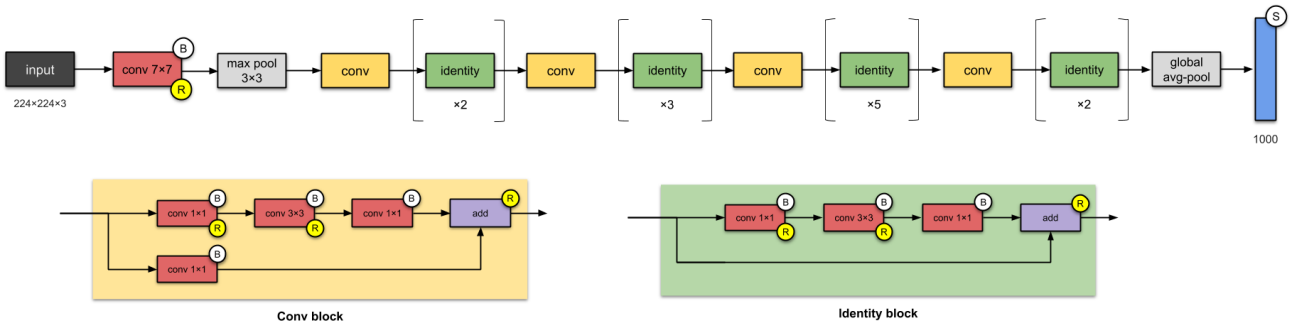


What architecture is this? 🤔

Inside AI

Illustrated: 10 CNN Architectures

A compiled visualisation of the common convolutional neural networks

Raimi Karim

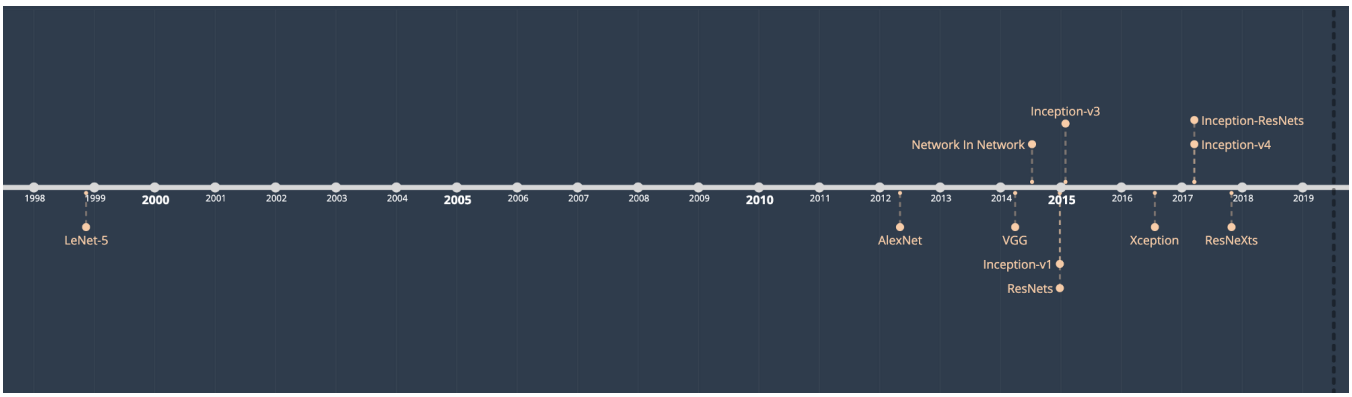
Jul 30 · 12 min read

(TL;DR — jump to the illustrations here)

How have you been keeping up with the different convolutional neural networks (CNNs)? In recent years, we have witnessed the birth of numerous CNNs. These networks have gotten so deep that it has become extremely difficult to visualise the entire model. We stop keeping track of them and treat them as blackbox models.

Fine, maybe you don't. But if you're guilty too then hey, you've come to the right place! This article is a visualisation of 10 *common* CNN architectures, hand-picked by yours truly. These illustrations provide a more compact view of the entire model, without having to scroll down a couple of times just to see the softmax layer. Apart from these images, I've also sprinkled some notes on how they 'evolved' over time — from 5 to 50 convolutional layers, from plain convolutional layers to modules, from 2–3 towers to 32 towers, from 7×7 to 5×5— but more on these later.

> By ‘common’, I am referring to those models whose pre-trained weights are usually shared by deep learning libraries (such as TensorFlow, Keras and PyTorch) for users to use, and models that are usually taught in classes. Some of these models have shown success in competitions like the ImageNet Large Scale Visual Recognition Challenge (ILSVRC).



The 10 architectures that will be discussed and the year their papers were published.

Model	Size	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth
VGG16	528 MB	0.713	0.901	138,357,544	23
InceptionV3	92 MB	0.779	0.937	23,851,784	159
ResNet50	98 MB	0.749	0.921	25,636,712	-
Xception	88 MB	0.790	0.945	22,910,480	126
InceptionResNetV2	215 MB	0.803	0.953	55,873,736	572
ResNeXt50	96 MB	0.777	0.938	25,097,128	-

The top-1 and top-5 accuracy refers to the model's performance on the ImageNet validation dataset.

Depth refers to the topological depth of the network. This includes activation layers, batch normalization layers etc.

Pre-trained weights which are available in Keras for 6 of the architectures that we will talk about. Adapted from a table in the Keras documentation.

The motivation for writing this is that there aren’t many blogs and articles out there with these compact visualisations (if you do know of any, please share them with me). So I decided to write one for our reference. For this purpose, I have read the papers and the code (mostly from TensorFlow and Keras) to come up with these vizzes.

Here I’d like to add that a plethora of CNN architectures we see in the wild are a result of many things — improved computer hardware, ImageNet competition, solving

specific tasks, new ideas and so on. Christian Szegedy, a researcher at Google once mentioned that

> "[m]ost of this progress is not just the result of more powerful hardware, larger datasets and bigger models, but mainly a consequence of new ideas, algorithms and improved network architectures." (Szegedy et al, 2014)

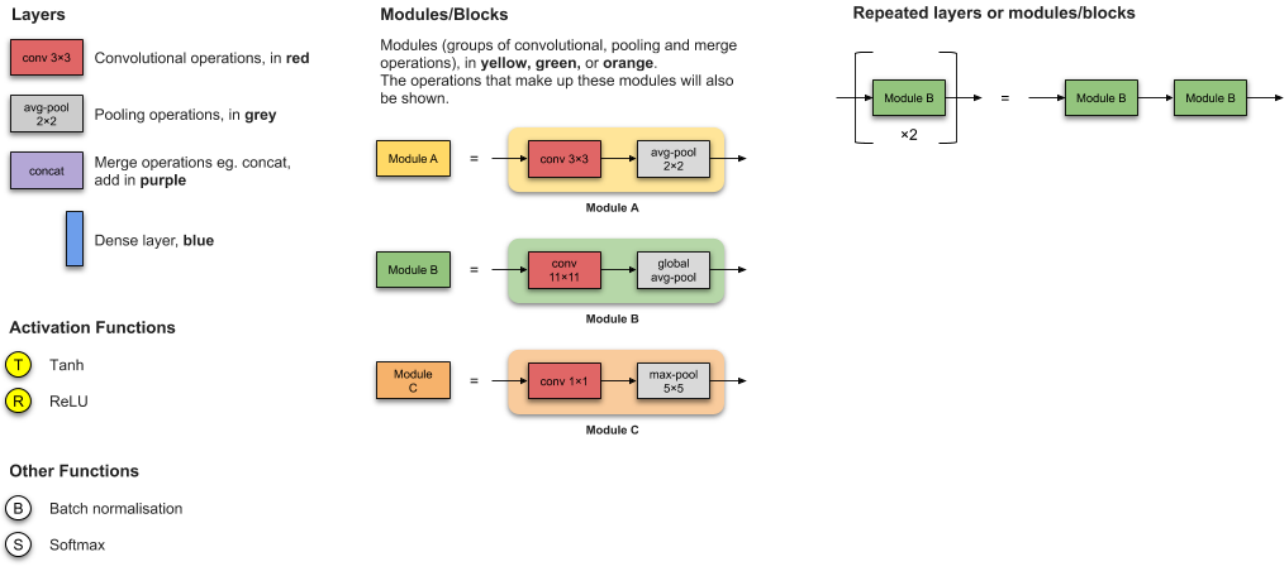
Now let's get on with these beasts and observe how network architectures improve over time!

> **A note on the visualisations**
> Note that I have excluded information like the number of convolutional filters, padding, stride, dropouts, and the flatten operation in the illustrations.

. . .

Contents (ordered by year of publication)

Legend



. . .

1. LeNet-5 (1998)

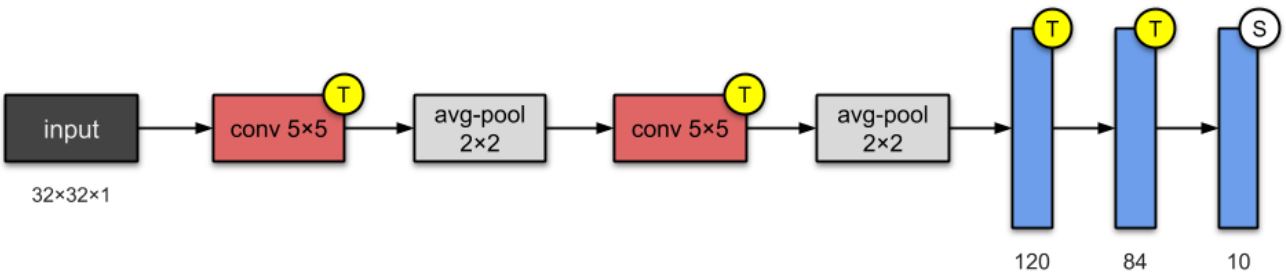


Fig. 1: LeNet-5 architecture, based on their paper

LeNet-5 is one of the simplest architectures. It has 2 convolutional and 3 fully-connected layers (hence "5" — it is very common for the names of neural networks to be derived from the number of *convolutional* and *fully connected* layers that they have). The average-pooling layer as we know it now was called a *sub-sampling layer* and it had trainable weights (which isn't the current practice of designing CNNs nowadays). This architecture has about **60,000 parameters**.

⭐ What's novel?

This architecture has become the standard ‘template’: stacking convolutions and pooling layers, and ending the network with one or more fully-connected layers.

📝 Publication

- Paper: Gradient-Based Learning Applied to Document Recognition
- Authors: Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner
- Published in: Proceedings of the IEEE (1998)

2. AlexNet (2012)

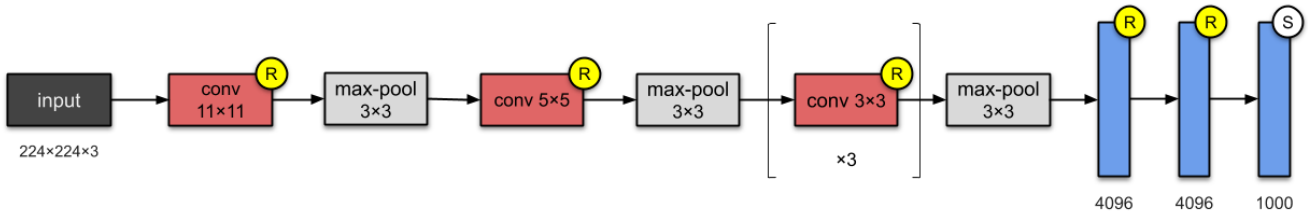


Fig. 2: AlexNet architecture, based on their paper.

With **60M parameters**, AlexNet has 8 layers — 5 convolutional and 3 fully-connected. AlexNet just stacked a few more layers onto LeNet-5. At the point of publication, the authors pointed out that their architecture was “one of the largest convolutional neural networks to date on the subsets of ImageNet.”

⭐ What’s novel?

1. They were the first to implement Rectified Linear Units (ReLUs) as activation functions.

2. Overlapping pooling in CNNs.

📝 Publication

- Paper: ImageNet Classification with Deep Convolutional Neural Networks
- Authors: Alex Krizhevsky, Ilya Sutskever, Geoffrey Hinton. University of Toronto, Canada.
- Published in: NeurIPS 2012

3. VGG-16 (2014)

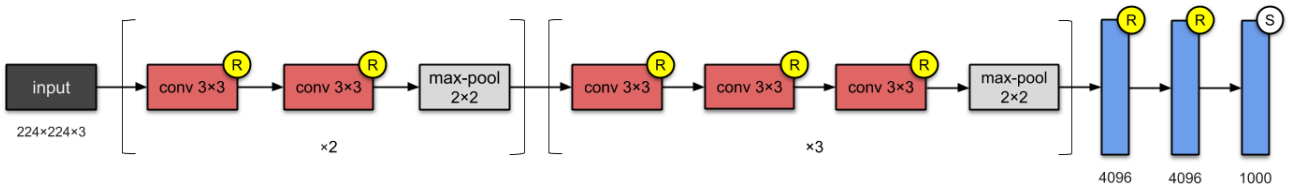


Fig. 3: VGG-16 architecture, based on their paper.

By now you would've already noticed that CNNs were starting to get deeper and deeper. This is because the most straightforward way of improving performance of deep neural networks is by increasing their size (Szegedy et. al). The folks at Visual Geometry Group (VGG) invented the VGG-16 which has 13 convolutional and 3 fully-connected layers, carrying with them the ReLU tradition from AlexNet. Again, this network just stacks more layers onto AlexNet. It consists of **138M parameters** and takes up about 500MB of storage space 😱 . They also designed a deeper variant, VGG-19.

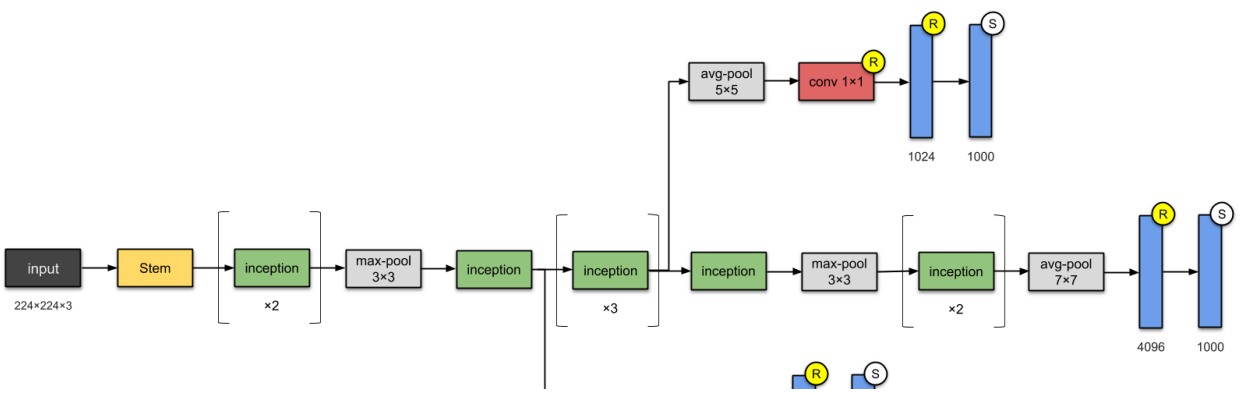
⭐ What's novel?

1. As mentioned in their abstract, the contribution from this paper is the designing of *deeper* networks (roughly twice as deep as AlexNet).

📝 Publication

- Paper: Very Deep Convolutional Networks for Large-Scale Image Recognition
- Authors: Karen Simonyan, Andrew Zisserman. University of Oxford, UK.
- arXiv preprint, 2014

4. Inception-v1 (2014)



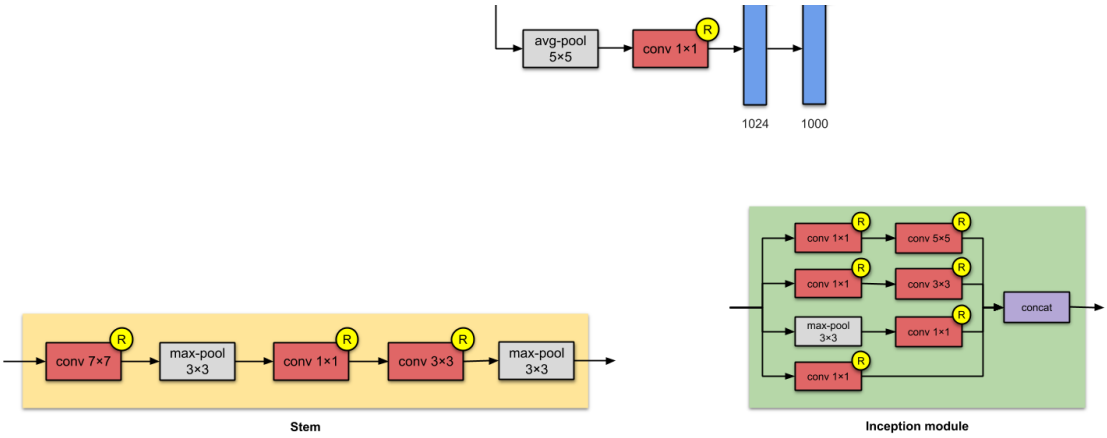


Fig. 4: Inception-v1 architecture. This CNN has two auxiliary networks (which are discarded at inference time). Architecture is based on Figure 3 in the paper.

This 22-layer architecture with **5M** parameters is called the Inception-v1. Here, the Network In Network (see Appendix) approach is heavily used, as mentioned in the paper. This is done by means of 'Inception modules'. The design of the architecture of an Inception module is a product of research on approximating sparse structures (read paper for more!). Each module presents 3 ideas:

1. Having **parallel towers** of convolutions with different filters, followed by concatenation, captures different features at 1×1, 3×3 and 5×5, thereby 'clustering' them. This idea is motivated by Arora et al. in the paper *Provable bounds for learning some deep representations*, suggesting a layer-by layer construction in which one should analyse the correlation statistics of the last layer and cluster them into groups of units with high correlation.

2. 1×1 convolutions are used for dimensionality reduction to remove computational bottlenecks.

3. 1×1 convolutions add nonlinearity *within* a convolution (based on the Network In Network paper).

4. The authors also introduced two **auxiliary classifiers** to encourage discrimination in the lower stages of the classifier, to increase the gradient signal that gets propagated back, and to provide additional regularisation. The **auxiliary networks** (the branches that are connected to the auxiliary classifier) are discarded at inference time.

It is worth noting that "[t]he main hallmark of this architecture is the improved utilisation of the computing resources inside the network."

> **Note:**
> The names of the modules (Stem and Inception) were not used for this version of Inception until its later versions i.e. Inception-v4 and Inception-ResNets. I have added them here for easy comparison.

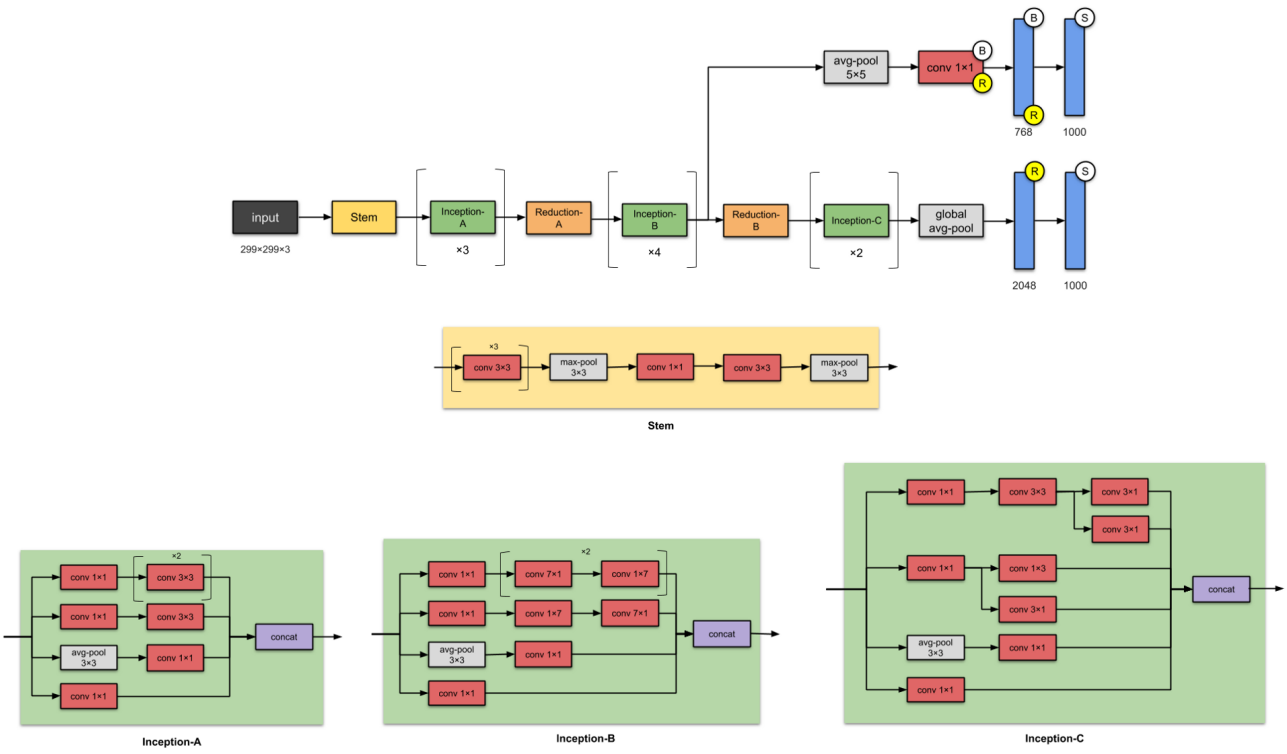
⭐ What's novel?

1. Building networks using dense modules/blocks. Instead of stacking convolutional layers, we stack modules or blocks, within which are convolutional layers. Hence the name Inception (with reference to the 2010 sci-fi movie *Inception* starring Leonardo DiCaprio).

📝 Publication

- Paper: Going Deeper with Convolutions
- Authors: Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, Andrew Rabinovich. Google, University of Michigan, University of North Carolina
- Published in: 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)

5. Inception-v3 (2015)



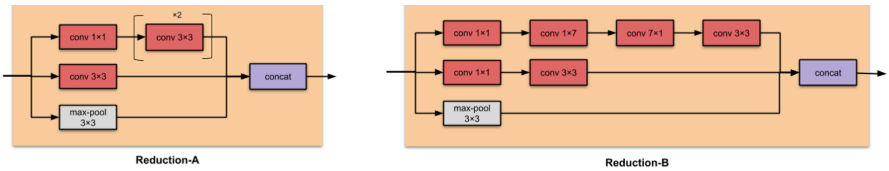


Fig. 5: Inception-v3 architecture. This CNN has an auxiliary network (which is discarded at inference time). *Note: All convolutional layers are followed by batch norm and ReLU activation. Architecture is based on their GitHub code.

Inception-v3 is a successor to Inception-v1, with **24M** parameters. Wait where's Inception-v2? Don't worry about it — it's an earlier prototype of v3 hence it's very similar to v3 but not commonly used. When the authors came out with Inception-v2, they ran many experiments on it, and recorded some successful tweaks. Inception-v3 is the network that incorporates these tweaks (tweaks to the optimiser, loss function and adding batch normalisation to the auxiliary layers in the auxiliary network).

The motivation for Inception-v2 and Inception-v3 is to avoid *representational bottlenecks* (this means drastically reducing the input dimensions of the next layer) and have more efficient computations by using factorisation methods.

> **Note:**
> The names of the modules (Stem, Inception-A, Inception-B etc.) were not used for this version of Inception until its later versions i.e. Inception-v4 and Inception-ResNets. I have added them here for easy comparison.

⭐ What's novel?

1. Among the first designers to use batch normalisation (not reflected in the above diagram for simplicity).

✨ What's improved from previous version, Inception-v1?

1. Factorising $n \times n$ convolutions into asymmetric convolutions: $1 \times n$ and $n \times 1$ convolutions
2. Factorise 5×5 convolution to two 3×3 convolution operations
3. Replace 7×7 to a series of 3×3 convolutions

📝 Publication

- Paper: Rethinking the Inception Architecture for Computer Vision

- Authors: Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jonathon Shlens, Zbigniew Wojna. Google, University College London
- Published in: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)

6. ResNet-50 (2015)

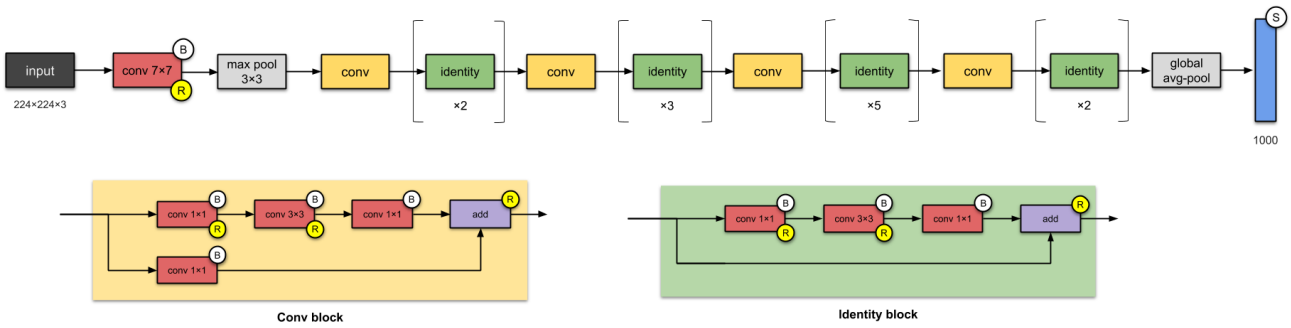


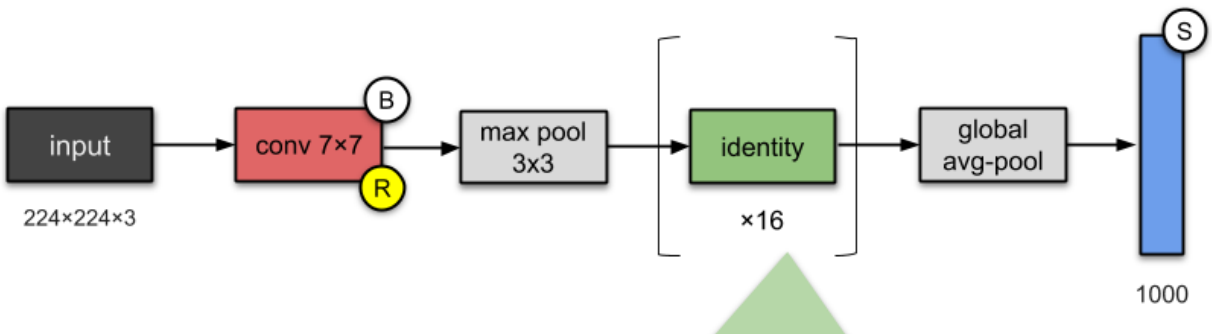
Fig. 6: ResNet-50 architecture, based on the GitHub code from keras-team.

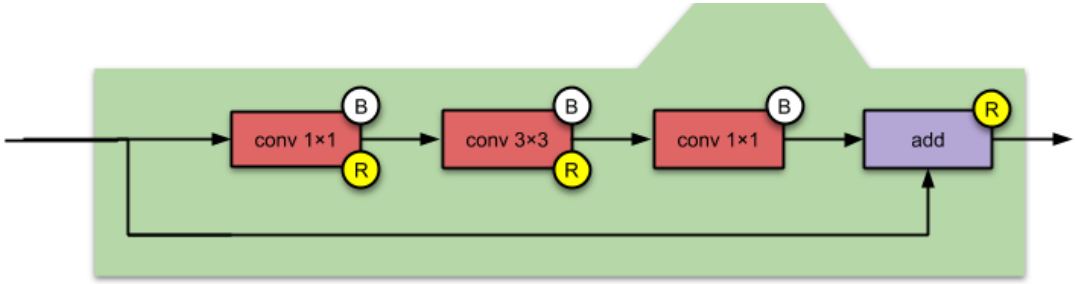
Yes, it's the answer to the question you see on the top of the article.

From the past few CNNs, we have seen nothing but an increasing number of layers in the design, and achieving better performance. But "with the network depth increasing, accuracy gets saturated (which might be unsurprising) and then degrades rapidly." The folks from Microsoft Research addressed this problem with ResNet — using skip connections (a.k.a. shortcut connections, residuals), while building deeper models.

ResNet is one of the early adopters of batch normalisation (the batch norm paper authored by Ioffe and Szegedy was submitted to ICML in 2015). Shown above is ResNet-50, with **26M** parameters.

The basic building block for ResNets are the conv and identity blocks. Because they look alike, you might simplify ResNet-50 like this (don't quote me for this!):





Identity block

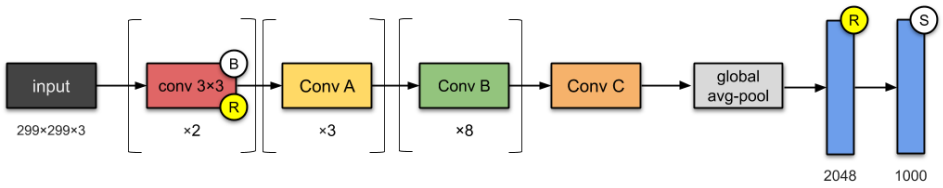
⭐ What's novel?

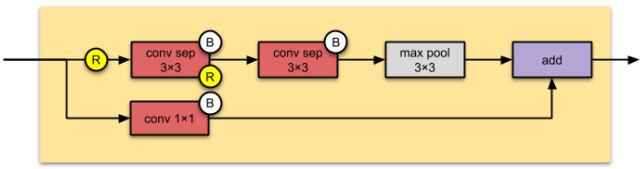
1. *Popularised* skip connections (they weren't the first to use skip connections).
2. Designing even deeper CNNs (up to 152 layers) without compromising model's generalisation power
3. Among the first to use batch normalisation.

📝 Publication

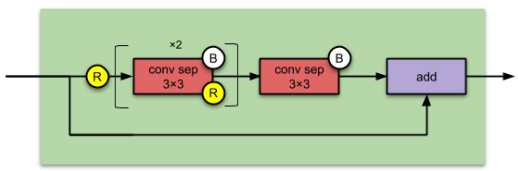
- Paper: Deep Residual Learning for Image Recognition
- Authors: Kaiming He, Xiangyu Zhang, Shaoqing Ren, Jian Sun. Microsoft
- Published in: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)

7. Xception (2016)

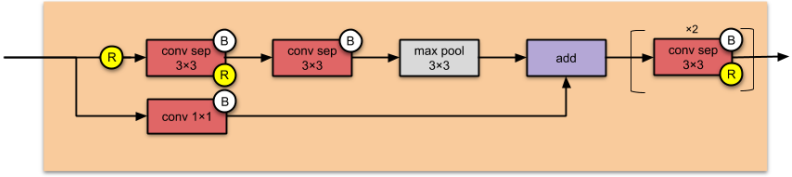




Conv A



Conv B



Conv C

Fig. 7: Xception architecture, based on the GitHub code from keras-team. Depthwise separable convolutions are denoted by 'conv sep.'

Xception is an adaptation from Inception, where the Inception modules have been replaced with depthwise separable convolutions. It has also roughly the same number of parameters as Inception-v1 (**23M**).

Xception takes the Inception hypothesis to an *eXtreme* (hence the name). What's the Inception hypothesis again? Thank goodness this was explicitly and concisely mentioned in this paper (thanks François!).

- Firstly, cross-channel (or cross-feature map) correlations are captured by 1×1 convolutions.
- Consequently, spatial correlations within each channel are captured via the regular 3×3 or 5×5 convolutions.

Taking this idea to an extreme means performing 1×1 to *every* channel, then performing a 3×3 to *each* output. This is identical to replacing the Inception module with depthwise separable convolutions.

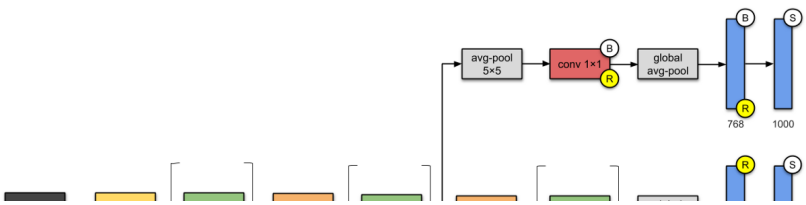
⭐ What's novel?

1. Introduced CNN based entirely on depthwise separable convolution layers.

📝 Publication

- Paper: Xception: Deep Learning with Depthwise Separable Convolutions
- Authors: François Chollet. Google.
- Published in: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)

8. Inception-v4 (2016)



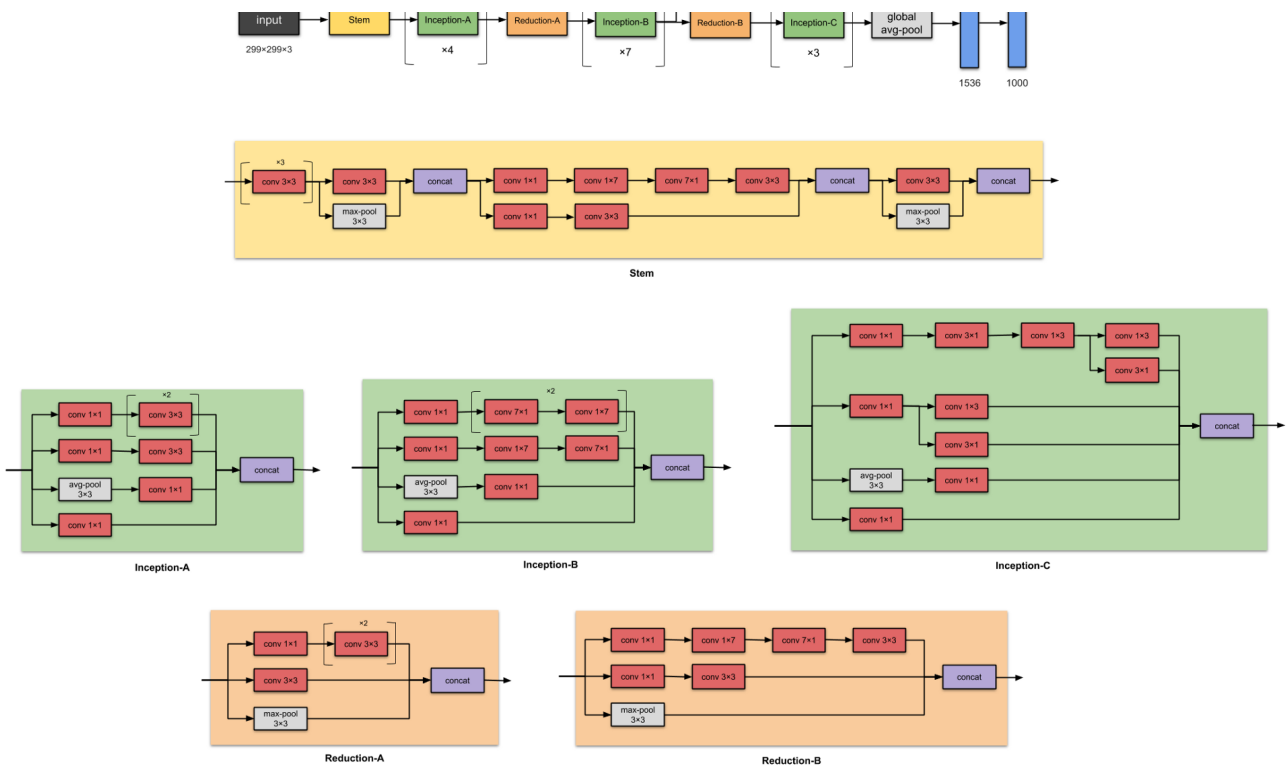


Fig. 8: Inception-v4 architecture. This CNN has an auxiliary network (which is discarded at inference time). *Note: All convolutional layers are followed by batch norm and ReLU activation. Architecture is based on their GitHub code.

The folks from Google strike again with Inception-v4, **43M** parameters. Again, this is an improvement from Inception-v3. The main difference is the Stem group and some minor changes in the Inception-C module. The authors also “made uniform choices for the Inception blocks for each grid size.” They also mentioned that having “residual connections leads to dramatically improved training speed.”

All in all, note that it was mentioned that Inception-v4 works better because of increased model size.

✨ What’s improved from the previous version, Inception-v3?

1. Change in Stem module.
2. Adding more Inception modules.
3. Uniform choices of Inception-v3 modules, meaning using the same number of filters for every module.

📝 Publication

- Paper: Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning
- Authors: Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke, Alex Alemi. Google.
- Published in: Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence

9. Inception-ResNet-V2 (2016)

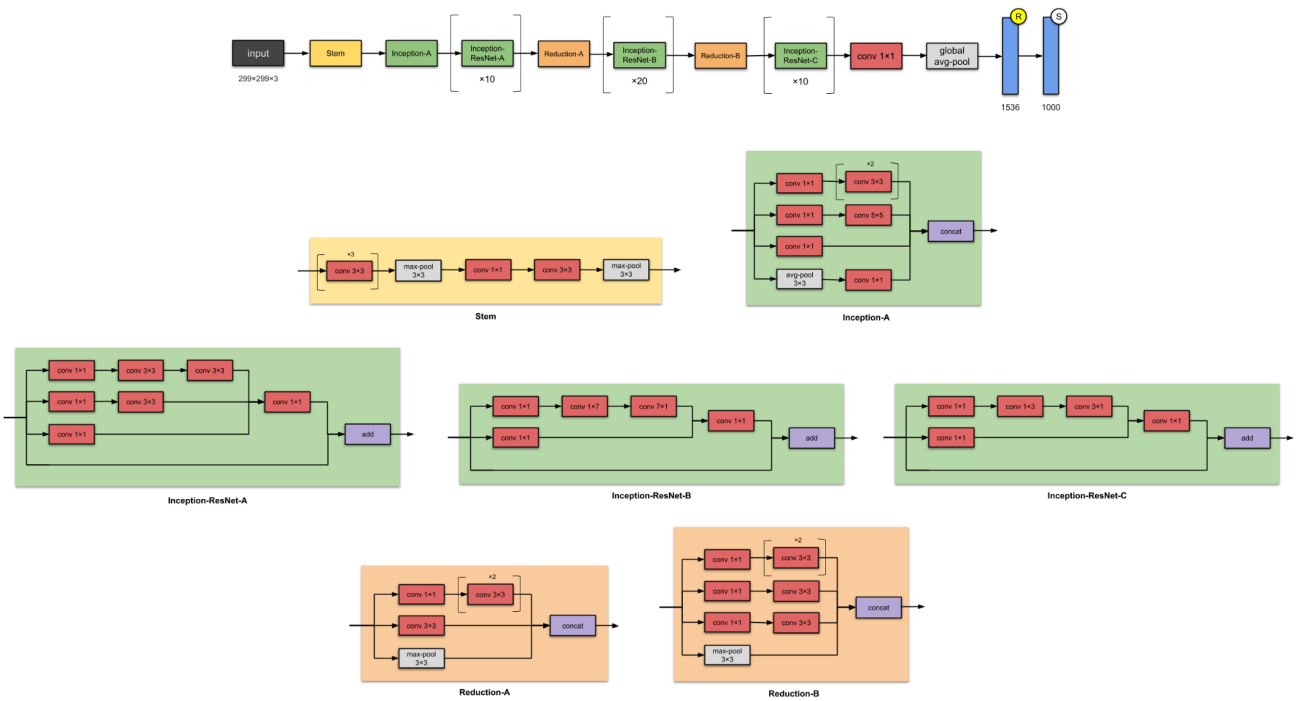


Fig. 9: Inception-ResNet-V2 architecture. *Note: All convolutional layers are followed by batch norm and ReLU activation. Architecture is based on their GitHub code.

In the same paper as Inception-v4, the same authors also introduced Inception-ResNets — a family of Inception-ResNet-v1 and Inception-ResNet-v2. The latter member of the family has **56M** parameters.

✨ What's improved from the previous version, Inception-v3?

1. Converting Inception modules to *Residual Inception blocks*.
2. Adding more Inception modules.
3. Adding a new type of Inception module (Inception-A) after the Stem module.

📝 Publication

- Paper: Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning
- Authors: Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke, Alex Alemi. Google
- Published in: Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence

10. ResNeXt-50 (2017)

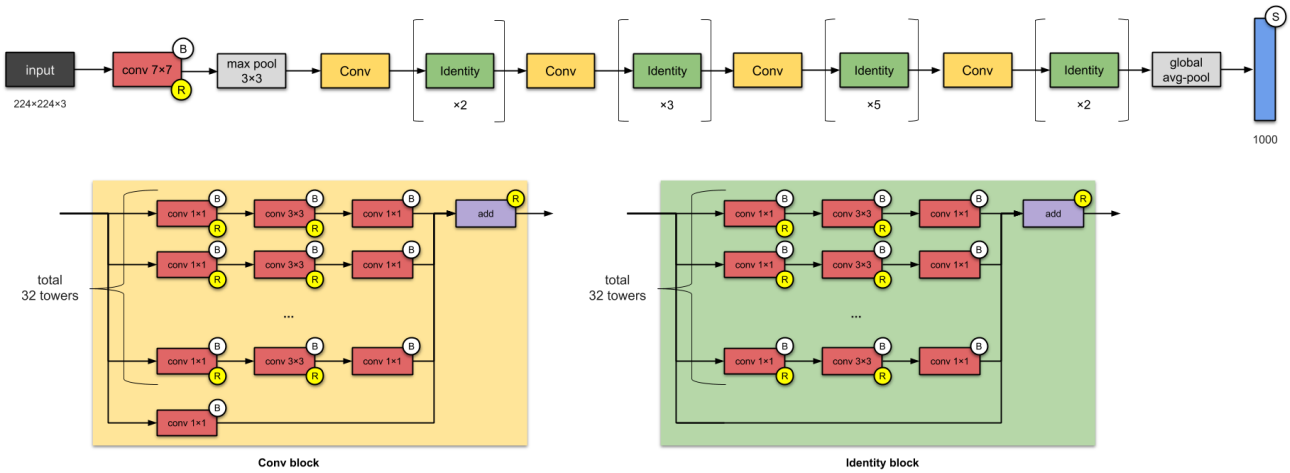


Fig. 10: ResNeXt architecture, based on their paper.

If you're thinking about ResNets, yes, they are related. ResNeXt-50 has **25M** parameters (ResNet-50 has 25.5M). What's different about ResNeXts is the adding of parallel towers/branches/paths within each module, as seen above indicated by 'total 32 towers.'

⭐ What's novel?

1. Scaling up the number of parallel towers ("cardinality") within a module (well I mean this has already been explored by the Inception network…)

📝 Publication

- Paper: Aggregated Residual Transformations for Deep Neural Networks
- Authors: Saining Xie, Ross Girshick, Piotr Dollár, Zhuowen Tu, Kaiming He. University of California San Diego, Facebook Research

- Published in: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)

Appendix: Network In Network (2014)

Recall that in a convolution, the value of a pixel is a linear combination of the weights in a filter and the current sliding window. The authors proposed that instead of this linear combination, let's have a mini neural network with 1 hidden layer. This is what they coined as Mlpconv. So what we're dealing with here is a (simple 1 hidden layer) network in a (convolutional neural) network.

This idea of Mlpconv is likened to 1×1 convolutions, and became the main feature for Inception architectures.

⭐ What's novel?

1. MLP convolutional layers, 1×1 convolutions
2. Global average pooling (taking average of each feature map, and feeding the resulting vector into the softmax layer)

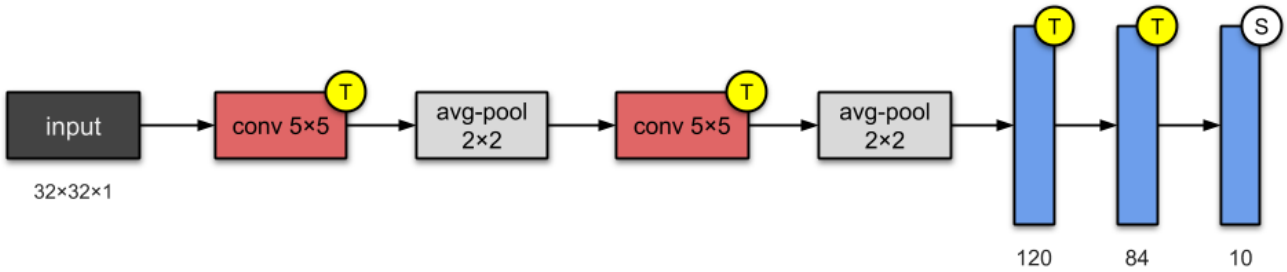
📝 Publication

- Paper: Network In Network
- Authors: Min Lin, Qiang Chen, Shuicheng Yan. National University of Singapore
- arXiv preprint, 2013

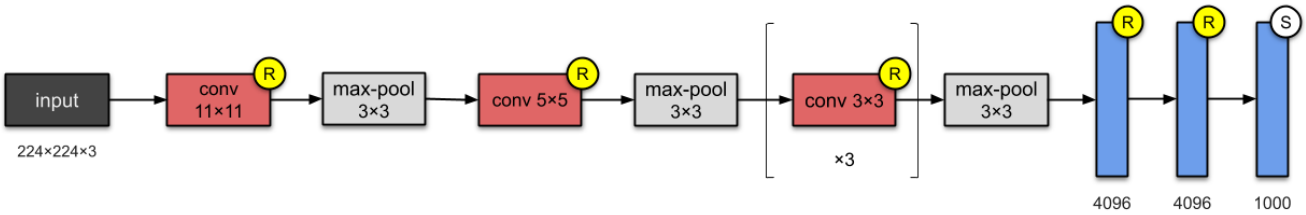
. . .

Let's show them here again for easy reference:

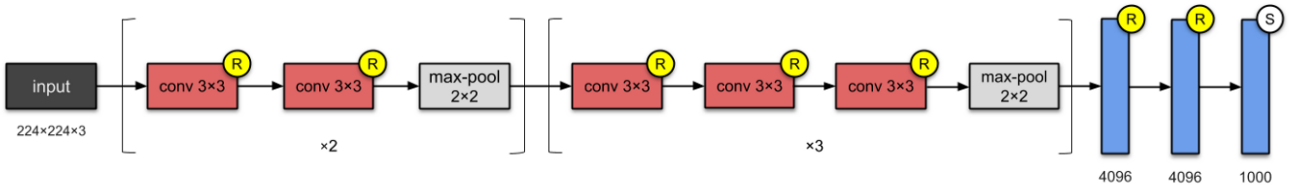
LeNet-5



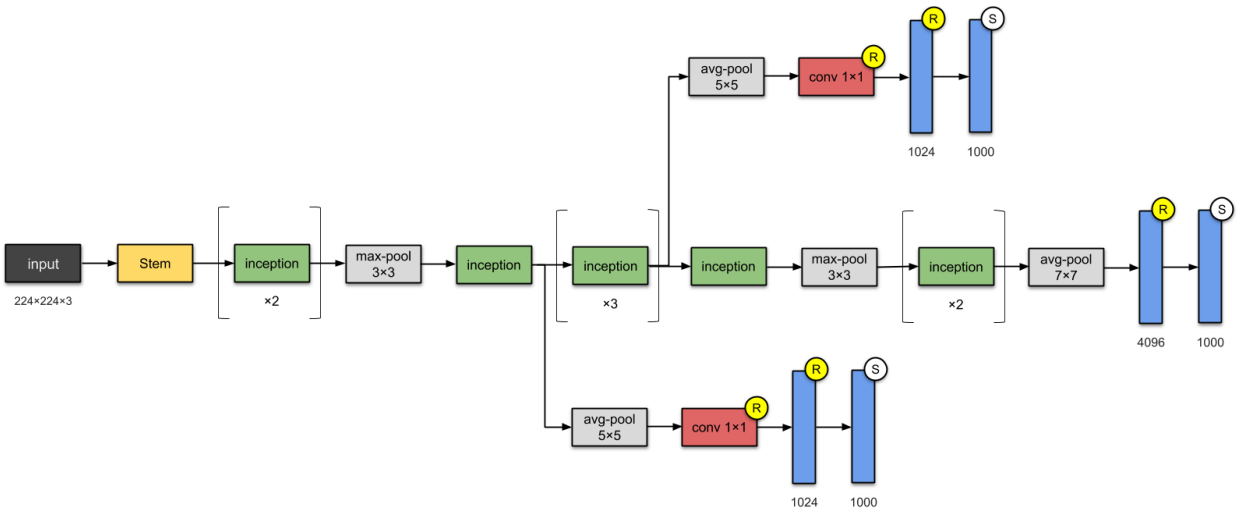
AlexNet

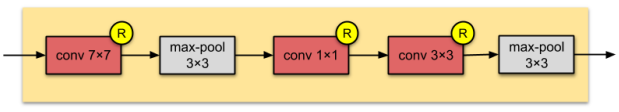


VGG-16

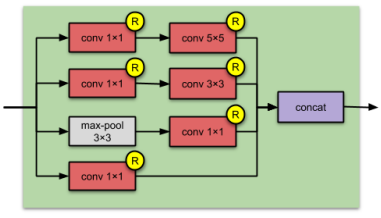


Inception-v1



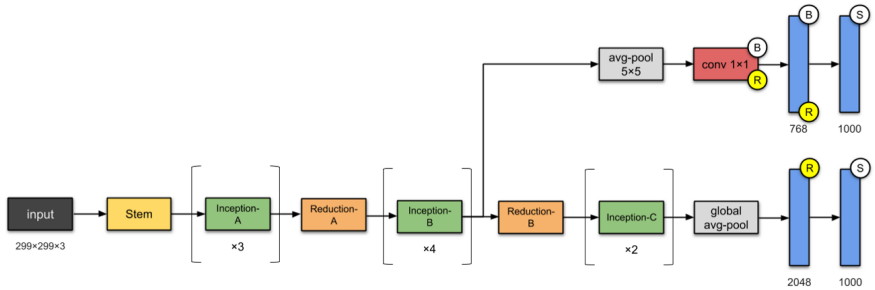


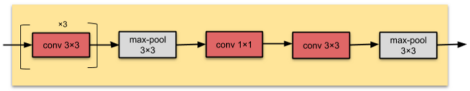
Stem



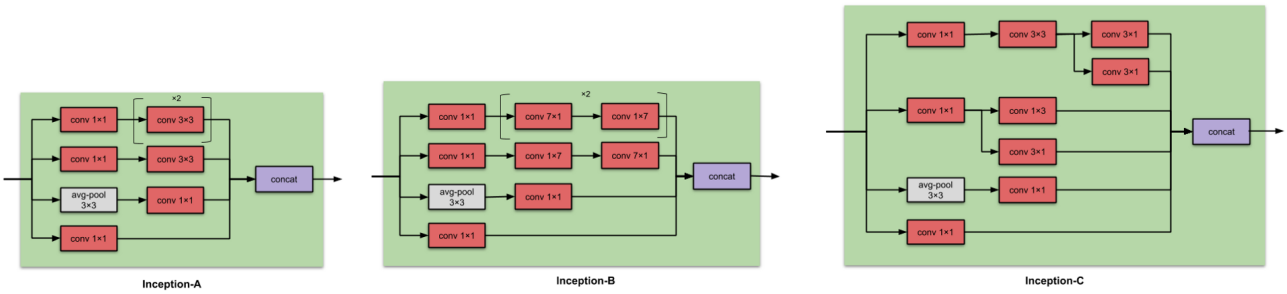
Inception module

Inception-v3





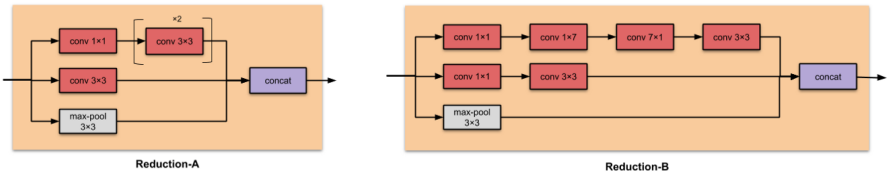
Stem



Inception-A

Inception-B

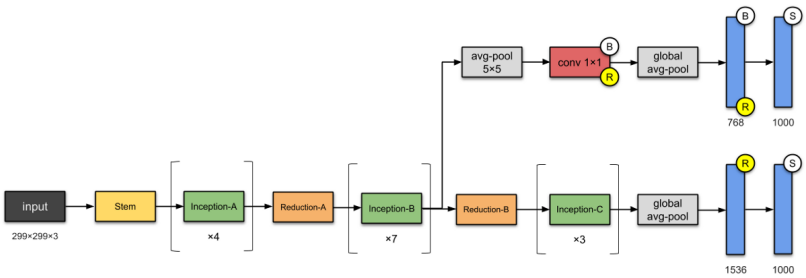
Inception-C

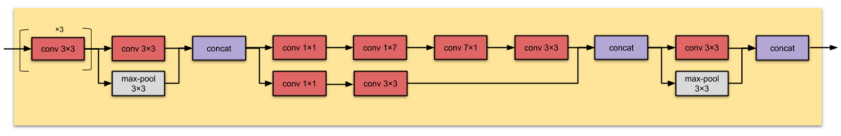


Reduction-A

Reduction-B

Inception-v4





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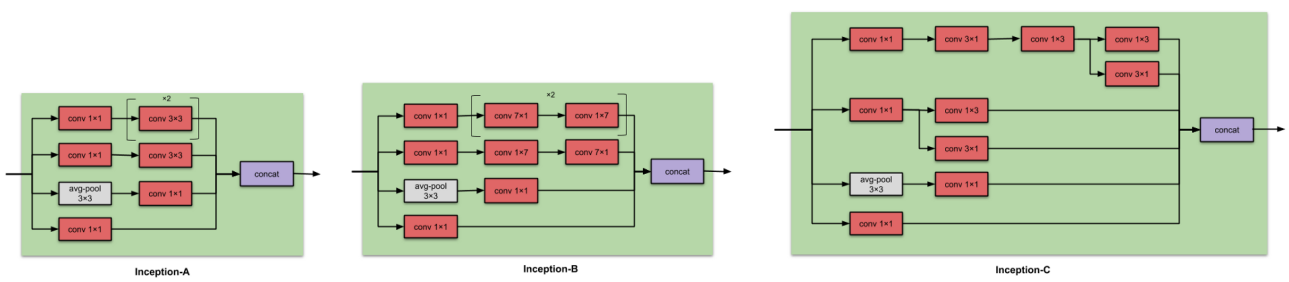
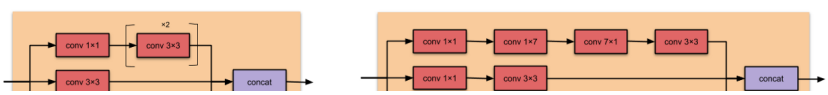


Inception-A

Inception-B

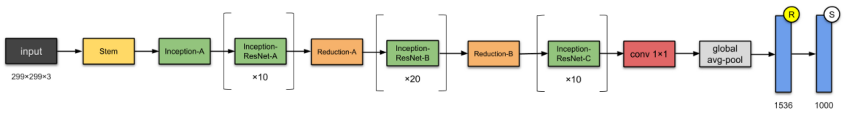
Inception-C



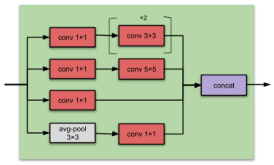
Reduction-A

Reduction-B

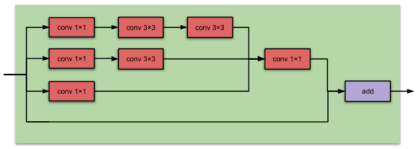
Inception-ResNet-V2



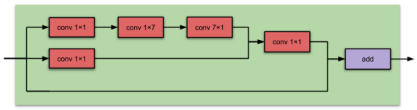
Stem



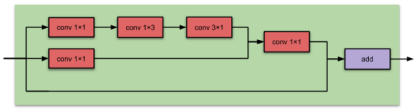
Inception-A



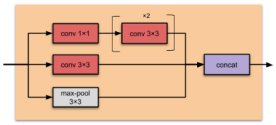
Inception-ResNet-A



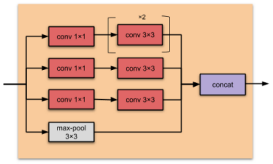
Inception-ResNet-B



Inception-ResNet-C

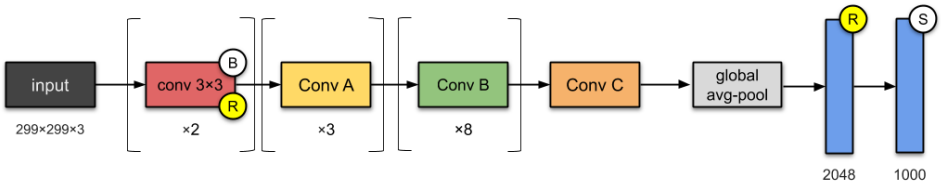


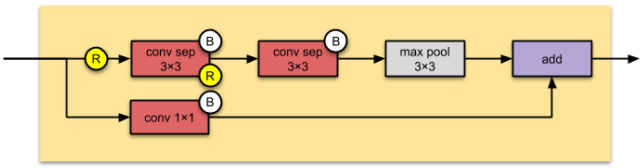
Reduction-A



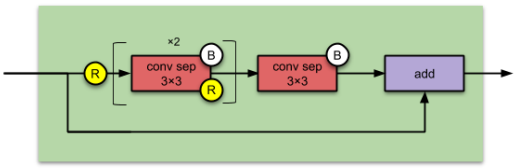
Reduction-B

Xception

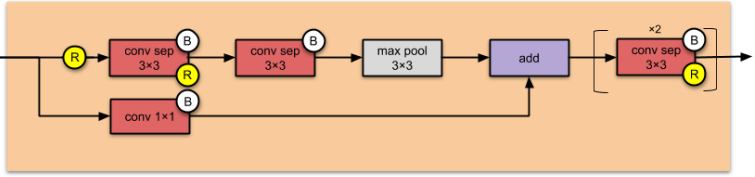




Conv A

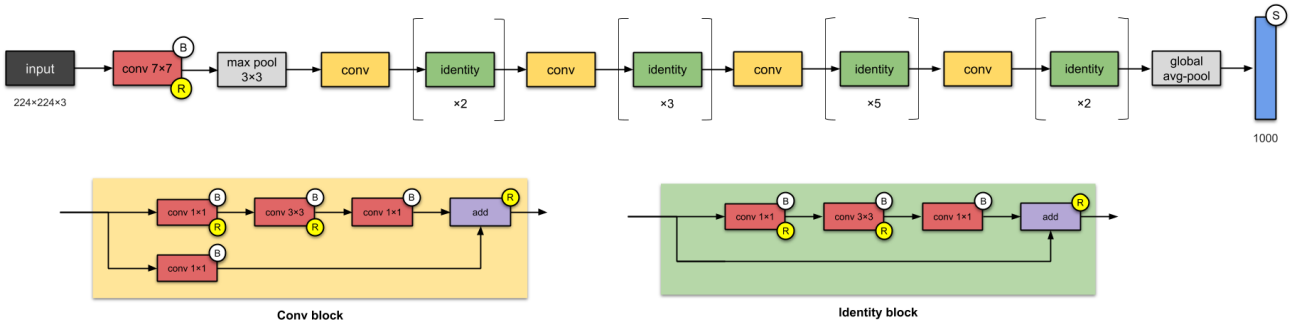


Conv B

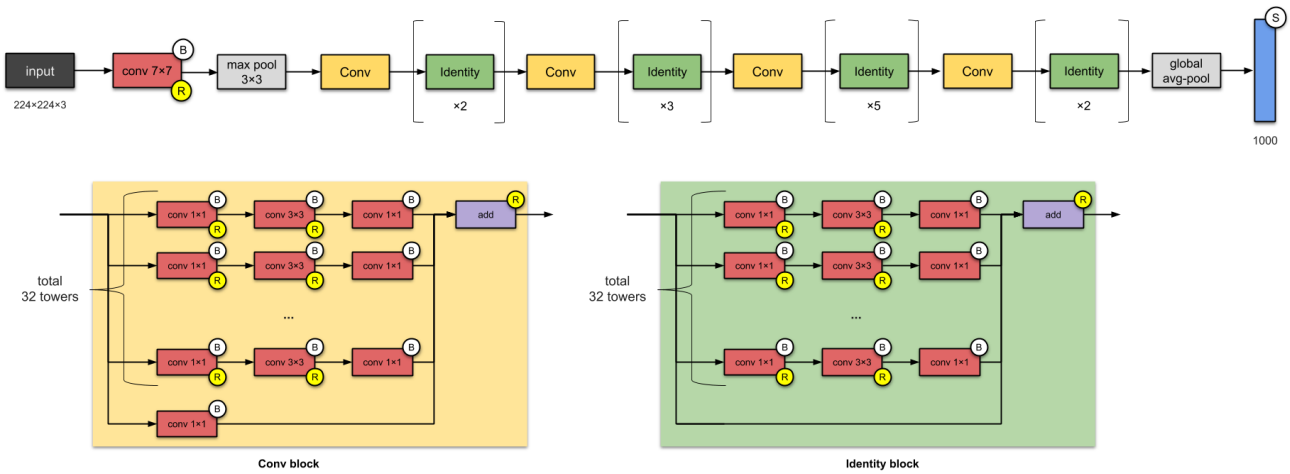


Conv C

ResNet-50



ResNeXt-50



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Resources for neural network visualisation

Here are some resources for you to visualise your neural network:

- Netron 😍
- TensorBoard API by TensorFlow
- `plot_model` API by Keras
- `pytorchviz` package

Similar articles

CNN Architectures: LeNet, AlexNet, VGG, GoogLeNet, ResNet and more ….

References

I have used the above-mentioned papers that produced the architectures for reference. On top of these, here are some others I used for this article:

https://github.com/tensorflow/models/tree/master/research/slim/nets (github.com/tensorflow)

Implementation of deep learning models from the Keras team (github.com/keras-team)

Lecture Notes on Convolutional Neural Network Architectures: from LeNet to ResNet (slazebni.cs.illinois.edu)

Review: NIN — Network In Network (Image Classification) (towardsdatascience.com)

Is there any error that you noticed in the visualisation? Is there anything else that you think I should've included? Drop me a comment below!

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Special thanks to Wei Qi, Ren Jie, Fu Nan, Shirlene and Derek for reviewing this article.

Follow me on Twitter or LinkedIn. You may also reach out to me via raimi.bkarim@gmail.com. Feel free to also visit my website at raibosome.github.io.

Thanks to Ren Jie Tan.

Towards Data Science Deep Learning Machine Learning Convolutional Network Visualization