Convolutional Models

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Goals

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- Give a taste of techniques used in SOTA vision models.
  - Come up with your own methods!

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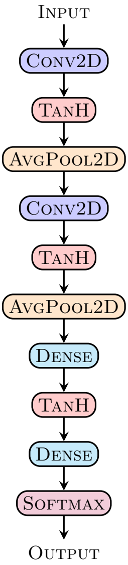
- Give a taste of techniques used in SOTA vision models.
  - Come up with your own methods!
- Highlight some **best practises** for CNN models.

LeNet

Introduced by LeCun et al. (1998), makes use of:

- (5×5) Convolutions
- (Average) Pooling



Convolution Operation

$$
\begin{array}{ccccccc}
0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0
\end{array}
*
\begin{array}{ccc}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{array}
=
\begin{array}{ccccc}
\boxed{2} & 0 & 1 & 0 & 1 \\
0 & 3 & 0 & 1 & 0 \\
0 & 0 & 3 & 0 & 0 \\
0 & 1 & 0 & 3 & 0 \\
1 & 0 & 1 & 0 & 2
\end{array}
$$

Convolution Operation

$$
\begin{matrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0
\end{matrix}
\quad * \quad
\begin{matrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{matrix}
\quad = \quad
\begin{matrix}
2 & 0 & 1 & 0 & 1 \\
0 & 3 & 0 & 1 & 0 \\
0 & \boxed{0} & 3 & 0 & 0 \\
0 & 1 & 0 & 3 & 0 \\
1 & 0 & 1 & 0 & 2
\end{matrix}
$$

Convolution Operation

$$
\begin{matrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 1 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0
\end{matrix}
\quad * \quad
\begin{matrix}
1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 1
\end{matrix}
\quad = \quad
\begin{matrix}
2 & 0 & 1 & 0 & 1 \\
0 & 3 & 0 & 1 & 0 \\
0 & 0 & 3 & 0 & 0 \\
0 & \boxed{1} & 0 & 3 & 0 \\
1 & 0 & 1 & 0 & 2
\end{matrix}
$$

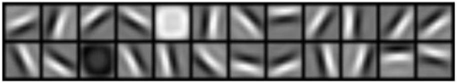
Convolution Operation

$$\begin{matrix} 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 \end{matrix} \quad * \quad \begin{matrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{matrix} \quad = \quad \begin{matrix} 1 & 0 & 1 & 0 & 2 \\ 0 & 1 & 0 & 3 & 0 \\ 0 & 0 & 3 & 0 & 0 \\ 0 & 3 & 0 & 1 & 0 \\ 2 & 0 & 1 & 0 & 1 \end{matrix}$$

Convolution Layer

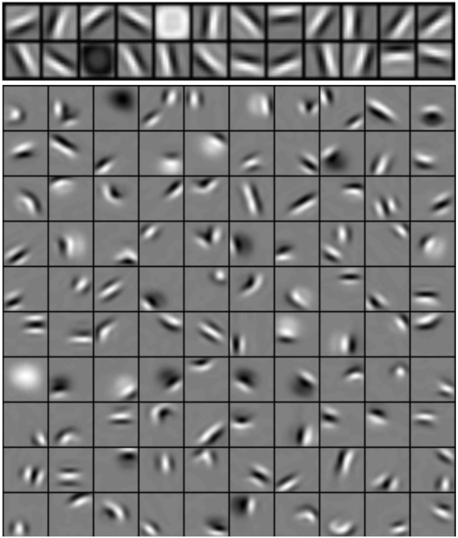
$$\textsc{Conv2D}\left(\begin{matrix} 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 0 & 0 & 1 \end{matrix}\right) \longrightarrow \begin{matrix} 1 & 0 & 1 & 0 & 2 \\ 0 & 1 & 0 & 3 & 0 \\ 0 & 0 & 3 & 0 & 0 \\ 0 & 3 & 0 & 1 & 0 \\ 2 & 0 & 1 & 0 & 1 \end{matrix}, \begin{matrix} 2 & 0 & 1 & 0 & 1 \\ 0 & 3 & 0 & 1 & 0 \\ 0 & 0 & 3 & 0 & 0 \\ 0 & 1 & 0 & 3 & 0 \\ 1 & 0 & 1 & 0 & 2 \end{matrix}, \dots$$

Hierarchical Features



(Lee et al., 2009)

Hierarchical Features



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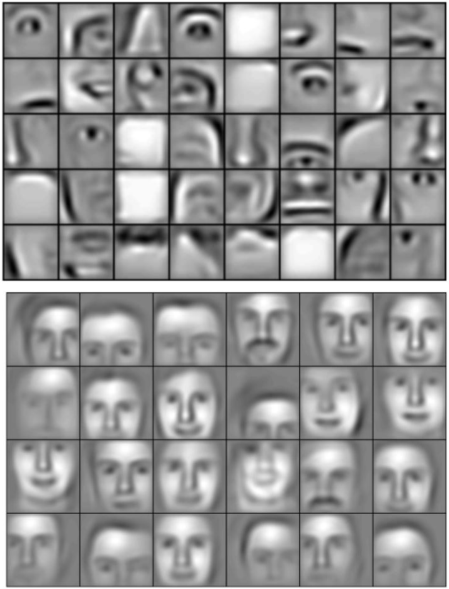


(Average) Pooling Layer

$$\textsc{AvgPool2D}\left(\begin{array}{cc|cc} 9 & 1 & 0 & 2 \\ 3 & 3 & 4 & 2 \\ \hline 9 & 5 & 0 & 2 \\ 9 & 9 & 2 & 0 \end{array}\right) \longrightarrow \begin{array}{ccc} 4 & 2 & 2 \\ 5 & 3 & 2 \\ 6 & 4 & 1 \end{array}$$

(Average) Pooling Layer

$$\textsc{AvgPool2D}\left(\begin{array}{cccc} 9 & 1 & 0 & 2 \\ 3 & 3 & 4 & 2 \\ 9 & 5 & 0 & 2 \\ 9 & 9 & 2 & 0 \end{array}\right) \longrightarrow \begin{array}{cc} 4 & 2 \\ 6 & 1 \end{array}$$

Receptive Fields

3×3 Conv

9	1	0	2	5
3	3	4	2	0
9	5	0	2	0
9	9	2	6	1
5	4	2	9	2

4	2	0
6	1	0
9	5	5

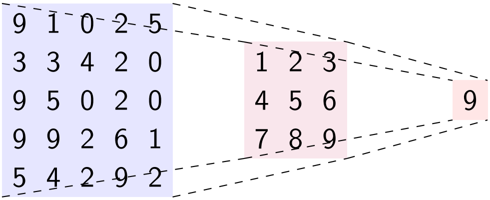
Receptive Fields

4×4 CONV

$$\begin{matrix} 9 & 1 & 0 & 2 & 5 \\ 3 & 3 & 4 & 2 & 0 \\ 9 & 5 & 0 & 2 & 0 \\ 9 & 9 & 2 & 6 & 1 \\ 5 & 4 & 2 & 9 & 2 \end{matrix} \qquad \begin{matrix} \boxed{4} & 2 & 0 \\ 6 & 1 & 0 \\ 9 & 5 & 5 \end{matrix}$$

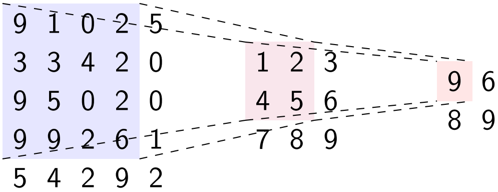
Receptive Fields

$3{\times}3$ CONV $\rightarrow$ $3{\times}3$ CONV

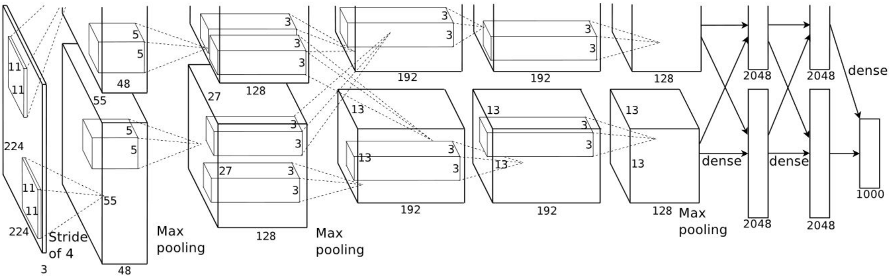


Receptive Fields

$3{\times}3$ CONV $\rightarrow$ $2{\times}2$ POOL



AlexNet

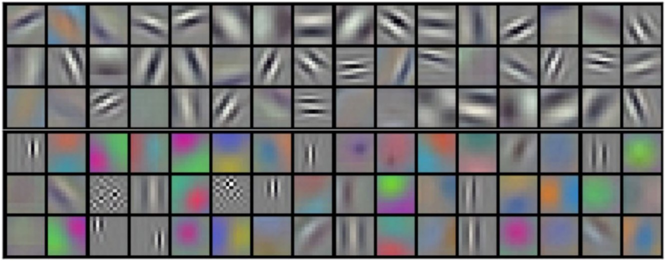


Introduced by Krizhevsky et al. (2012), makes use of:

- Grouped convolutions (various sizes)
- (Overlapping) **Max** pooling
- **ReLU** non-linearity
- Local response norm
- **Dropout**

AlexNet

Learned Features



(Max) Pooling Layer

$$\textsc{MaxPool2D}\begin{pmatrix} 9 & 1 & 0 & 2 \\ 3 & 3 & 4 & 2 \\ 9 & 5 & 0 & 2 \\ 9 & 9 & 2 & 0 \end{pmatrix} \longrightarrow \begin{matrix} 9 & 4 & 4 \\ 9 & 5 & 4 \\ 9 & 9 & 2 \end{matrix}$$

ReLU Activation Layer

$$\textsc{ReLU}\begin{pmatrix} 2 & -1 & 0 & 2 \\ 1 & 3 & -4 & -2 \\ 4 & 5 & 0 & 2 \\ -2 & -8 & 0 & -3 \end{pmatrix} \longrightarrow \begin{matrix} 2 & 0 & 0 & 2 \\ 1 & 3 & 0 & 0 \\ 4 & 5 & 0 & 2 \\ 0 & 0 & 0 & 0 \end{matrix}$$

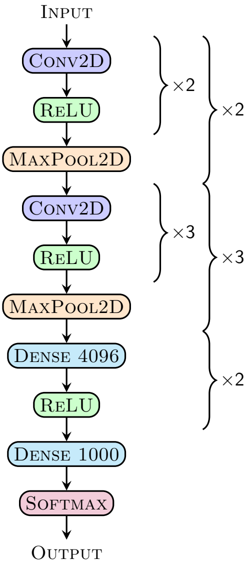
Dropout Layer

$$\textsc{Dropout}\begin{pmatrix} 7 & 2 & 2 & 1 \\ 3 & 1 & 8 & 4 \\ 2 & 6 & 4 & 2 \\ 3 & 3 & 5 & 1 \end{pmatrix} \longrightarrow \begin{array}{cccc} 0 & 4 & 4 & 2 \\ 6 & 0 & 0 & 0 \\ 4 & 0 & 8 & 0 \\ 6 & 6 & 0 & 0 \end{array}$$

VGG

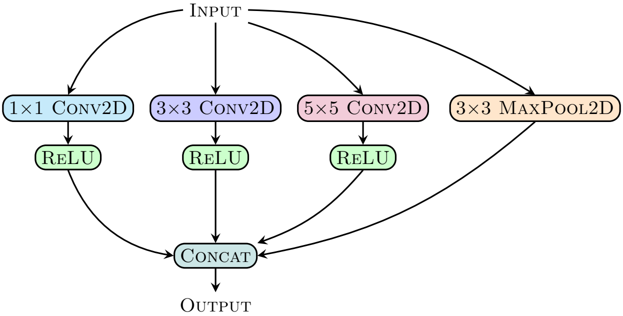
Introduced by Simonyan and Zisserman (2014).

- Only **3×3 Convolutions**
- Only **2×2 Max Pooling**



Inception V1

AKA GoogLeNet

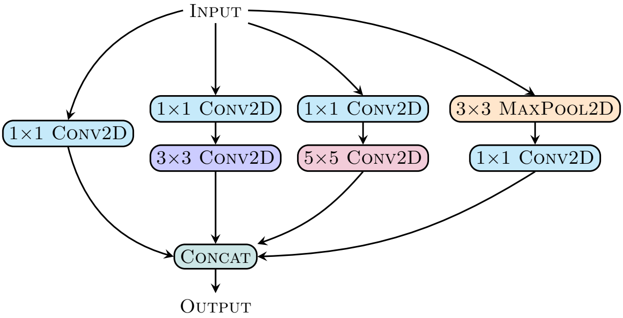


Introduced by Szegedy et al. (2014).

- Go a bit wider rather than deeper (still 27 layers).
  - With *Inception Modules* (9 of them).
- Convolutions of different sizes make a come back!
- Including **1×1 Convolutions**??? (Lin et al., 2013)

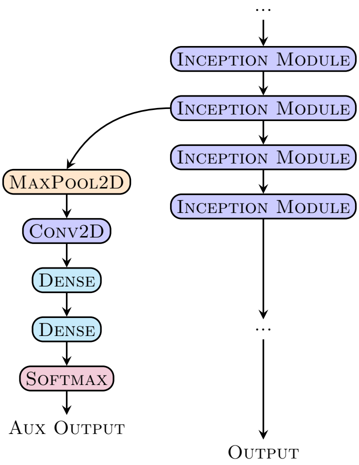
Inception V1

AKA GoogLeNet



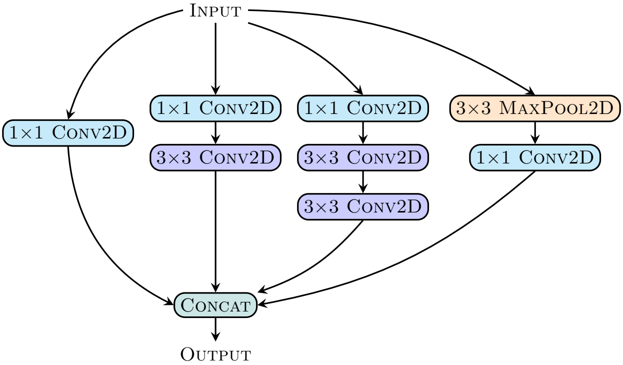
Inception V1

Auxiliary Classifier – Vanishing Gradients

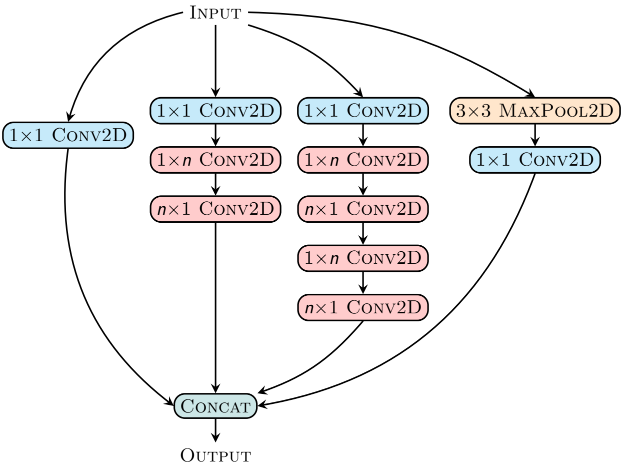


Inception V2

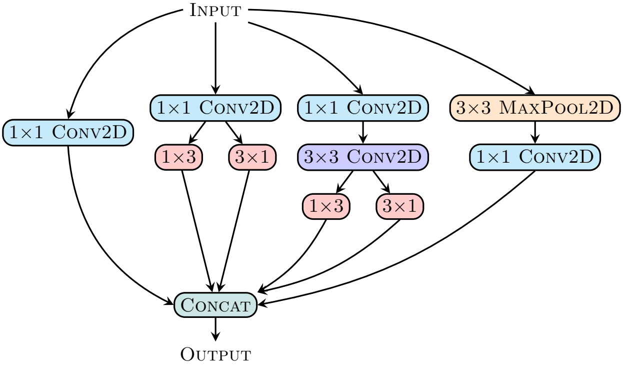
Introduced by Szegedy et al. (2015).



Inception V2



Inception V2



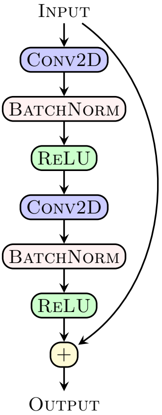
Inception V3

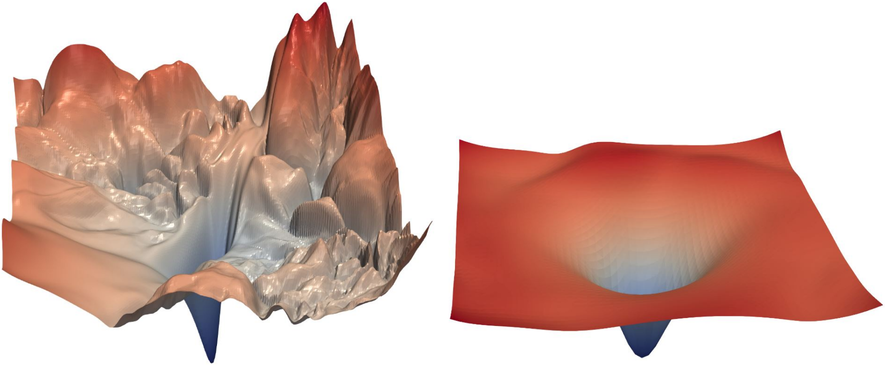
Also introduced by Szegedy et al. (2015).

- 7×7 Convolutions make a comeback!
- Various training improvements.
  - **Batch normalisation**.
  - Label smoothing.
  - RMSProp.

Introduced by He et al. (2015).

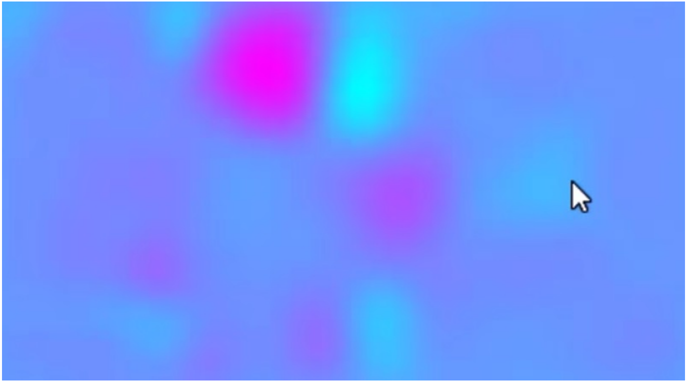
- **Residual connections**.
  - Bye-bye vanishing gradients.
  - Much deeper (100s of layers)!
- Fully-Convolutional
  - Dense $\rightarrow$ global average pooling.
  - Less over-fitting.
  - Heat-maps!
- Only 3×3 convolutions.
- **Little max pooling**.





(Li et al., 2017)

(Adapted from FastAI's Practical Deep Learning for Coders 2017)



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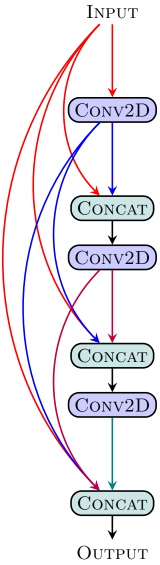
DenseNet

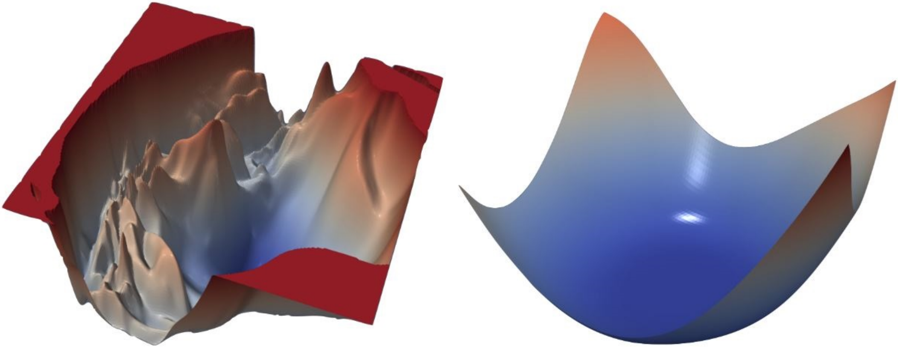
Introduced by Huang et al. (2016).

- **Dense connections**.
- 121 layers (but more like 10).
- 1×1 convolutions as *bottleneck* layers before expensive 3×3 convolutions.



DenseNet

What the skip connection does

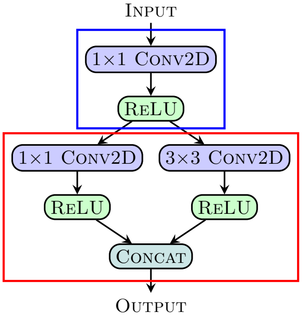


(Li et al., 2017)

SqueezeNet

Introduced by Iandola et al. (2016).

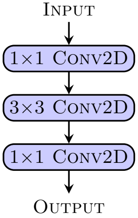
- $3 \times 3 \rightarrow 1 \times 1$ convolutions.
- Reduce number of channels.
- Downsample later in the net.
- Fire module
  - Squeeze and Expansion layers.
- Same accuracy as AlexNet but *50*$\times$ fewer weights.
  - No dense layers.
  - $<$ 0.5MB model size.



MobileNet

Introduced by Howard et al. (2017).

- Depthwise separable convolutions.
- Very flexible *family* of nets.
- Also fully-convolutional.



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  - e.g. Conv Seq2Seq (Gehring et al., 2017).

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Thank You!

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SZEGEDY, Christian, LIU, Wei, JIA, Yangqing, SERMANET, Pierre, REED, Scott, ANGUELOV, Dragomir, ERHAN, Dumitru, VANHOUCKE, Vincent and RABINOVICH, Andrew (2014). Going deeper with convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 1–9.

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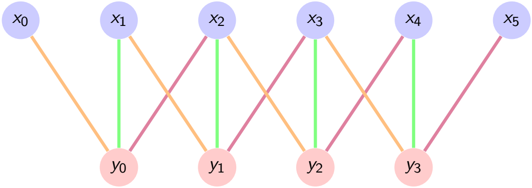
Parameter Sharing

Convolution Layer



Fully-connected Layer