Recent Advances in Computer Vision

Image Classification

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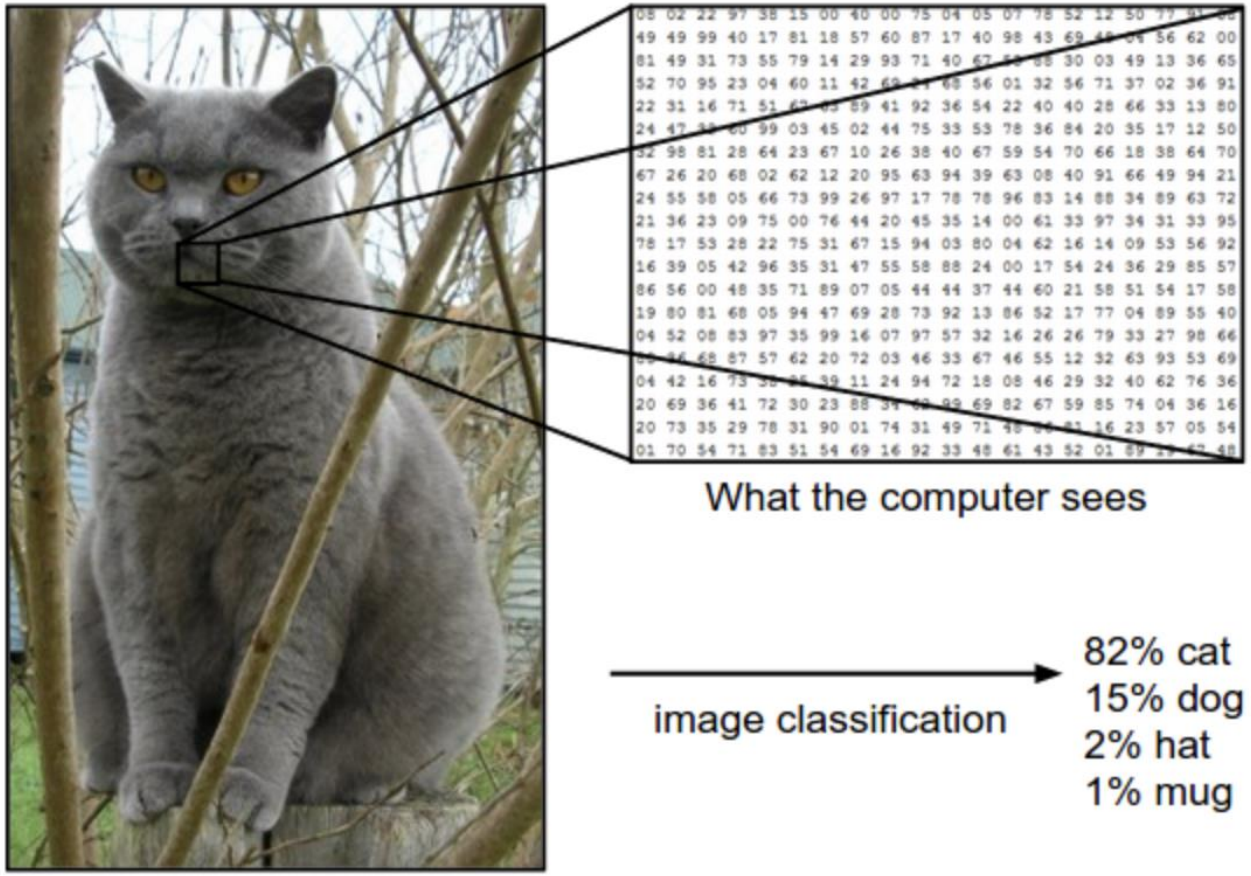
2020.04.20

Today

- image classification
  - Data driven approach
  - Parametric approach
  - Image classification SOTA
- DenseNet

Image classification



https://cs231n.github.io/

Data driven approach

```
def train(images, labels):
  # Machine learning!
  return model
```

→ Memorize all data and labels

```
def predict(model, test_images):
  # Use model to predict labels
  return test_labels
```

→ Predict the label of the most similar training image

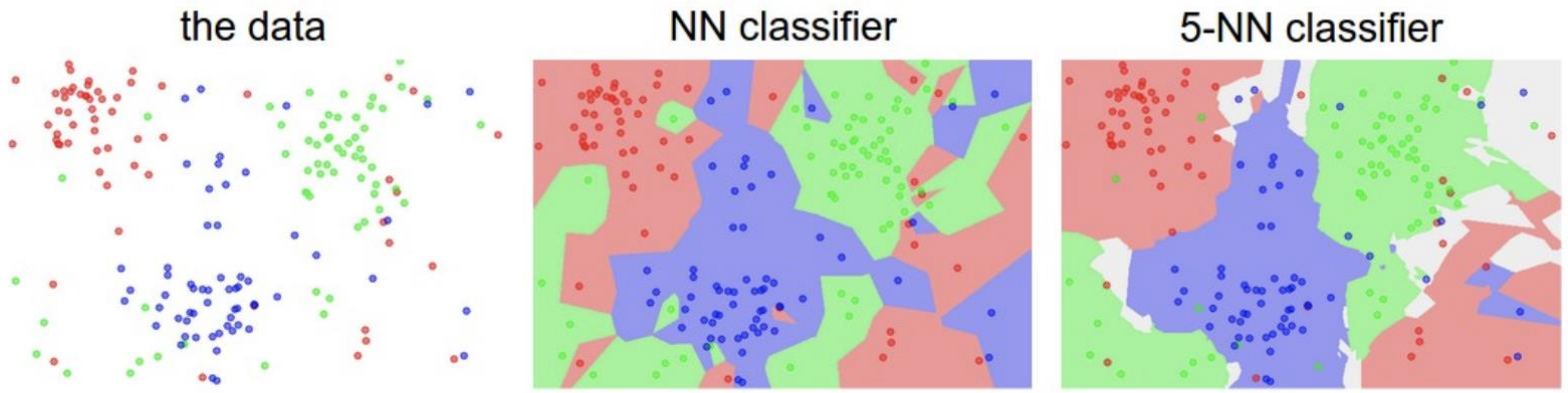
K Nearest Neighbor

```python
import numpy as np

class NearestNeighbor:
  def __init__(self):
    pass

  def train(self, X, y):
    """ X is N x D where each row is an example. Y is 1-dimension of size N """
    # the nearest neighbor classifier simply remembers all the training data
    self.Xtr = X
    self.ytr = y

  def predict(self, X):
    """ X is N x D where each row is an example we wish to predict label for """
    num_test = X.shape[0]
    # lets make sure that the output type matches the input type
    Ypred = np.zeros(num_test, dtype = self.ytr.dtype)

    # loop over all test rows
    for i in xrange(num_test):
      # find the nearest training image to the i'th test image
      # using the L1 distance (sum of absolute value differences)
      distances = np.sum(np.abs(self.Xtr - X[i,:]), axis = 1)
      min_index = np.argmin(distances) # get the index with smallest distance
      Ypred[i] = self.ytr[min_index] # predict the label of the nearest example

    return Ypred
```

Nearest Neighbor classifier

For each test image:
  Find closest train image
  Predict label of nearest image

K Nearest Neighbor



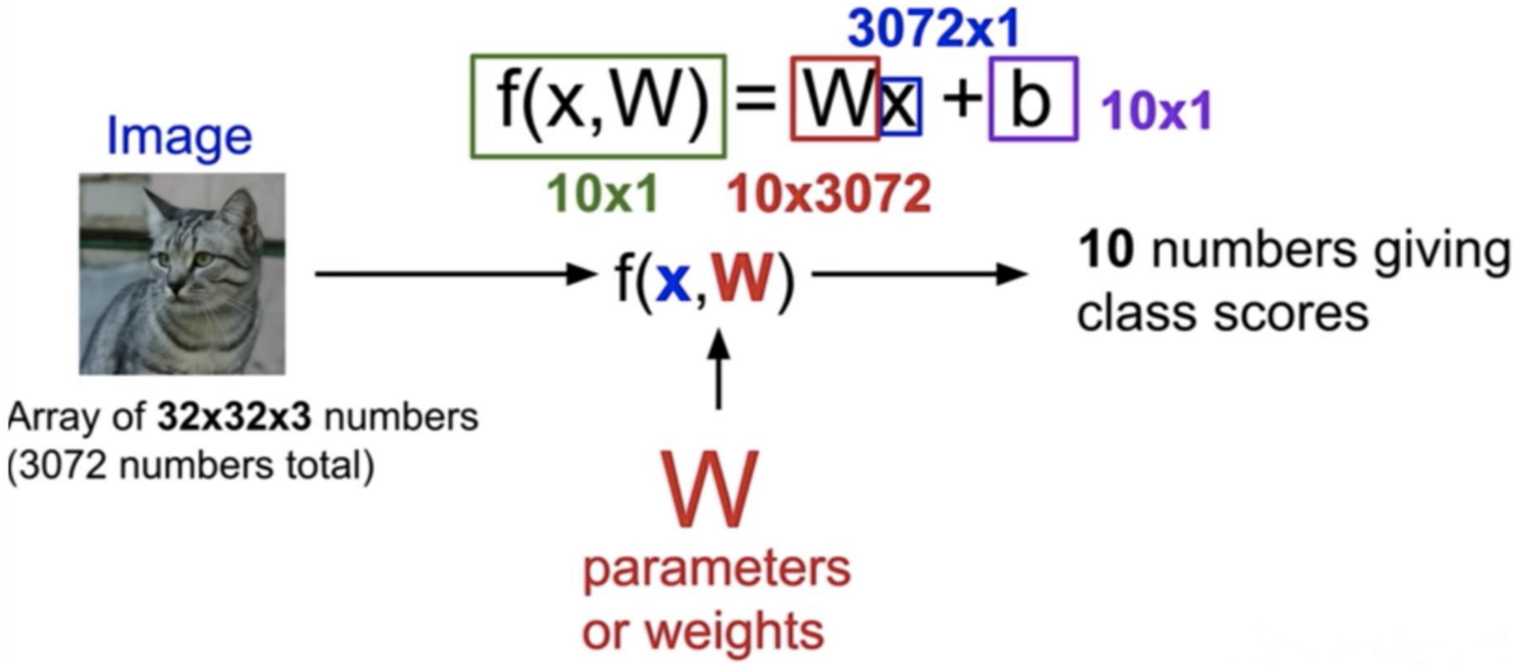
K Nearest Neighbor

- Very slow at test time
- Distance metrics on pixels are not informative

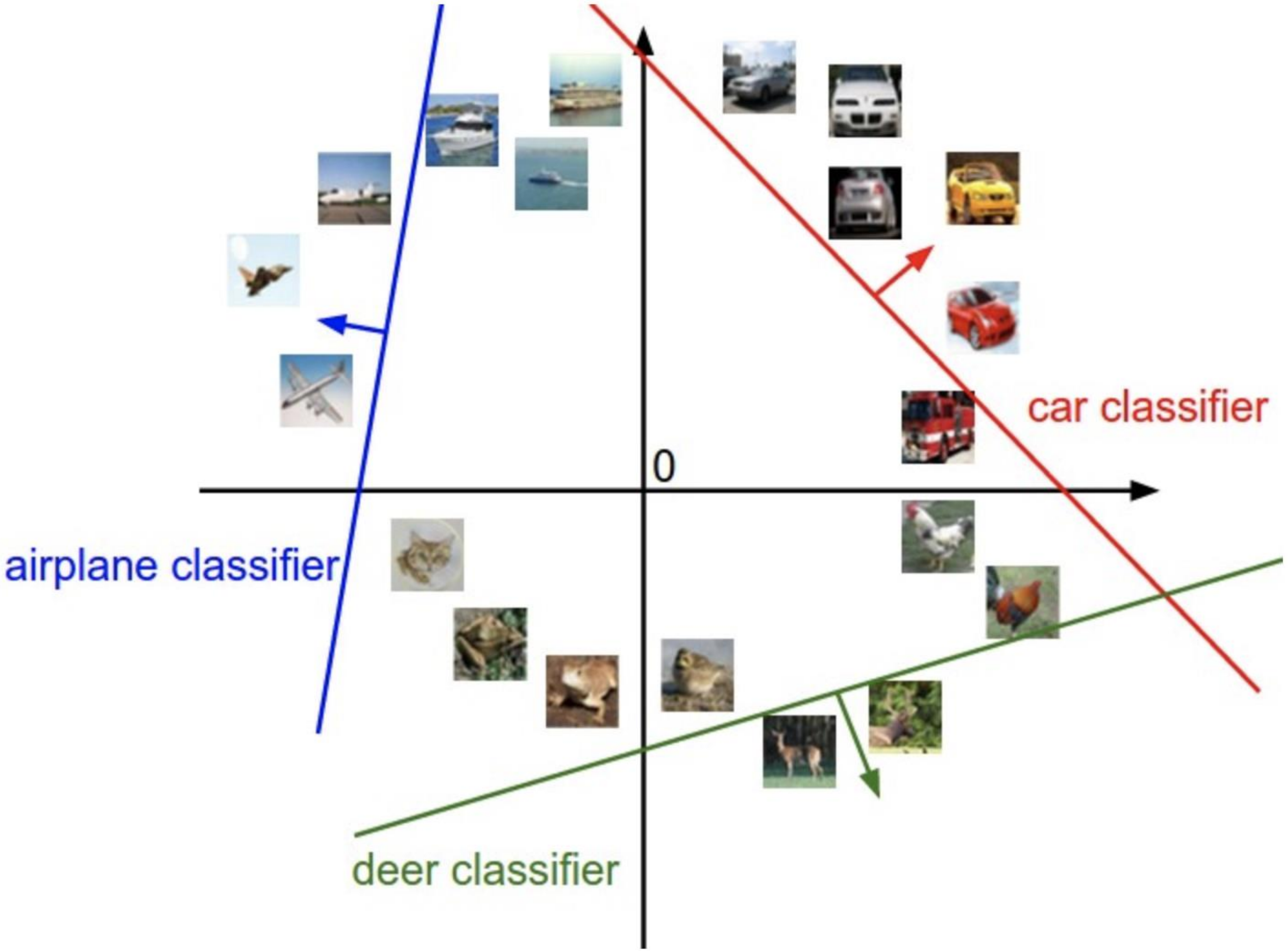
nal image is public domain

(all 3 images have same L2 distance to the one on the left)

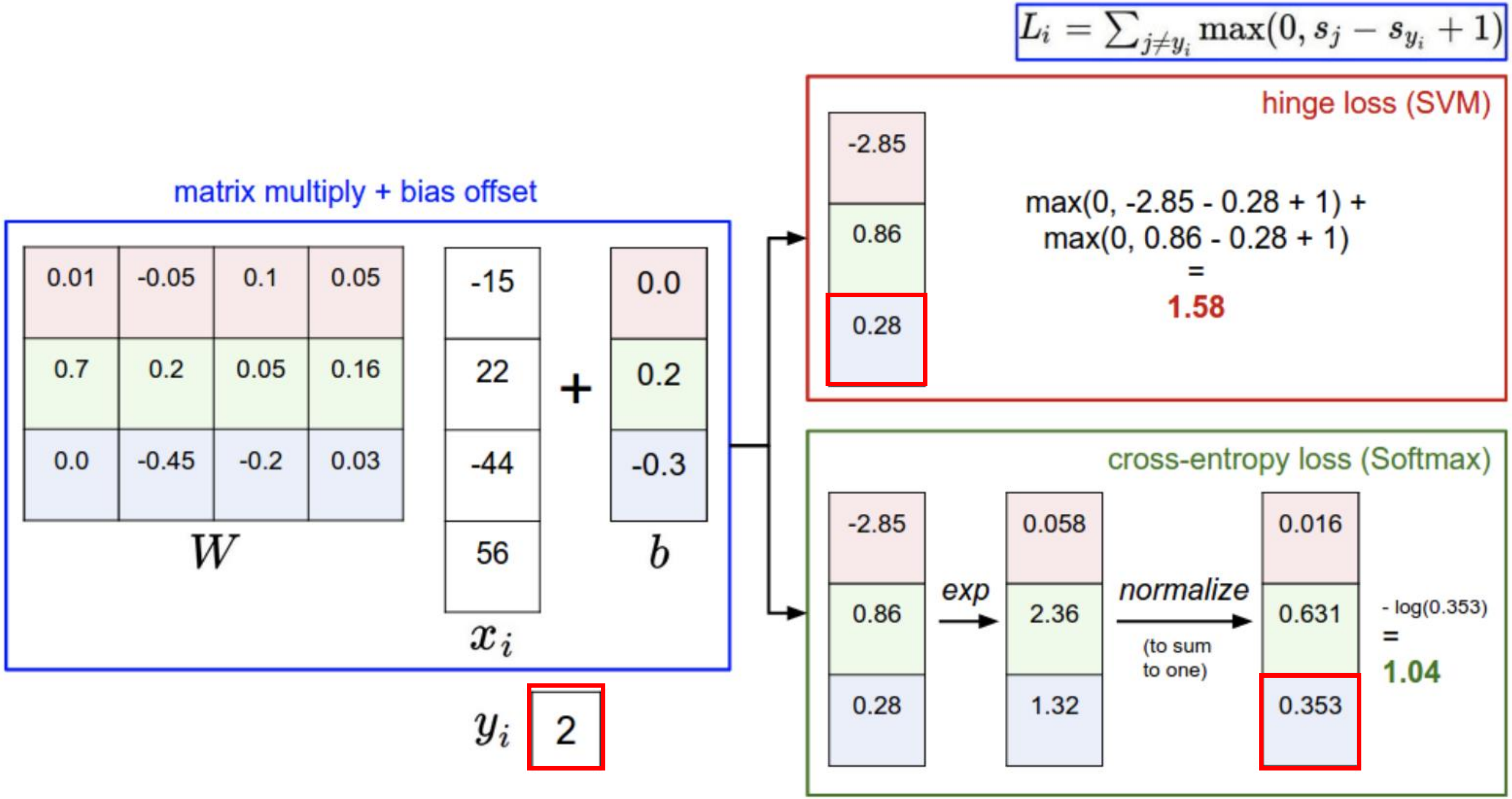
Parametric approach



Linear Classification

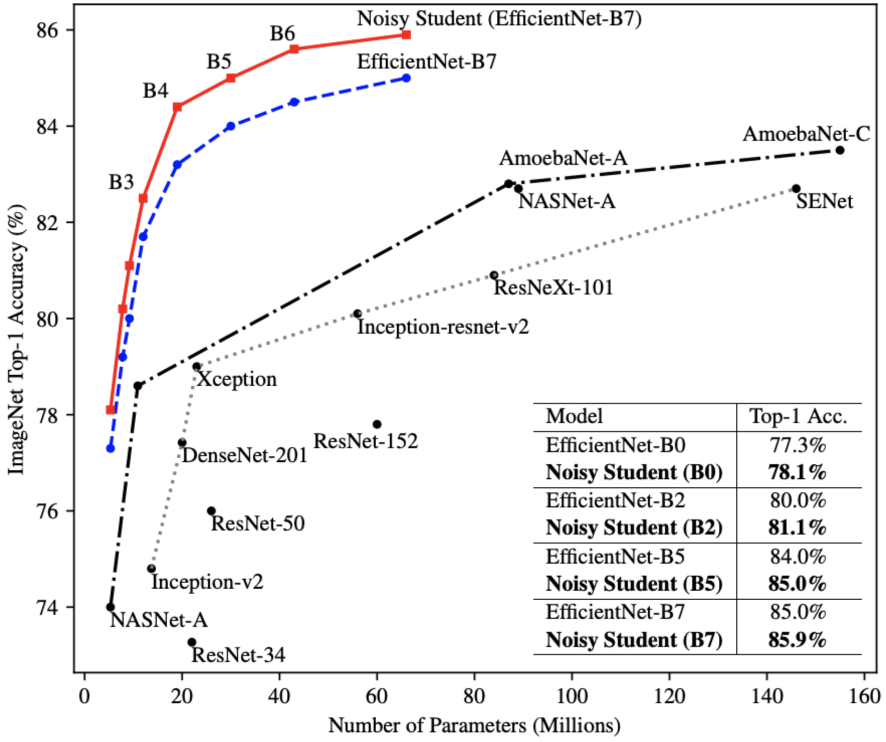


SVM & Softmax



$L_i = \sum_{j \neq y_i} \max(0, s_j - s_{y_i} + 1)$
hinge loss (SVM)
-2.85
0.86
0.28
max(0, -2.85 - 0.28 + 1) +
max(0, 0.86 - 0.28 + 1)
=
1.58
matrix multiply + bias offset
0.01 -0.05 0.1 0.05
0.7 0.2 0.05 0.16
0.0 -0.45 -0.2 0.03
W
-15
22
-44
56
x_i
+
0.0
0.2
-0.3
b
y_i
2
cross-entropy loss (Softmax)
-2.85
0.86
0.28
exp
0.058
2.36
1.32
normalize
(to sum to one)
0.016
0.631
0.353
- log(0.353)
=
1.04

Image classification - SOTA

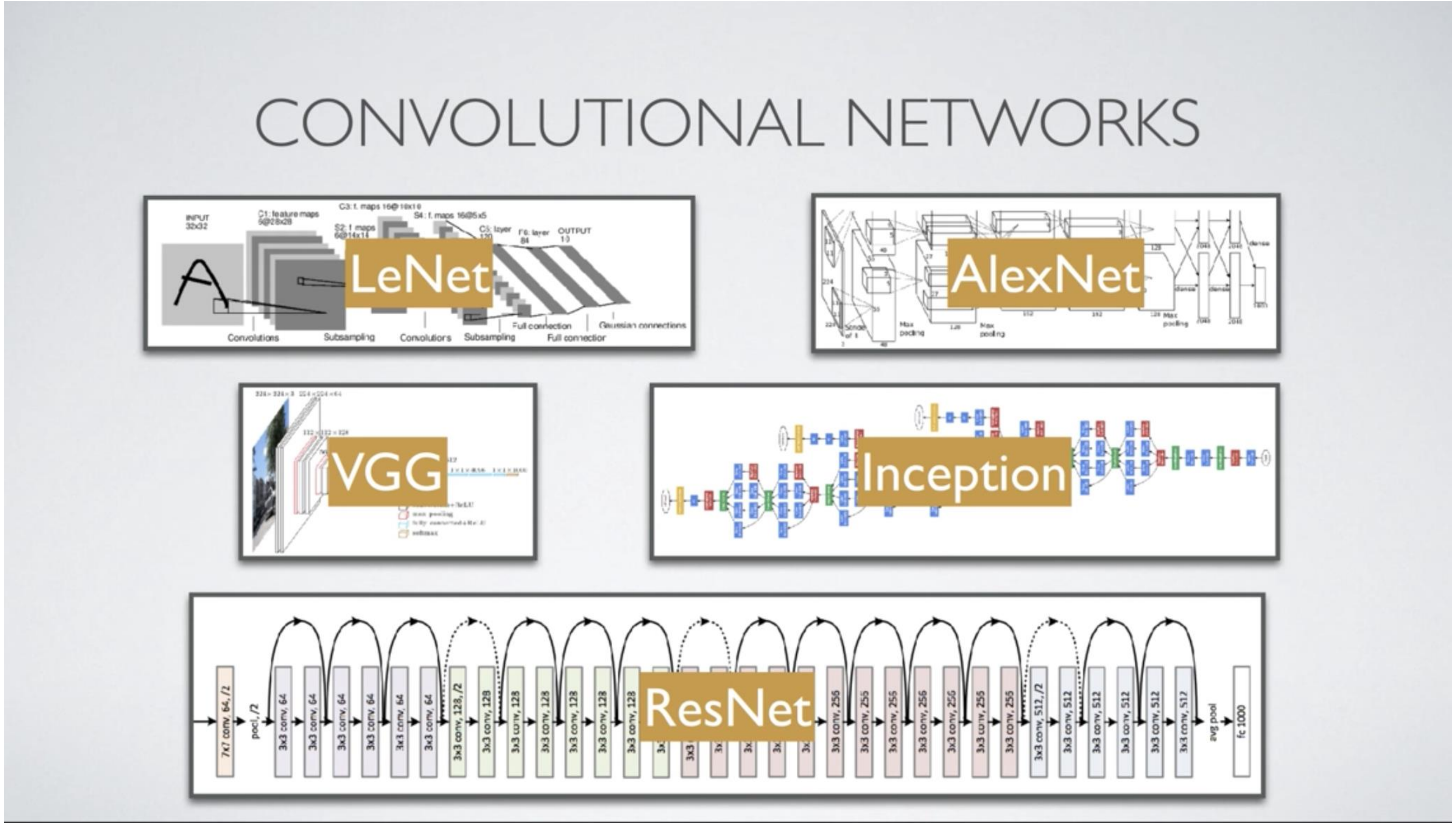


Method	# Params	Extra Data	Top-1 Acc.	Top-5 Acc.
ResNet-50 [28]	26M	-	76.0%	93.0%
ResNet-152 [28]	60M	-	77.8%	93.8%
DenseNet-264 [34]	34M	-	77.9%	93.9%
Inception-v3 [76]	24M	-	78.8%	94.4%
Xception [14]	23M	-	79.0%	94.5%
Inception-v4 [74]	48M	-	80.0%	95.0%
Inception-resnet-v2 [74]	56M	-	80.1%	95.1%
ResNeXt-101 [85]	84M	-	80.9%	95.6%
PolyNet [93]	92M	-	81.3%	95.8%
SENet [33]	146M	-	82.7%	96.2%
NASNet-A [97]	89M	-	82.7%	96.2%
AmoebaNet-A [61]	87M	-	82.8%	96.1%
PNASNet [46]	86M	-	82.9%	96.2%
AmoebaNet-C [16]	155M	-	83.5%	96.5%
GPipe [36]	557M	-	84.3%	97.0%
EfficientNet-B7 [78]	66M	-	85.0%	97.2%
EfficientNet-L2 [78]	480M	-	85.5%	97.5%
ResNet-50 Billion-scale [86]	26M	3.5B images labeled with tags	81.2%	96.0%
ResNeXt-101 Billion-scale [86]	193M		84.8%	-
ResNeXt-101 WSL [51]	829M		85.4%	97.6%
FixRes ResNeXt-101 WSL [80]	829M		86.4%	98.0%
Noisy Student (L2)	480M	300M unlabeled images	**88.4%**	**98.7%**

Self-training with Noisy Student improves ImageNet classification. 2019.11

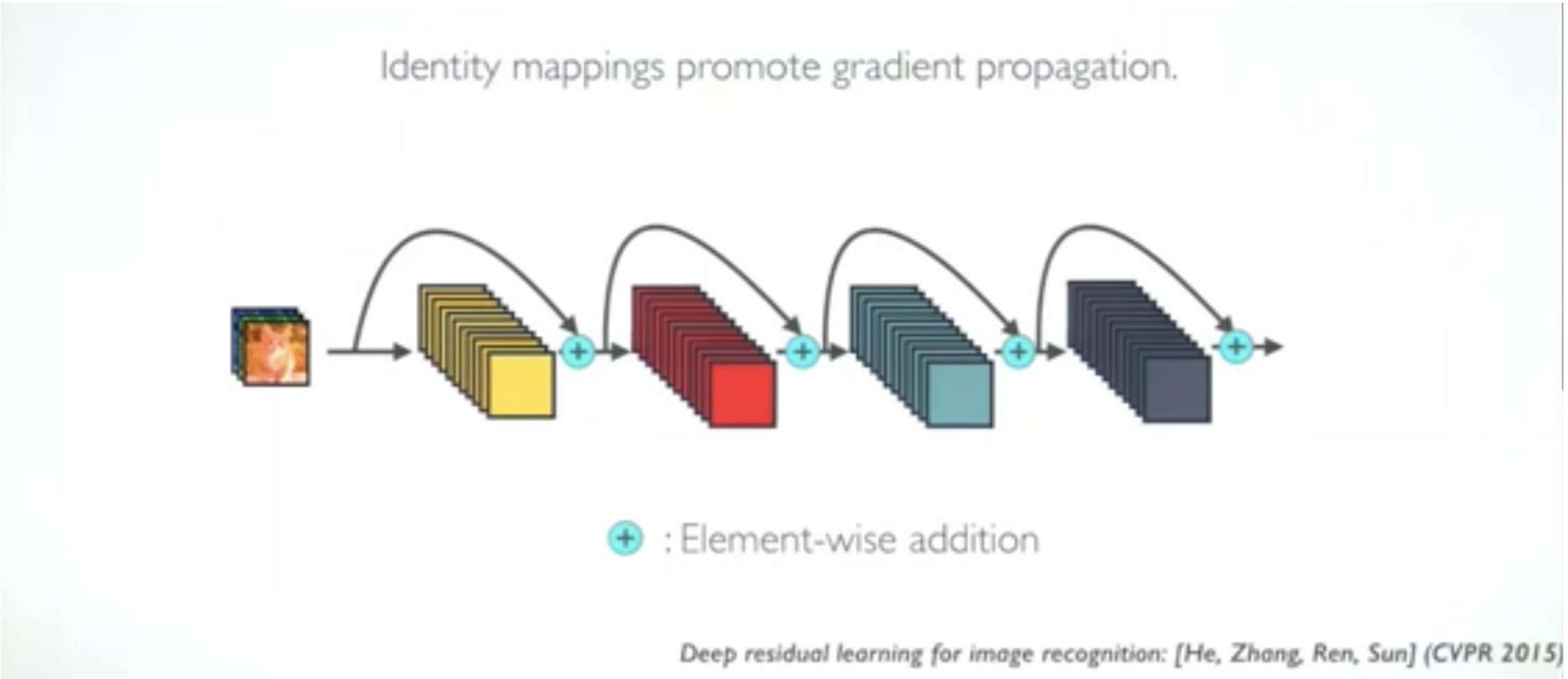
Densely Connected Convolutional Networks

Introduction

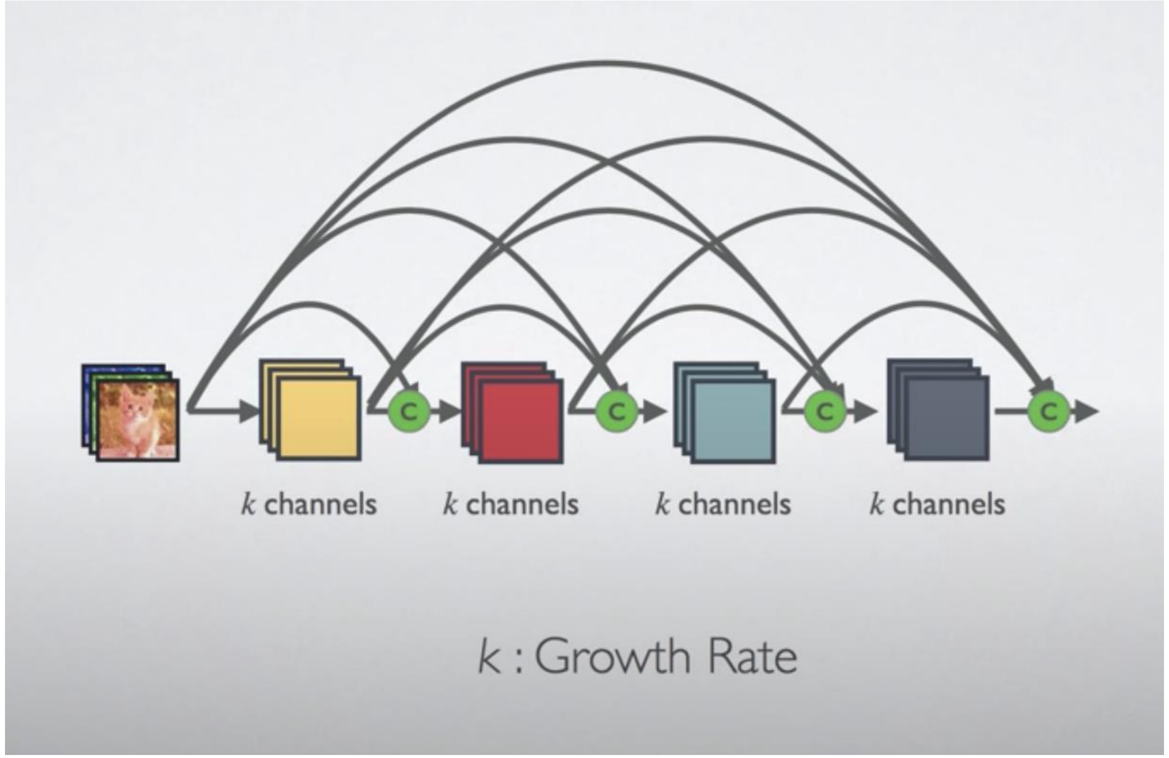


https://www.youtube.com/watch?v=-W6y8xnd--U

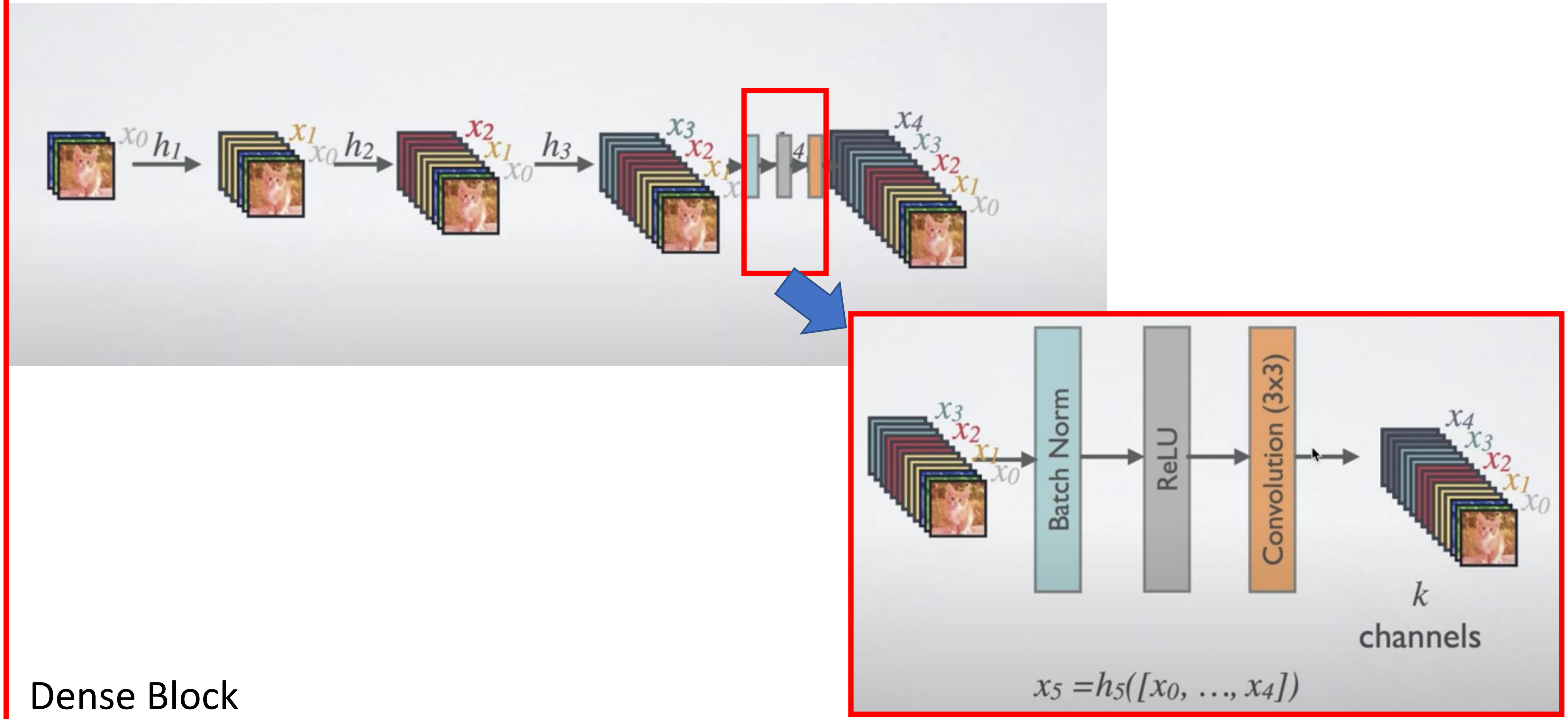
ResNet Connectivity



Dense and Slim



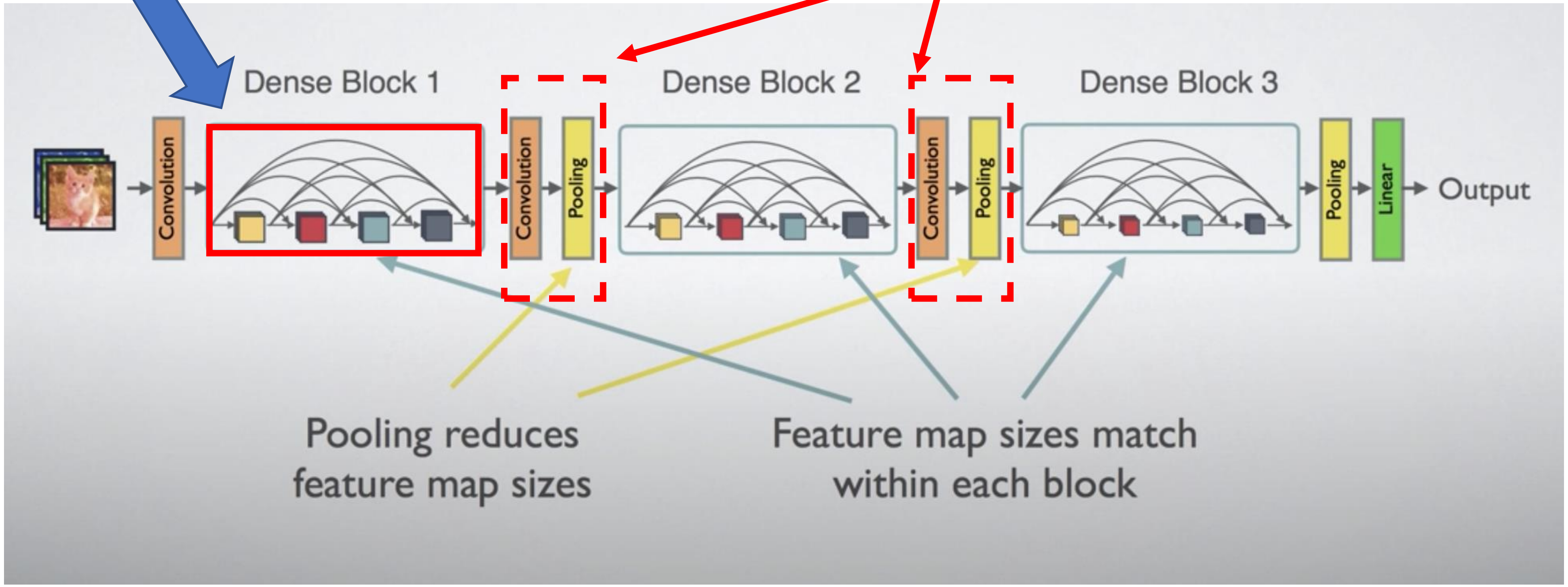
Forward Propagation



Dense Block

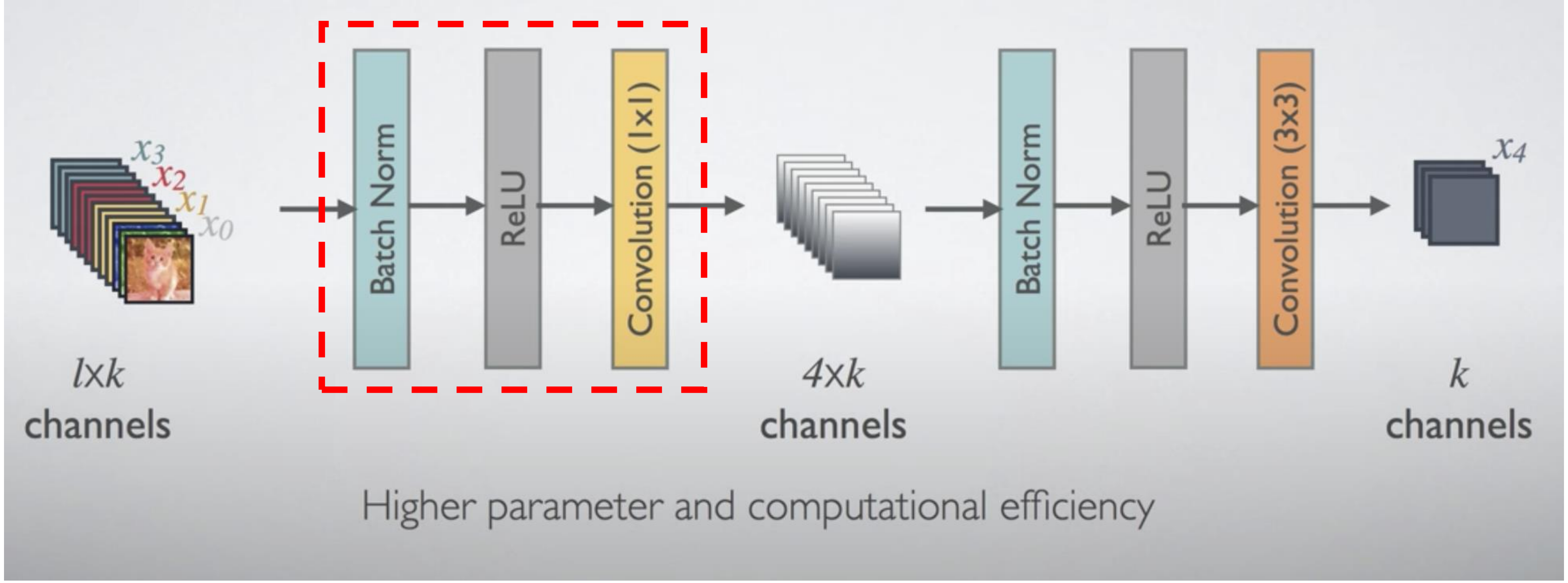
DenseNet

- transition layer
  - 1*1 conv
  - 2*2 avg pooling



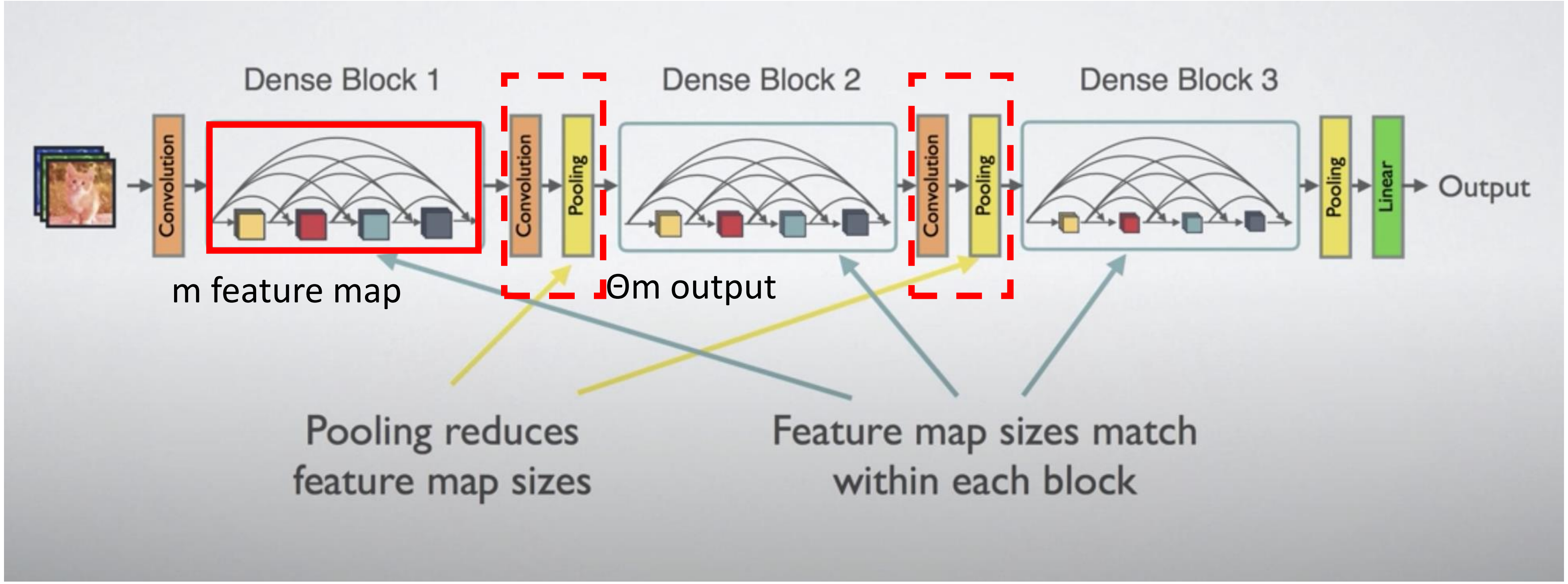
DenseNet-B

Bottleneck layer



DenseNet -C

- compression
  - reduce the number of feature-maps at transition layers
  - DenseNet-C: with θ < 1 (set θ = 0.5 in this paper experiment)
  - DenseNet-BC : When both the bottleneck and transition layers with θ < 1 are used

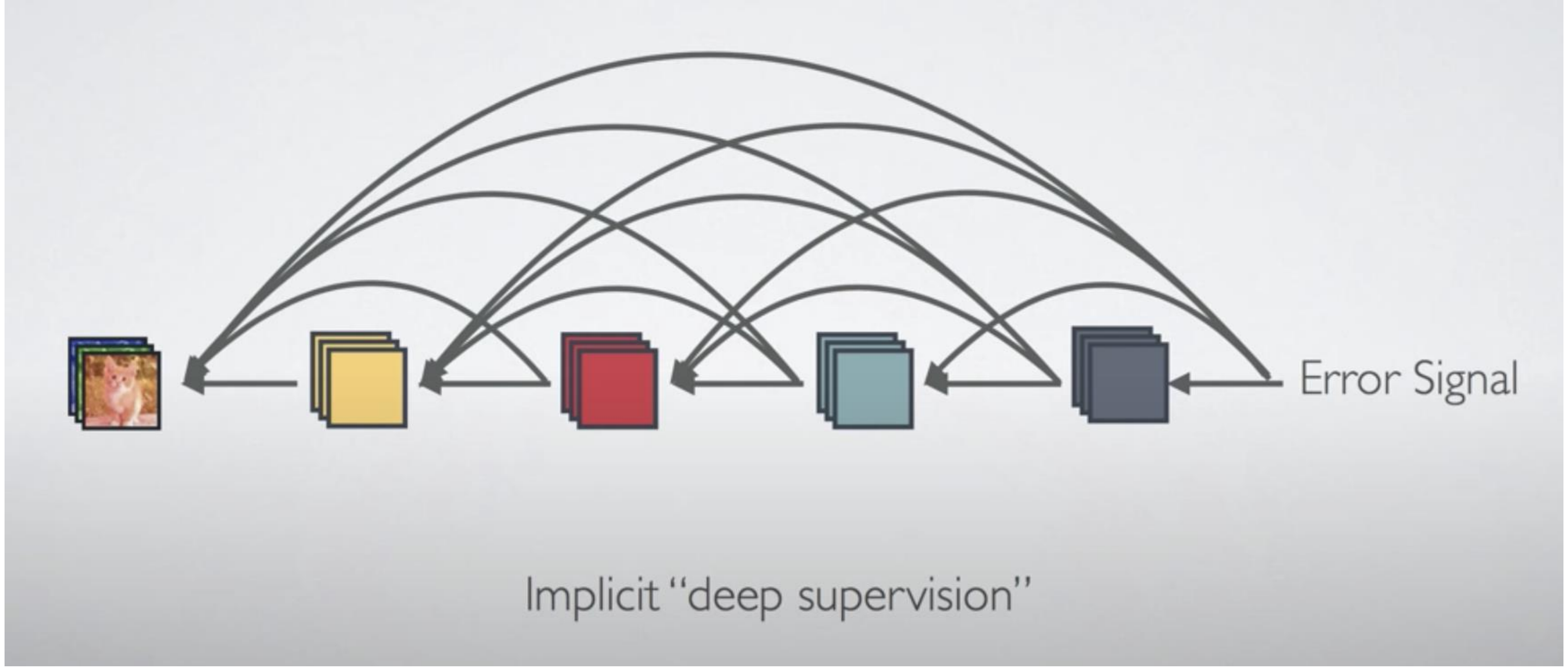


DenseNet Architectures

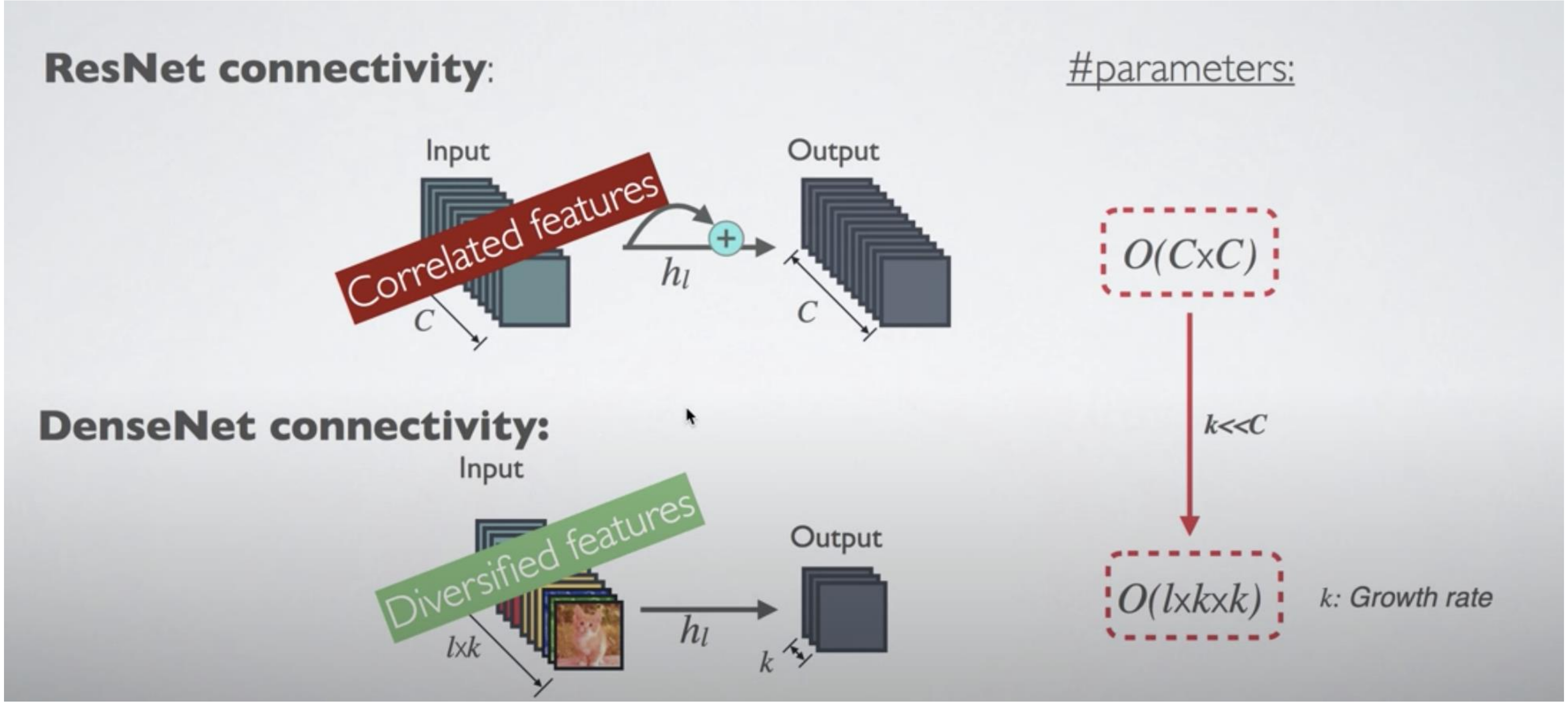
Layers	Output Size	DenseNet-121	DenseNet-169	DenseNet-201	DenseNet-264
Convolution	112×112	7×7 conv, stride 2			
Pooling	56×56	3×3 max pool, stride 2			
Dense Block (1)	56×56	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 6$
Transition Layer (1)	56×56	1×1 conv			
	28×28	2×2 average pool, stride 2			
Dense Block (2)	28×28	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 12$
Transition Layer (2)	28×28	1×1 conv			
	14×14	2×2 average pool, stride 2			
Dense Block (3)	14×14	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 24$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 64$
Transition Layer (3)	14×14	1×1 conv			
	7×7	2×2 average pool, stride 2			
Dense Block (4)	7×7	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 16$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 32$	$\begin{bmatrix} 1 \times 1 \text{ conv} \\ 3 \times 3 \text{ conv} \end{bmatrix} \times 48$
Classification Layer	1×1	7×7 global average pool			
		1000D fully-connected, softmax			

Table 1: DenseNet architectures for ImageNet. The growth rate for all the networks is $k = 32$. Note that each "conv" layer shown in the table corresponds the sequence BN-ReLU-Conv.

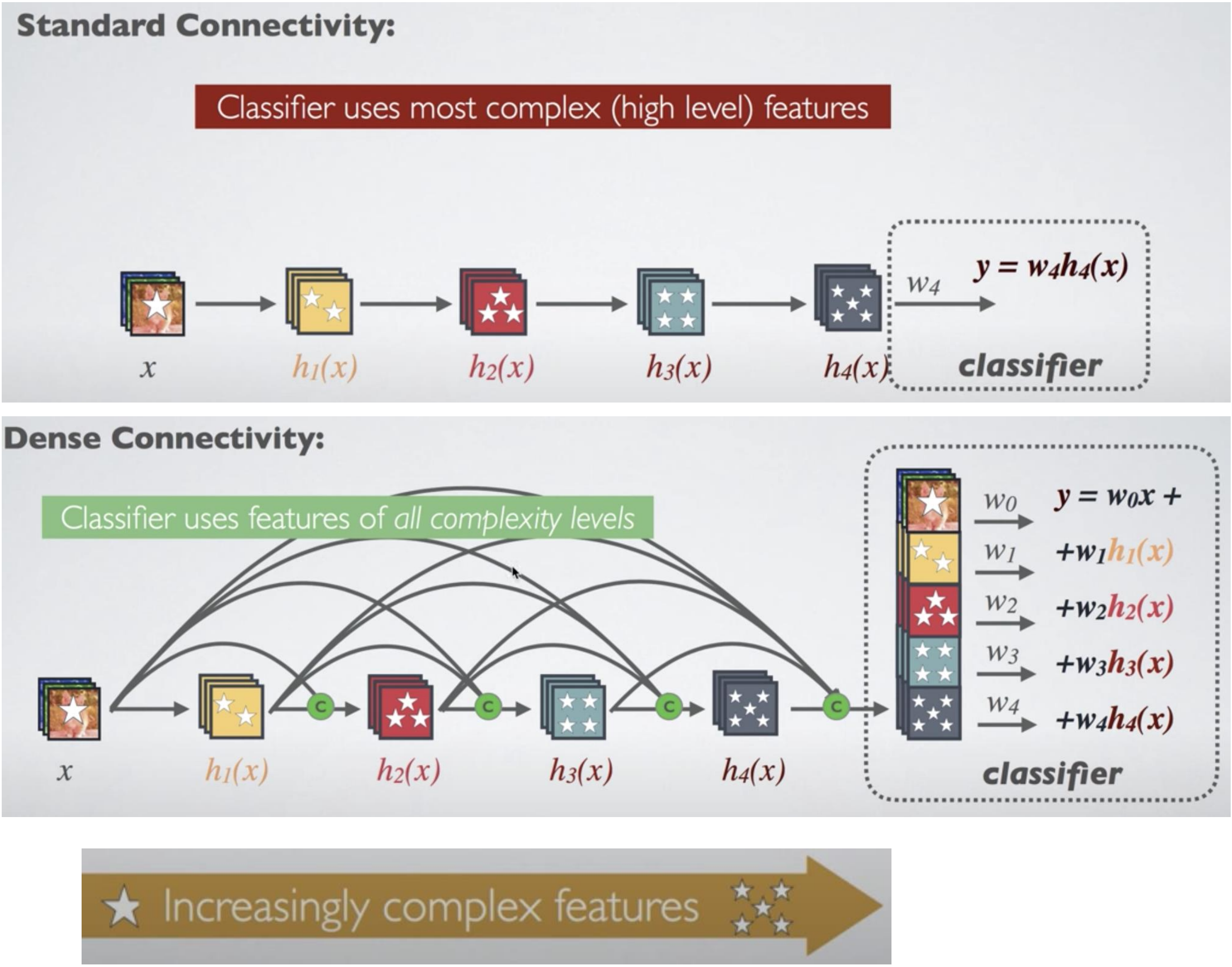
Advantage 1: Strong gradient flow



Advantage 2: parameter & computational efficiency



Advantage 3: Maintains low complexity feature



Experiments

Method	Depth	Params	C10	C10+	C100	C100+	SVHN
Network in Network [22]	-	-	10.41	8.81	35.68	-	2.35
All-CNN [32]	-	-	9.08	7.25	-	33.71	-
Deeply Supervised Net [20]	-	-	9.69	7.97	-	34.57	1.92
Highway Network [34]	-	-	-	7.72	-	32.39	-
FractalNet [17]	21	38.6M	10.18	5.22	35.34	23.30	2.01
with Dropout/Drop-path	21	38.6M	7.33	4.60	28.20	23.73	1.87
ResNet [11]	110	1.7M	-	6.61	-	-	-
ResNet (reported by [13])	110	1.7M	13.63	6.41	44.74	27.22	2.01
ResNet with Stochastic Depth [13]	110	1.7M	11.66	5.23	37.80	24.58	1.75
	1202	10.2M	-	4.91	-	-	-
Wide ResNet [42]	16	11.0M	-	4.81	-	22.07	-
	28	36.5M	-	4.17	-	20.50	-
with Dropout	16	2.7M	-	-	-	-	1.64
ResNet (pre-activation) [12]	164	1.7M	11.26*	5.46	35.58*	24.33	-
	1001	10.2M	10.56*	4.62	33.47*	22.71	-
DenseNet ($k = 12$)	40	1.0M	**7.00**	5.24	**27.55**	24.42	1.79
DenseNet ($k = 12$)	100	7.0M	**5.77**	**4.10**	**23.79**	**20.20**	1.67
DenseNet ($k = 24$)	100	27.2M	**5.83**	**3.74**	**23.42**	**19.25**	**1.59**
DenseNet-BC ($k = 12$)	100	0.8M	**5.92**	4.51	**24.15**	22.27	1.76
DenseNet-BC ($k = 24$)	250	15.3M	**5.19**	**3.62**	**19.64**	**17.60**	1.74
DenseNet-BC ($k = 40$)	190	25.6M	-	**3.46**	-	**17.18**	-

Table 2: Error rates (%) on CIFAR and SVHN datasets. k denotes network's growth rate. Results that surpass all competing methods are **bold** and the overall best results are **blue**. "+" indicates standard data augmentation (translation and/or mirroring). $*$ indicates results run by ourselves. All the results of DenseNets without data augmentation (C10, C100, SVHN) are obtained using Dropout. DenseNets achieve lower error rates while using fewer parameters than ResNet. Without data augmentation, DenseNet performs better by a large margin.

Experiments

Model	top-1	top-5
DenseNet-121	25.02 / 23.61	7.71 / 6.66
DenseNet-169	23.80 / 22.08	6.85 / 5.92
DenseNet-201	22.58 / 21.46	6.34 / 5.54
DenseNet-264	22.15 / 20.80	6.12 / 5.29

Table 3: The top-1 and top-5 error rates on the ImageNet validation set, with single-crop / 10-crop testing.

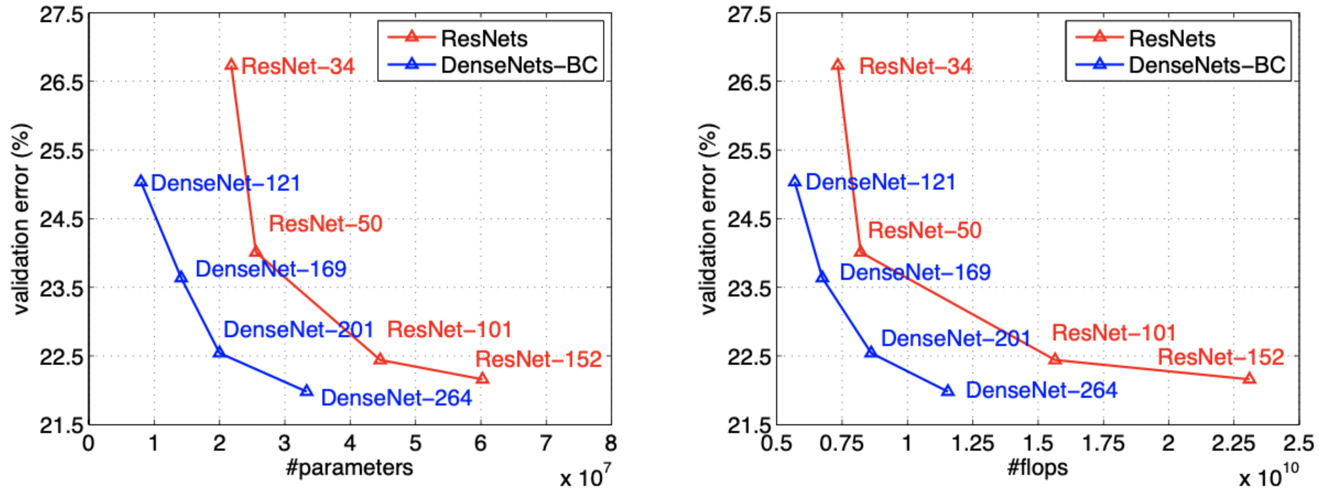


Figure 3: Comparison of the DenseNets and ResNets top-1 error rates (single-crop testing) on the ImageNet validation dataset as a function of learned parameters (*left*) and FLOPs during test-time (*right*).

Experiments

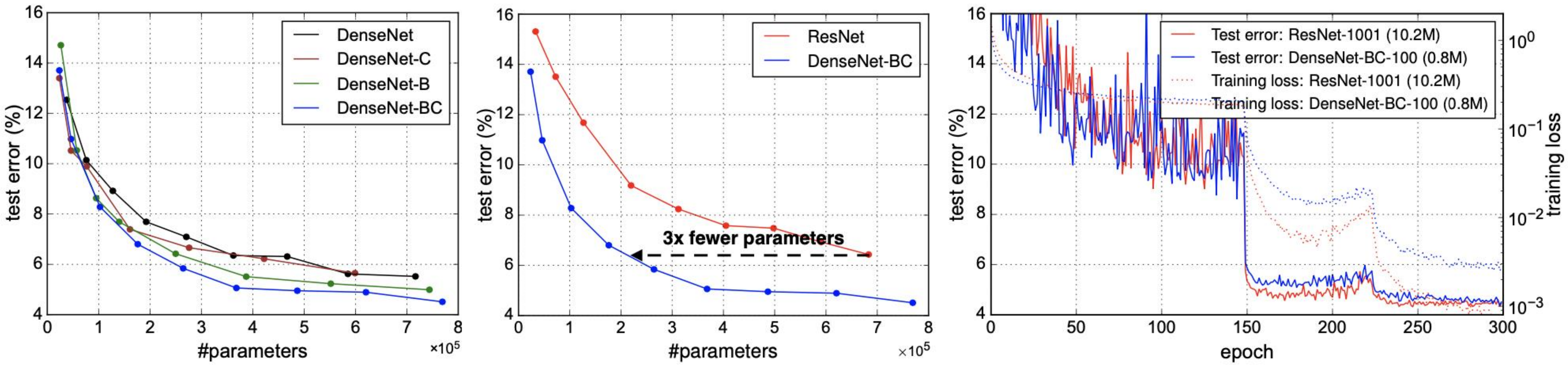


Figure 4: *Left:* Comparison of the parameter efficiency on C10+ between DenseNet variations. *Middle:* Comparison of the parameter efficiency between DenseNet-BC and (pre-activation) ResNets. DenseNet-BC requires about 1/3 of the parameters as ResNet to achieve comparable accuracy. *Right:* Training and testing curves of the 1001-layer pre-activation ResNet [12] with more than 10M parameters and a 100-layer DenseNet with only 0.8M parameters.

Experiments

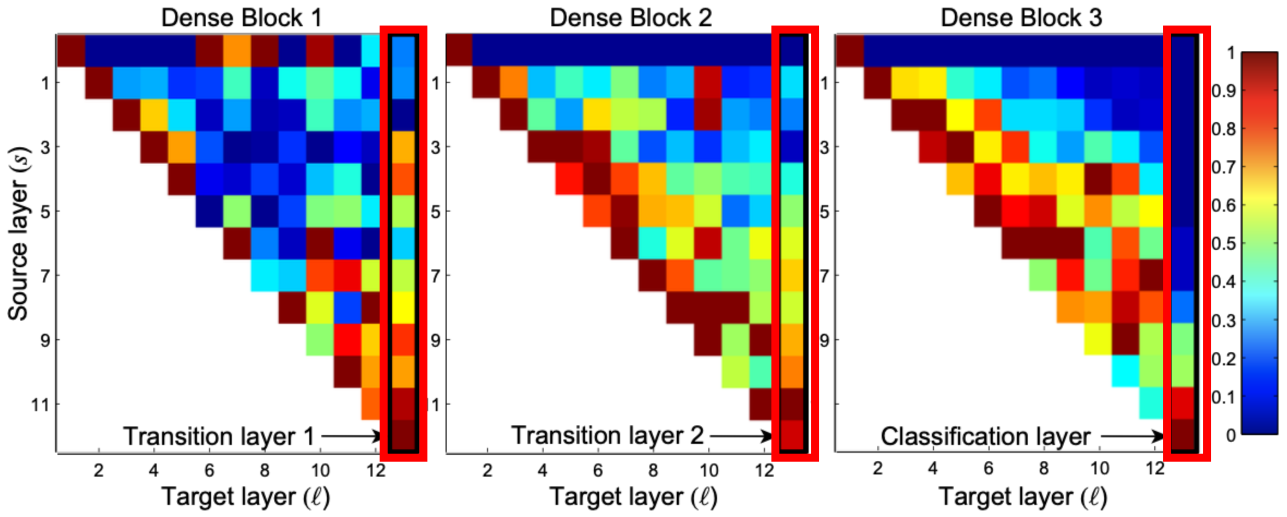
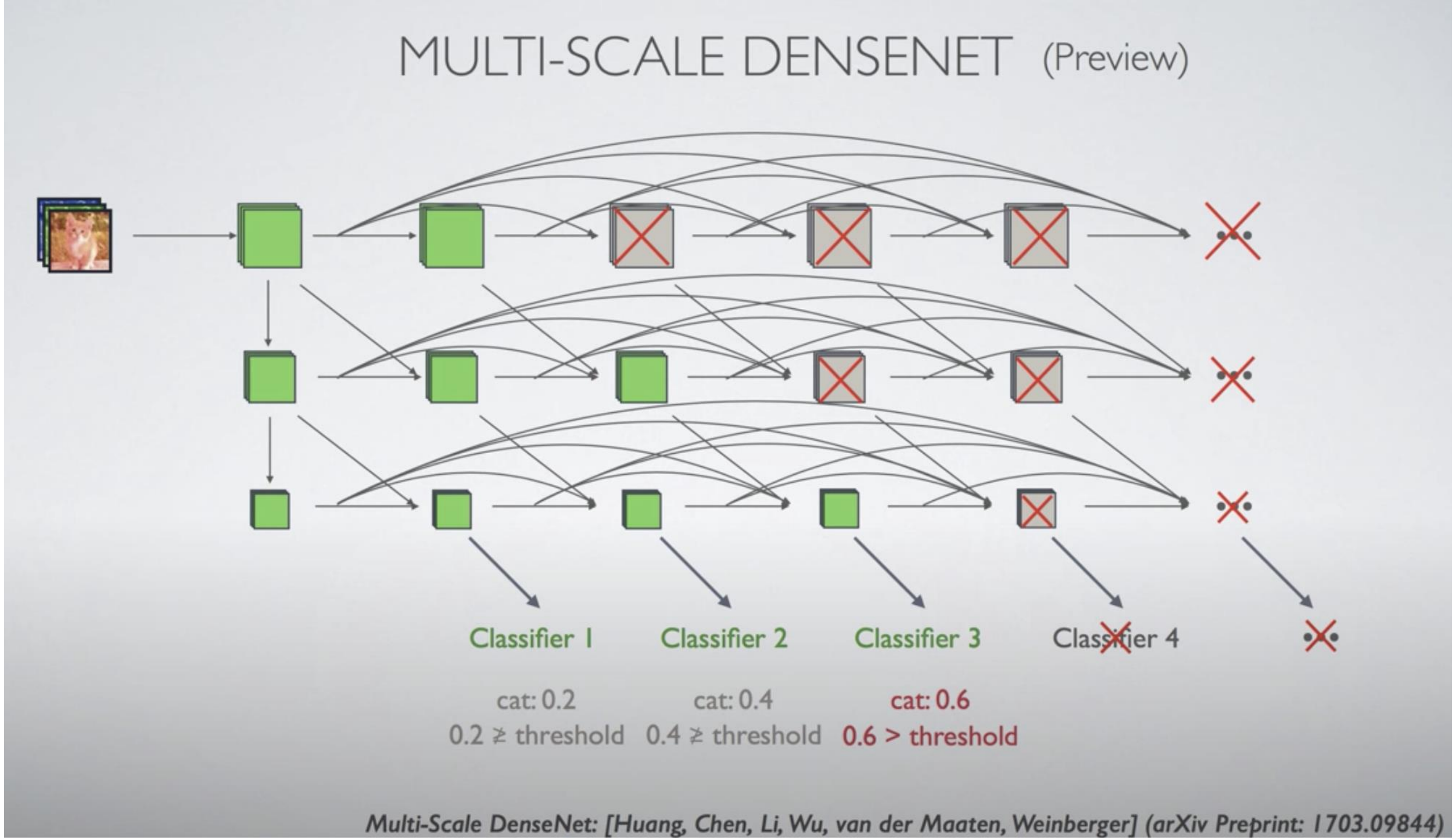
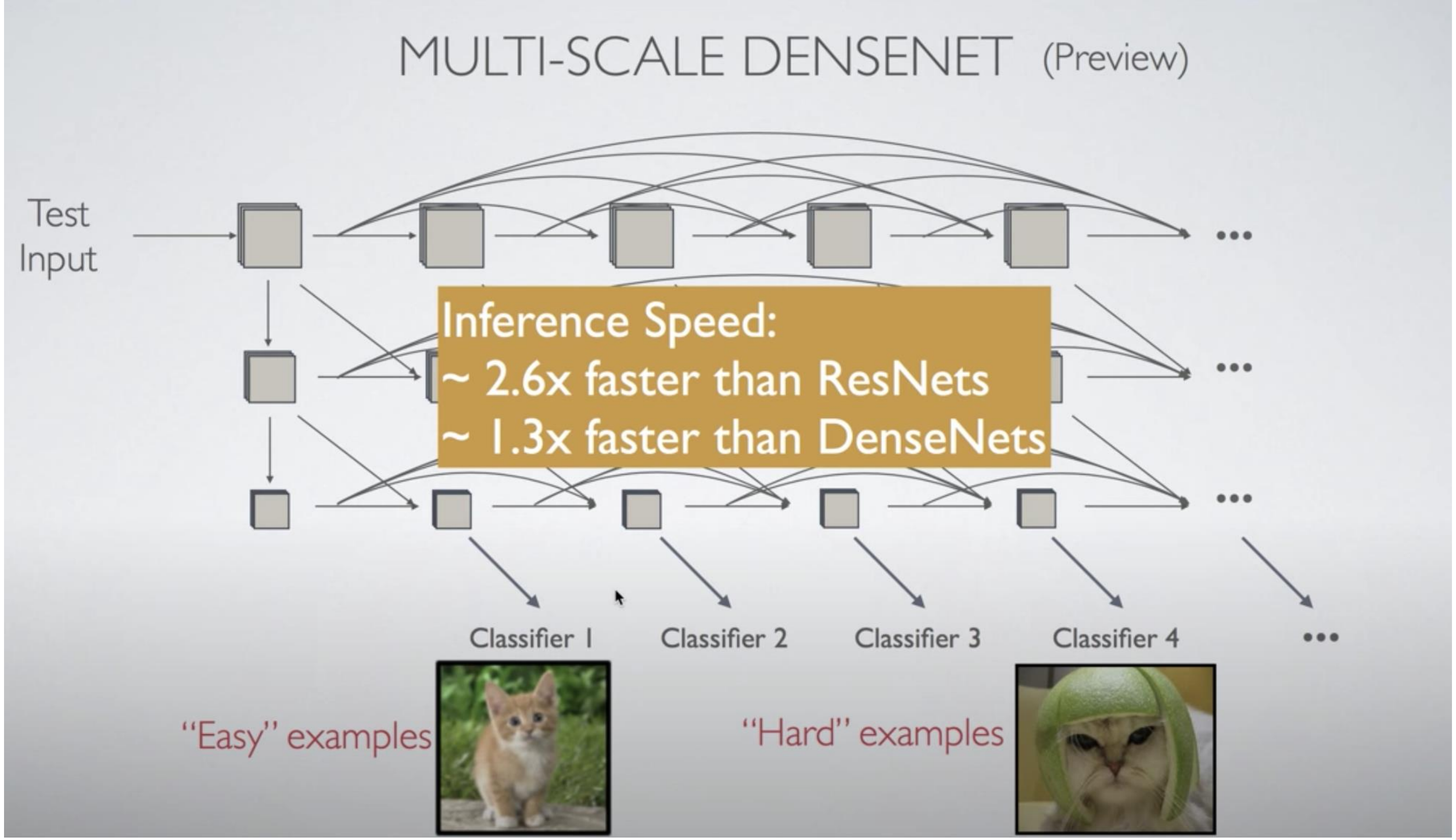


Figure 5: The average absolute filter weights of convolutional layers in a trained DenseNet. The color of pixel (s, ℓ) encodes the average $L1$ norm (normalized by number of input feature-maps) of the weights connecting convolutional layer s to ℓ within a dense block. Three columns highlighted by black rectangles correspond to two transition layers and the classification layer. The first row encodes weights connected to the input layer of the dense block.

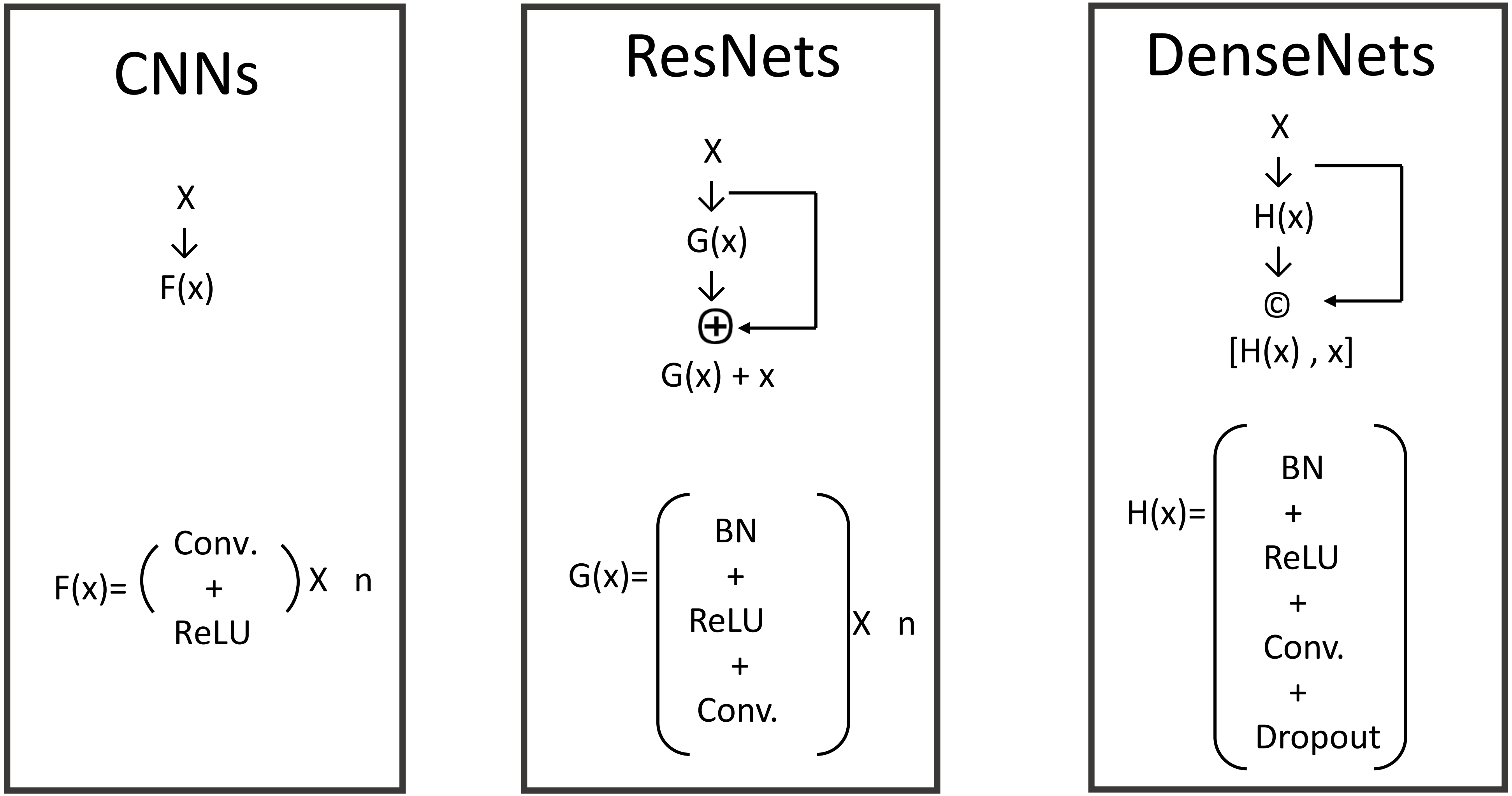
Multi scale DenseNet



Multi scale DenseNet



CNNs vs ResNets vs DenseNets



Implementation

```python
class BasicBlock(nn.Module):
    def __init__(self, in_planes, out_planes, dropRate=0.0):
        super(BasicBlock, self).__init__()
        self.bn1 = nn.BatchNorm2d(in_planes)
        self.relu = nn.ReLU(inplace=True)
        self.conv1 = nn.Conv2d(in_planes, out_planes, kernel_size=3, stride=1,
                               padding=1, bias=False)
        self.droprate = dropRate
    def forward(self, x):
        out = self.conv1(self.relu(self.bn1(x)))
        if self.droprate > 0:
            out = F.dropout(out, p=self.droprate, training=self.training)
        return torch.cat([x, out], 1)
```

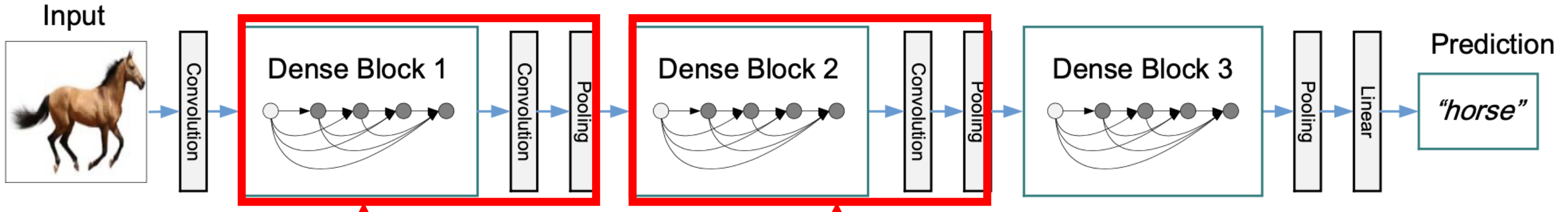
```python
class BottleneckBlock(nn.Module):
    def __init__(self, in_planes, out_planes, dropRate=0.0):
        super(BottleneckBlock, self).__init__()
        inter_planes = out_planes * 4
        self.bn1 = nn.BatchNorm2d(in_planes)
        self.relu = nn.ReLU(inplace=True)
        self.conv1 = nn.Conv2d(in_planes, inter_planes, kernel_size=1, stride=1,
                               padding=0, bias=False)
        self.bn2 = nn.BatchNorm2d(inter_planes)
        self.conv2 = nn.Conv2d(inter_planes, out_planes, kernel_size=3, stride=1,
                               padding=1, bias=False)
        self.droprate = dropRate
    def forward(self, x):
        out = self.conv1(self.relu(self.bn1(x)))
        if self.droprate > 0:
            out = F.dropout(out, p=self.droprate, inplace=False, training=self.training)
        out = self.conv2(self.relu(self.bn2(out)))
        if self.droprate > 0:
            out = F.dropout(out, p=self.droprate, inplace=False, training=self.training)
        return torch.cat([x, out], 1)
```

Implementation

```
class TransitionBlock(nn.Module):
    def __init__(self, in_planes, out_planes, dropRate=0.0):
        super(TransitionBlock, self).__init__()
        self.bn1 = nn.BatchNorm2d(in_planes)
        self.relu = nn.ReLU(inplace=True)
        self.conv1 = nn.Conv2d(in_planes, out_planes, kernel_size=1, stride=1,
                               padding=0, bias=False)
        self.droprate = dropRate
    def forward(self, x):
        out = self.conv1(self.relu(self.bn1(x)))
        if self.droprate > 0:
            out = F.dropout(out, p=self.droprate, inplace=False, training=self.training)
        return F.avg_pool2d(out, 2)
```

Implementation

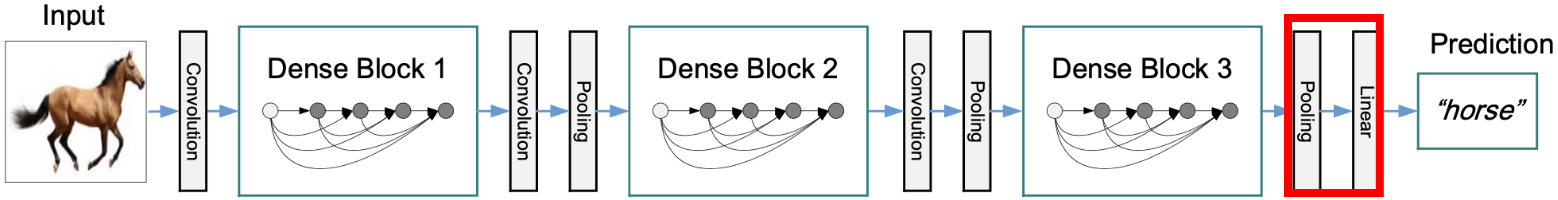
```python
class DenseNet3(nn.Module):
    def __init__(self, depth, num_classes, growth_rate=12,
                 reduction=0.5, bottleneck=True, dropRate=0.0):
        super(DenseNet3, self).__init__()
        in_planes = 2 * growth_rate
        n = (depth - 4) / 3
        if bottleneck == True:
            n = n/2
            block = BottleneckBlock
        else:
            block = BasicBlock
        n = int(n)
        # 1st conv before any dense block
        self.conv1 = nn.Conv2d(3, in_planes, kernel_size=3, stride=1,
                               padding=1, bias=False)
        # 1st block
        self.block1 = DenseBlock(n, in_planes, growth_rate, block, dropRate)
        in_planes = int(in_planes+n*growth_rate)
        self.trans1 = TransitionBlock(in_planes, int(math.floor(in_planes*reduction)), dropRate=dropRate)
        in_planes = int(math.floor(in_planes*reduction))
        # 2nd block
        self.block2 = DenseBlock(n, in_planes, growth_rate, block, dropRate)
        in_planes = int(in_planes+n*growth_rate)
        self.trans2 = TransitionBlock(in_planes, int(math.floor(in_planes*reduction)), dropRate=dropRate)
        in_planes = int(math.floor(in_planes*reduction))
        # 3rd block
        self.block3 = DenseBlock(n, in_planes, growth_rate, block, dropRate)
        in_planes = int(in_planes+n*growth_rate)
        # global average pooling and classifier
        self.bn1 = nn.BatchNorm2d(in_planes)
        self.relu = nn.ReLU(inplace=True)
        self.fc = nn.Linear(in_planes, num_classes)
        self.in_planes = in_planes
```




```python
def forward(self, x):
    out = self.conv1(x)
    out = self.trans1(self.block1(out))
    out = self.trans2(self.block2(out))
    out = self.block3(out)
    out = self.relu(self.bn1(out))
    out = F.avg_pool2d(out, 8)
    out = out.view(-1, self.in_planes)
    return self.fc(out)
```

Implementation

```python
class DenseNet3(nn.Module):
    def __init__(self, depth, num_classes, growth_rate=12,
                 reduction=0.5, bottleneck=True, dropRate=0.0):
        super(DenseNet3, self).__init__()
        in_planes = 2 * growth_rate
        n = (depth - 4) / 3
        if bottleneck == True:
            n = n/2
            block = BottleneckBlock
        else:
            block = BasicBlock
        n = int(n)
        # 1st conv before any dense block
        self.conv1 = nn.Conv2d(3, in_planes, kernel_size=3, stride=1,
                               padding=1, bias=False)
        # 1st block
        self.block1 = DenseBlock(n, in_planes, growth_rate, block, dropRate)
        in_planes = int(in_planes+n*growth_rate)
        self.trans1 = TransitionBlock(in_planes, int(math.floor(in_planes*reduction)), dropRate=dropRate)
        in_planes = int(math.floor(in_planes*reduction))
        # 2nd block
        self.block2 = DenseBlock(n, in_planes, growth_rate, block, dropRate)
        in_planes = int(in_planes+n*growth_rate)
        self.trans2 = TransitionBlock(in_planes, int(math.floor(in_planes*reduction)), dropRate=dropRate)
        in_planes = int(math.floor(in_planes*reduction))
        # 3rd block
        self.block3 = DenseBlock(n, in_planes, growth_rate, block, dropRate)
        in_planes = int(in_planes+n*growth_rate)
        # global average pooling and classifier
        self.bn1 = nn.BatchNorm2d(in_planes)
        self.relu = nn.ReLU(inplace=True)
        self.fc = nn.Linear(in_planes, num_classes)
        self.in_planes = in_planes
```




```python
def forward(self, x):
    out = self.conv1(x)
    out = self.trans1(self.block1(out))
    out = self.trans2(self.block2(out))
    out = self.block3(out)
    out = self.relu(self.bn1(out))
    out = F.avg_pool2d(out, 8)
    out = out.view(-1, self.in_planes)
    return self.fc(out)
```

Any Question?