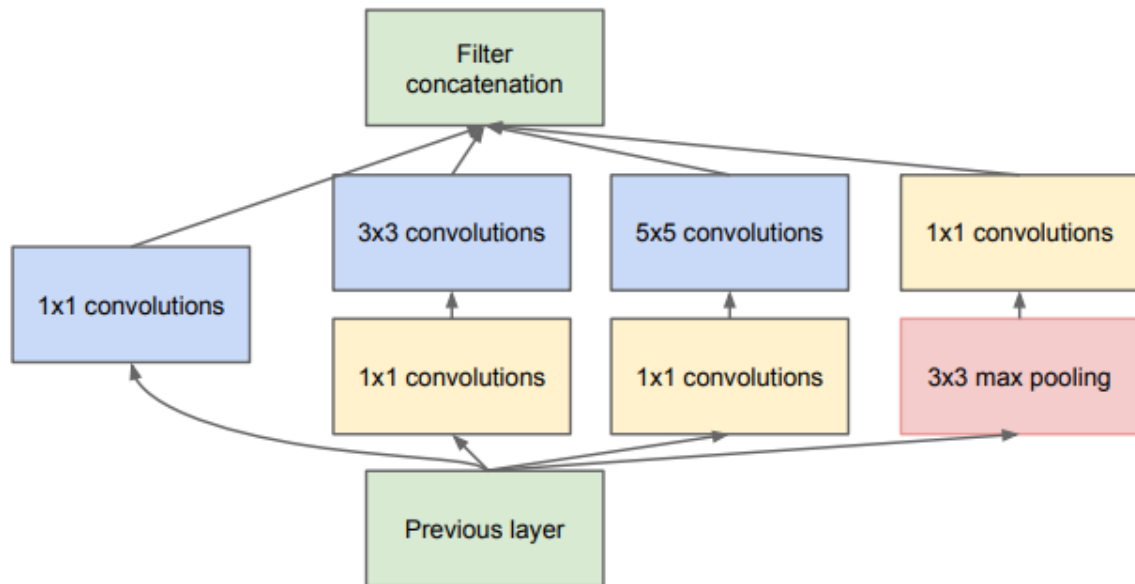


- [#paper/to-read](#) ~ Computer Vision
  - <https://arxiv.org/abs/1409.4842>
  - Sequel papers:
    - [Inception-v2 and Inception-v3](#)
    - [Inception-v4 and Inception-ResNet](#)
    - [Xception](#)
  - Mentioned papers:
    - [Provable Bounds for Deep Representations](#)
    - [Network In Network](#)
    - [R-CNN](#)
    - [Scalable Object Detection](#)
  - Mentioned topics:
    - [Hebbian Theory](#)
    - [Jaccard Index](#)
    - [Polyak Averaging](#)
    - [Supapixel](#)
    - [Generalized Linear Model, GLM](#)
- <https://towardsdatascience.com/a-simple-guide-to-the-versions-of-the-inception-network-7fc52b863202>

## • Summary

- Since salient parts in an image can be very different in size, an **inception module** uses convolutions (and pooling filters) of different

sizes on the same level.



- $1 \times 1$  convolutions reduce the number of input channels to prevent the explosion of required compute in the higher inception modules.
  - Note that for **Max Pooling**, the  $1 \times 1$  convolution goes after it. Otherwise the max pooling operation would be in vain.
- The main idea behind this pattern is based on finding how an optimal local sparse structure can be approximated with dense components.
  - Units from earliest layers correspond to some region of the input image and these units are grouped into **Filter Banks**.
    - Later on, features from these units are aggregated by  $1 \times 1$  convolutions.
      - These convolutions also serve as **Non-linearity** providers.
- The second (and necessary) idea is to apply **Dimensionality Reduction** whenever computational **Complexity** would increase too much otherwise.
  - The paper mentions occasional **Max Pooling** layers with stride 2 that halve the resolution.
- **GoogLeNet** as the main example in the paper.
  - It employs **auxiliary Loss** after some of the inception modules in the middle of the architecture, that mitigates the **Vanishing**

## • Questions

- May there be any obstacles for mixing this architectural approach with [Depthwise Separable Convolutions](#) from [MobileNets](#)?

## • Ideas

- What if we create sparse convolutions of the size  $N \times N$  where  $N$  is big enough and each convolution is randomly masked with the [Probability](#) of  $p$ ?
    - Seems that it was used widely for some time since [this paper](#) was published.
  - This raises the question whether there is any hope for a next, intermediate step: an architecture that makes use of the extra sparsity, even at filter level, as suggested by the theory, but exploits our current hardware by utilizing computations on dense matrices.
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