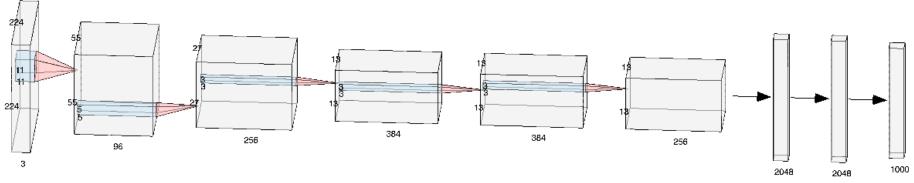
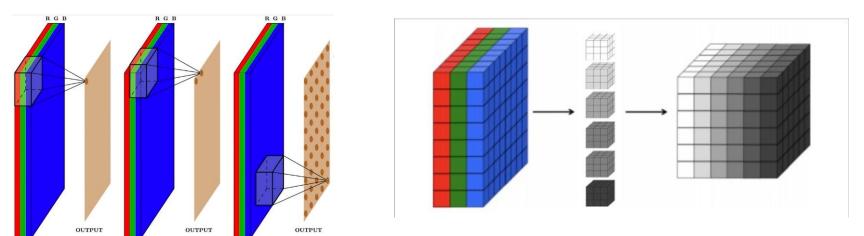
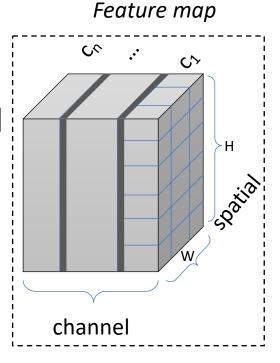
#### SENet(Squeeze and Excitation Networks)



 CNN extracts informative features by fusing spatial and channel-wise information together within local receptive fields

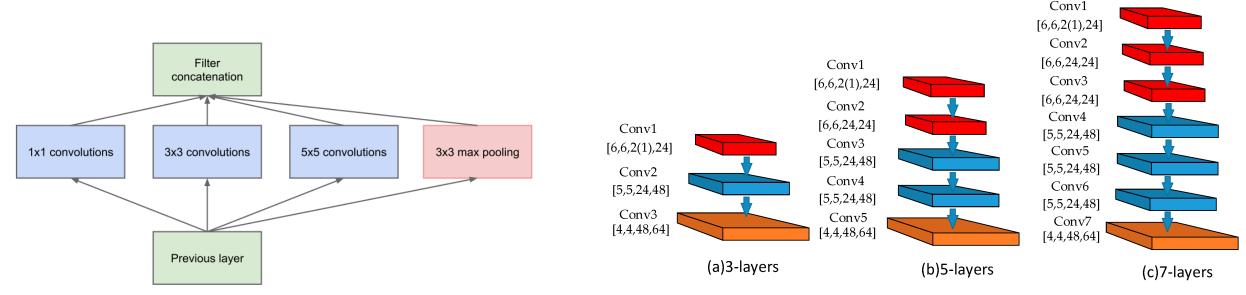




 For each convolutional layer, a set of filters are learned to express local spatial connectivity patterns along input channels

#### Introduction

- By stacking a series of convolutional layers interleaved with non-linearities and downsampling, CNNs are capable of capturing hierarchical patterns with global receptive fields as powerful image descriptions.
- **Inception** architectures (**GoogleNet**), which showed that the network can achieve competitive accuracy by embedding multi-scale processes in its modules



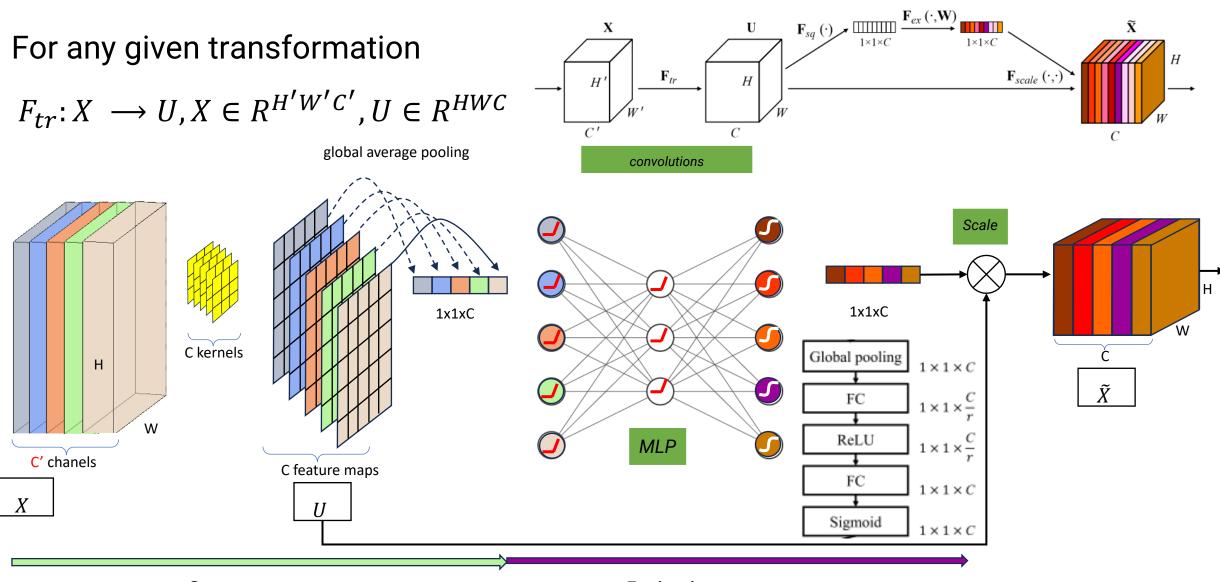
#### Introduction

- In this paper, we investigate a different aspect of architectural design the channel relationship, by introducing a new architectural unit, which we term the "Squeeze-and Excitation" (SE) block. Our goal is to improve the representational power of a network by explicitly modelling the interdependencies between the channels of its convolutional features
- All of this works by fusing the spatial and channel information of an image. The
  different filters will first find spatial features in each input channel before adding
  the information across all available output channels.

A Siamese Neural Network for Non-Invasive Baggage Re-Identification

by Pier Luigi Mazzeo <sup>1</sup> ⊠ <sup>0</sup>, Christian Libetta <sup>2</sup> ⊠, Paolo Spagnolo <sup>1,\*</sup> ⊠ <sup>0</sup> and Cosimo Distante <sup>1</sup> ⊠ <sup>0</sup>

## SE (Squeeze and Excitation) Block



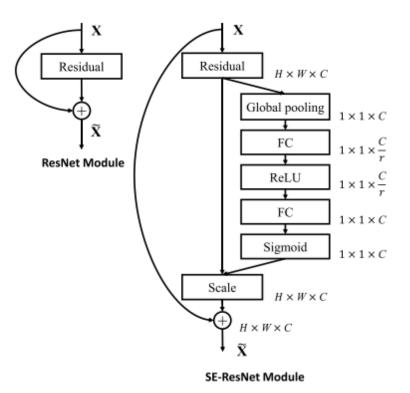
Squeeze aggregates the feature maps

Excitation learned importance weights

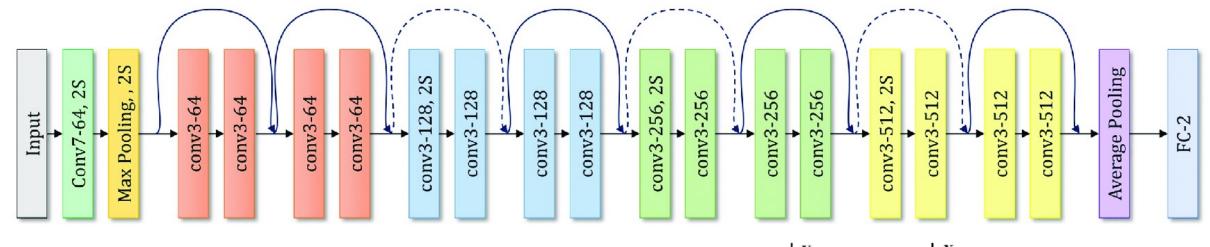
#### SEBlock

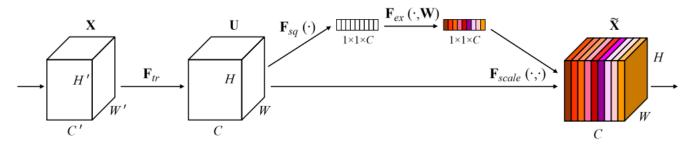
class SEBlock(nn.Module):

```
_(self, input_channels, reduction_ratio=16):
  super(SEBlock, self).__init__()
   self.avg_pool = nn.AdaptiveAvgPool2d(1)
   self.fc1 = nn.Linear(input_channels, input_channels // reduction_ratio, <mark>bias=False</mark>)
  self.relu = nn.ReLU(inplace=True)
   self.fc2 = nn.Linear(input_channels // reduction_ratio, input_channels, <mark>bias=False</mark>)
  self.sigmoid = nn.Sigmoid()
def forward(self, x):
  batch_size, channels, _, _ = x.size()
  y = self.avg_pool(x).view(batch_size, channels)
  y = self.fc1(y)
  y = self.relu(y)
  y = self.fc2(y)
  y = self.sigmoid(y).view(batch_size, channels, 1, 1)
  return x * y.expand_as(x)
```



### Implementation: Resnet18 - SENetwork

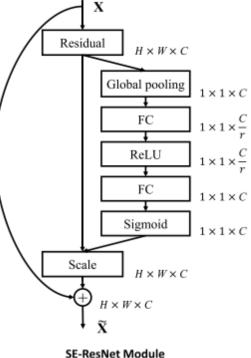




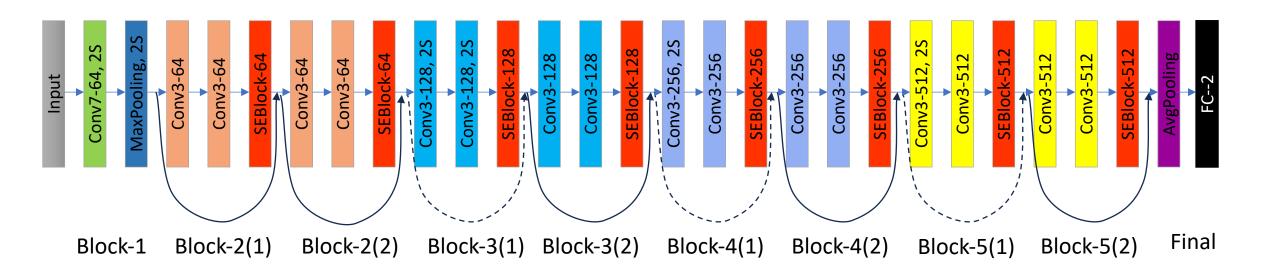
Residual  $\widetilde{X}$   $\widetilde{X}$ ResNet Module

• To integrate SE blocks into the ResNet18 model:

- 1. Define the SEBlock.
- Add SEBlock instances after each block of the ResNet18 architecture



### SEResNet18



## SEResnet18

	E:\thanh\ntu_group\thinh\Image-Classification\SEResnet18\train_se_resnet18.py
	Training: 100% 40/40 [00:35<00:00, 1.14it/s]
	Valid: 100%  12/12 [00:03<00:00, 3.04it/
	Epoch 0: Validation loss = 1.593268911043803, Validation accuracy: 0.5
	Validation accuracy increased (0> 0.5). Model saved
	Training: 100%  40/40 [00:34<00:00, 1.15it/s]
	Valid: 100%  12/12 [00:03<00:00, 3.04it/
	Epoch 1: Validation loss = 0.7448241660992304, Validation accuracy: 0.6537295778592428
	Validation accuracy increased (0.5> 0.6537295778592428). Model saved
	Training: 100%  40/40 [00:34<00:00, 1.15it/s]
	Valid: 100%  12/12 [00:03<00:00, 3.04it/
	Epoch 2: Validation loss = 0.8086711913347244, Validation accuracy: 0.6246566226085027
	Training: 100%  40/40 [00:38<00:00, 1.03it/s]
	Valid: 100%  12/12 [00:03<00:00, 3.05it/
	Epoch 3: Validation loss = 0.5508396079142889, Validation accuracy: 0.7178877095381418
	Validation accuracy increased (0.6537295778592428> 0.7178877095381418). Model saved
	Training: 100%  40/40 [00:49<00:00, 1.25s/it]
	Valid: 100%  12/12 [00:03<00:00, 3.05it/
	Epoch 4: Validation loss = 0.9465955793857574, Validation accuracy: 0.6052251011133194
•	Training: 100% 40/40 [00:35<00:00, 1.14it/s]
	Valid: 100%  12/12 [00:03<00:00, 3.06it/
•	Epoch 5: Validation loss = 0.4808992240577936, Validation accuracy: 0.8208229939142863
	Validation accuracy increased (0.7178877095381418> 0.8208229939142863). Model saved
	Training: 100% 40/40 [00:34<00:00, 1.14it/s]
	Valid: 100%    12/12 [00:03<00:00, 3.02it/
	Epoch 6: Validation loss = 1.2058287014563878, Validation accuracy: 0.5446381519238154
	Training: 100%  40/40 [00:35<00:00, 1.14it/s]
	Valid: 100%
	Epoch 7: Validation loss = 0.33514292041460675, Validation accuracy: 0.8705415378014246
•	Validation accuracy increased (0.8208229939142863> 0.8705415378014246). Model saved
•	Training: 100% 40/40 [00:35<00:00, 1.14it/s]
•	Valid: 100%
	Epoch 8: Validation loss = 0.7108310361703237, Validation accuracy: 0.7303647299607595
•	Training: 100% 40/40 [00:35<00:00, 1.14it/s]
	Valid: 100%  12/12 [00:03<00:00, 3.04it/
	Epoch 9: Validation loss = 0.3489784523844719, Validation accuracy: 0.8559288581212362

# Resnet18

	E:\thanh\ntu_group\thinh\Image-Classification\SEResnet18\train_resnet18.py
	Training: 100% 40/40 [01:31<00:00, 2.28s/it]
•	Valid: 100%  12/12 [00:09<00:00, 1.28it/s
•	Epoch 0: Validation loss = 1.7880469659964244, Validation accuracy: 0.5
•	Validation accuracy increased (0> 0.5). Model saved
•	Training: 100%  40/40 [00:34<00:00, 1.17it/s]
•	Valid: 100%  12/12 [00:03<00:00, 3.12it/s
•	Epoch 1: Validation loss = 0.6179960519075394, Validation accuracy: 0.7065854867299398
•	Validation accuracy increased (0.5> 0.7065854867299398). Model saved
•	Training: 100% 40/40 [00:33<00:00, 1.20it/s]
•	Valid: 100%  12/12 [00:03<00:00, 3.17it/s
•	Epoch 2: Validation loss = 1.8959488968054454, Validation accuracy: 0.5098905762036642
•	Training: 100% 40/40 [00:33<00:00, 1.20it/s]
•	Valid: 100%  12/12 [00:03<00:00, 3.17it/s
•	Epoch 3: Validation loss = 1.9621925055980682, Validation accuracy: 0.5
•	Training: 100% 40/40 [01:18<00:00, 1.96s/it]
•	Valid: 100%  12/12 [00:09<00:00, 1.23it/s
•	Epoch 4: Validation loss = 1.4488181670506795, Validation accuracy: 0.508959099650383
•	Training: 100% 40/40 [02:03<00:00, 3.08s/it]
•	Valid: 100%  12/12 [00:09<00:00, 1.29it/s
•	Epoch 5: Validation loss = 1.660115271806717, Validation accuracy: 0.49278322358926135
•	Training: 100% 40/40 [02:00<00:00, 3.01s/it]
•	Valid: 100%  12/12 [00:09<00:00, 1.21it/s
•	Epoch 6: Validation loss = 2.0973944067955017, Validation accuracy: 0.5
•	Training: 100% 40/40 [01:33<00:00, 2.33s/it]
•	Valid: 100%  12/12 [00:03<00:00, 3.13it/s
•	Epoch 7: Validation loss = 0.7050559955338637, Validation accuracy: 0.747499868273735
•	Validation accuracy increased (0.7065854867299398> 0.747499868273735). Model saved
•	Training: 100% 40/40 [01:23<00:00, 2.09s/it]
•	Valid: 100%  12/12 [00:09<00:00, 1.23it/s
•	Epoch 8: Validation loss = 0.4437953482071559, Validation accuracy: 0.8310285409291586
•	Validation accuracy increased (0.747499868273735> 0.8310285409291586). Model saved
•	Training: 100% 40/40 [02:03<00:00, 3.09s/it]
•	Valid: 92%   11/12 [00:08<00:00, 1.17it/s]
•	Epoch 9: Validation loss = 1.2620619237422943, Validation accuracy: 0.6665227264165878
•	Valid: 100%  12/12 [00:09<00:00, 1.27it/s