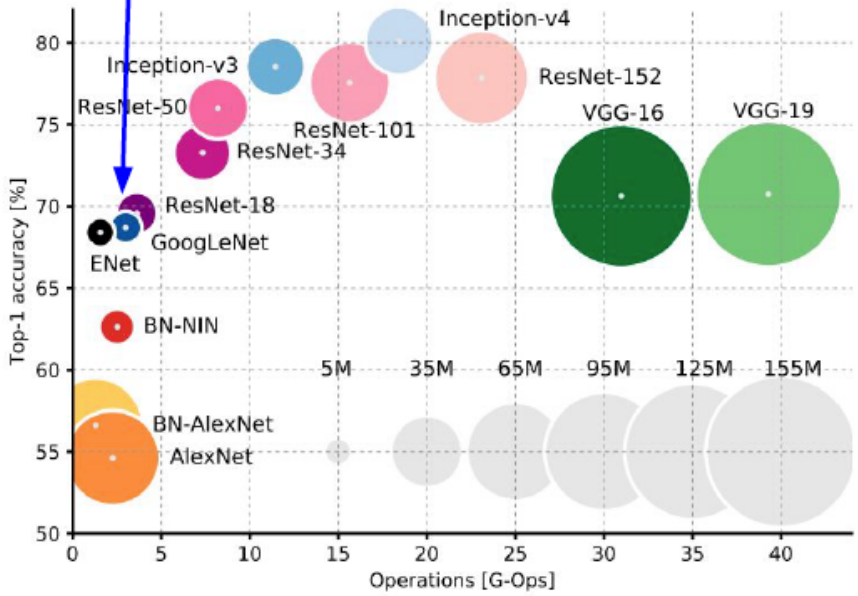
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Arquiteturas CNN

Comparando a complexidade

GoogLeNet:
mais eficiente



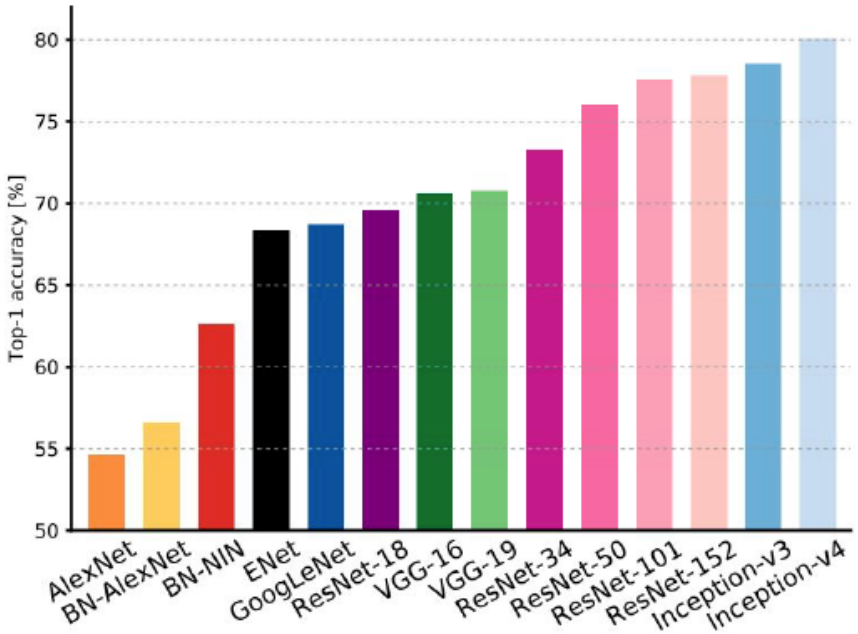


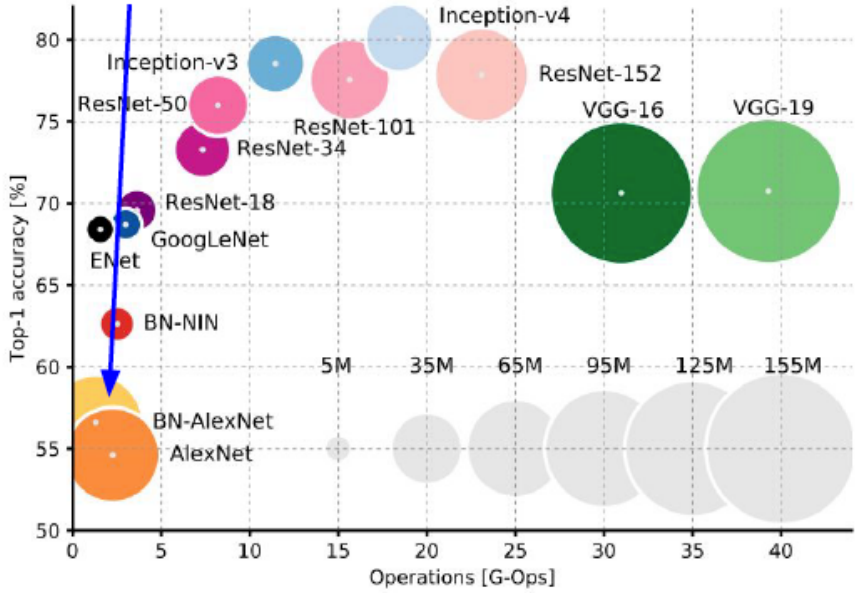
An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Arquiteturas CNN

Comparando a complexidade

AlexNet:
arquitetura menor, mas modelo maior
acurácia mais baixa





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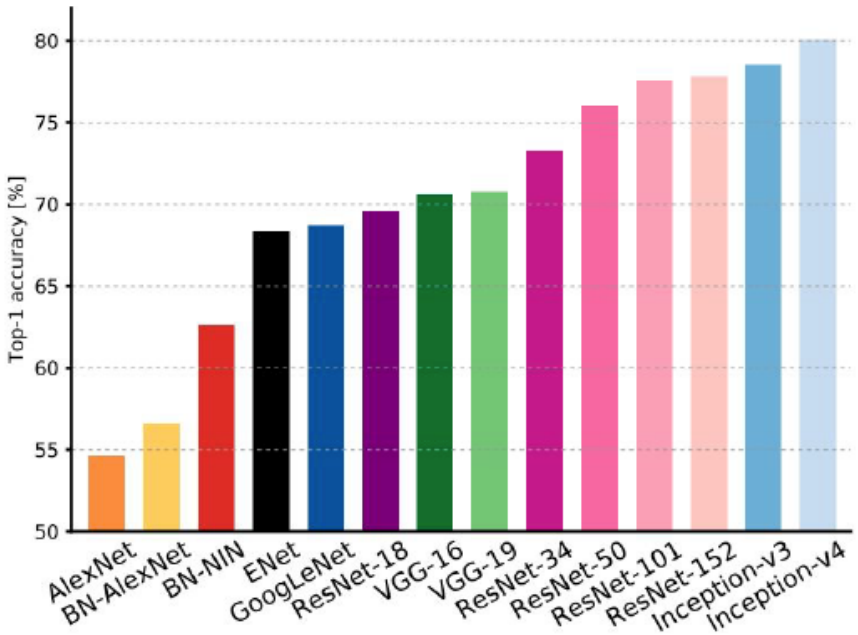
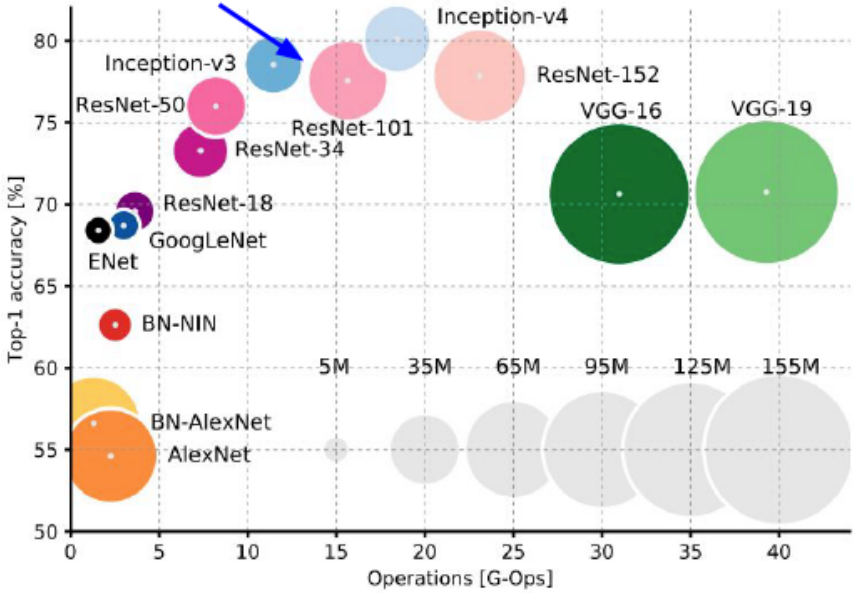
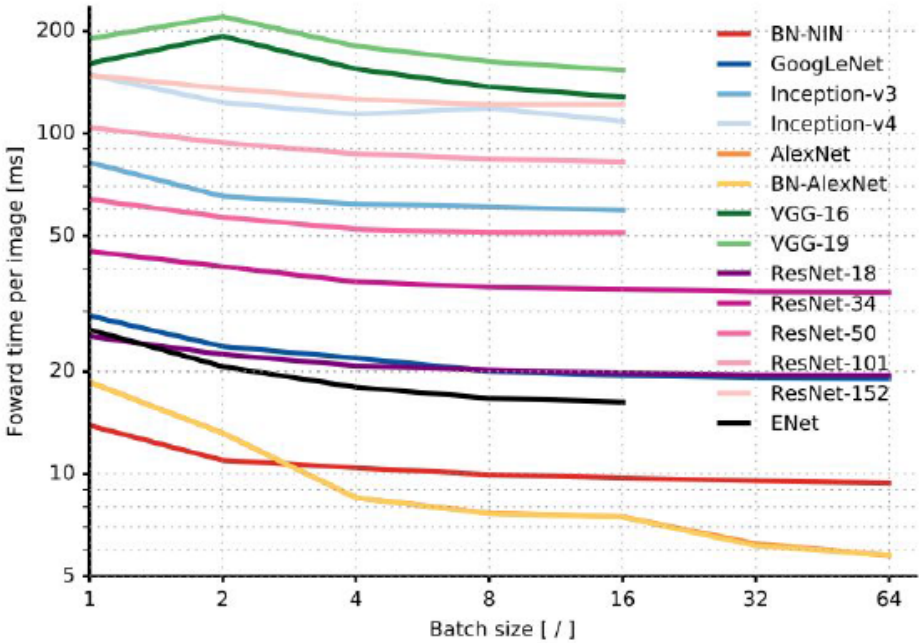


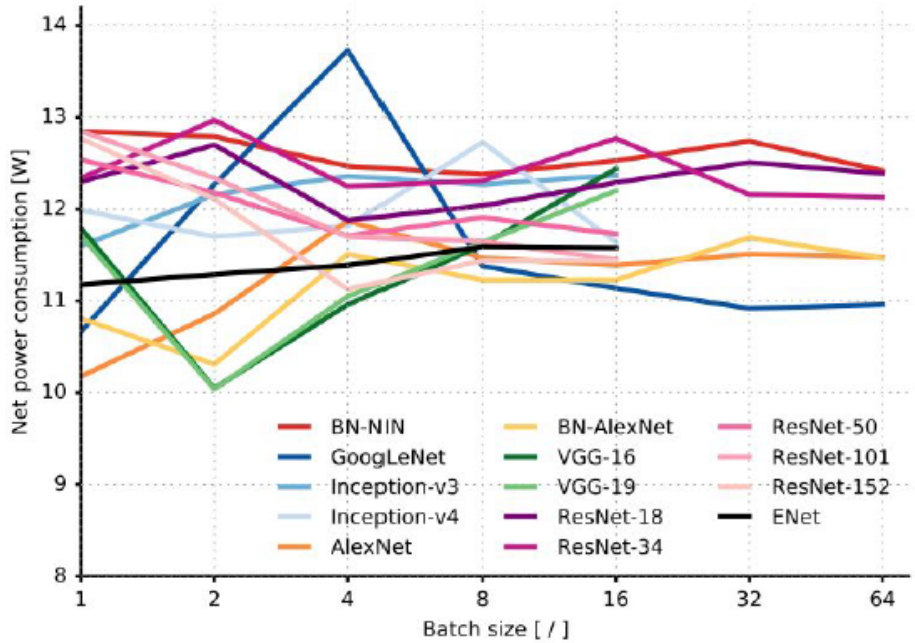
ResNet:
Eficiência depende do modelo, acurácia alta



An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Tempo de um forward pass e consumo de energia





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