Motivation and Problem SE Block: The Proposed Solution Integration and Architecture Results Ablation Studies and Insights Conclusion

## Squeeze-and-Excitation Networks - Jie Hu and al.

#### Papa Laity NDIAYE

African Master's Of Machine Intelligence (AMMI), AIMS-Senegal

August 5, 2025



### Overview

- Motivation and Problem
- 2 SE Block: The Proposed Solution
- 3 Integration and Architecture
- 4 Results
- 5 Ablation Studies and Insights
- 6 Conclusion



Motivation and Problem SE Block: The Proposed Solution Integration and Architecture Results Ablation Studies and Insights Conclusion

#### Motivation

- CNNs merge spatial and channel-wise information.
- Traditional architectures treat all channels equally.
- However, not all channels are equally informative.
- Goal: dynamically recalibrate channel importance.



# Squeeze-and-Excitation Block (SE)

#### Two main operations:

- Squeeze:
  - Global average pooling across spatial dimensions.
  - Converts feature maps into a channel descriptor.
- 2 Excitation:
  - Two FC layers with ReLU and sigmoid.
  - Learns weights for each channel.

Final step: multiply input feature maps by these learned weights.



## Integration into Existing Architectures

- SE blocks are lightweight and modular.
- Can be inserted into existing networks like:
  - ResNet (SE-ResNet)
  - Inception (SE-Inception)
  - ResNeXt, MobileNet, ShuffleNet...
- Minimal computational overhead.

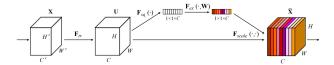


Figure: SE block integration schema



# Performance on ImageNet

- SE-ResNet-50: 6.62% top-5 error vs. 7.48% for ResNet-50.
- Comparable to deeper ResNet-101 with half the FLOPs.
- SE blocks improve performance across all depths.



# Beyond ImageNet

- CIFAR-10/100: consistent error reduction (1-3%).
- COCO (object detection): +2% AP on Faster R-CNN.
- Places365: better top-1 and top-5 accuracy.
- ILSVRC 2017: 1st place, 2.251% top-5 error.



### Ablation Studies

- Squeeze: global avg pooling better than max pooling.
- Excitation: sigmoid superior to tanh or ReLU.
- Reduction ratio r: best trade-off at r = 16.
- Position: works best before residual sum.



## What Does SE Learn?

- Early SE blocks are class-agnostic.
- Later SE blocks are class-discriminative.
- SE blocks can reveal feature importance per class or input.





### Conclusion

- SE blocks enhance CNNs by modelling inter-channel dependencies.
- Simple, plug-and-play module with minimal cost.
- Achieves state-of-the-art performance across many tasks.
- Insightful tool for channel-wise attention and possible pruning.



Motivation and Problem SE Block: The Proposed Solution Integration and Architecture Results Ablation Studies and Insights Conclusion

## Squeeze-and-Excitation Networks - Jie Hu and al.

#### Papa Laity NDIAYE

African Master's Of Machine Intelligence (AMMI), AIMS-Senegal

August 5, 2025

