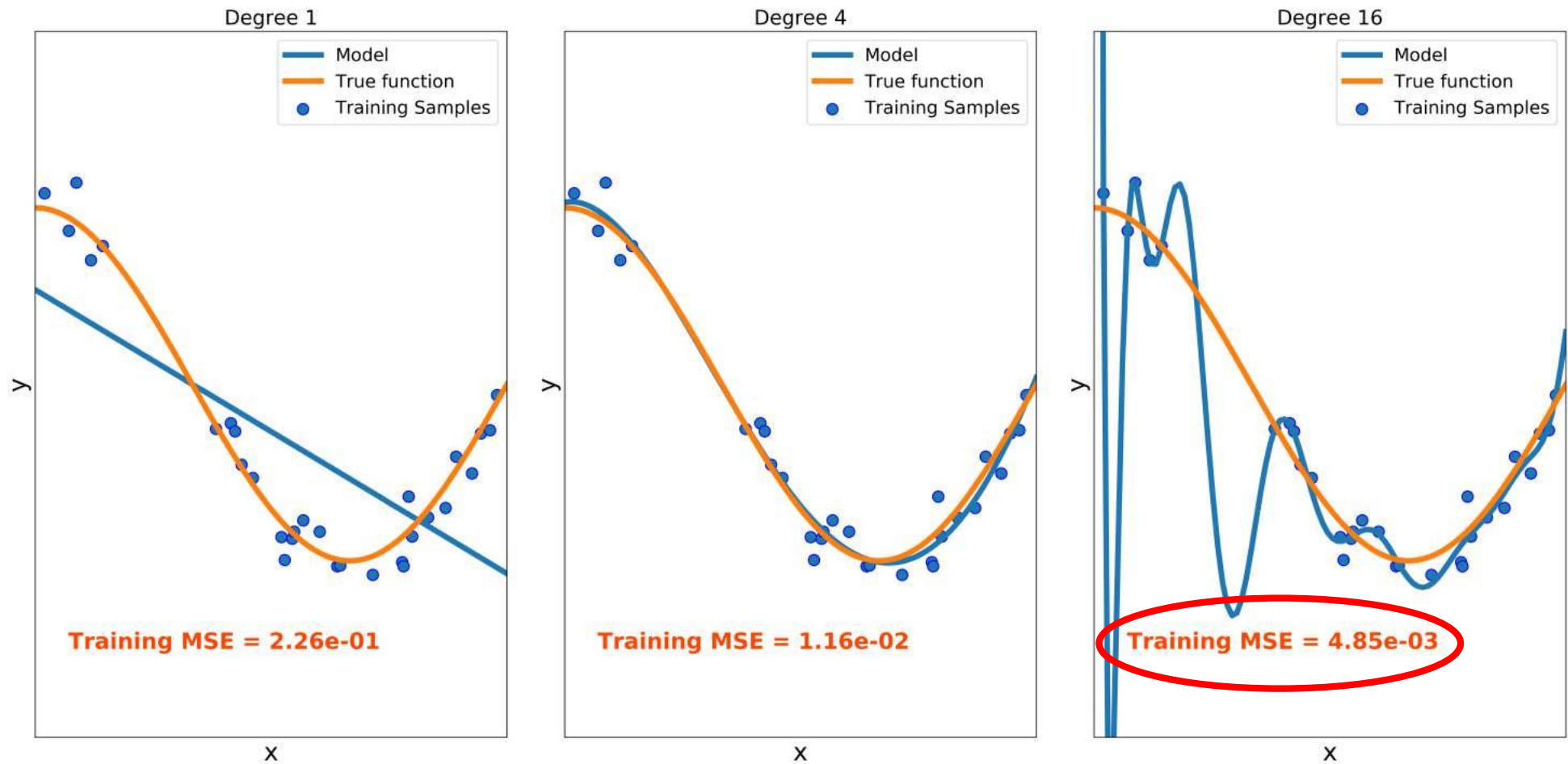
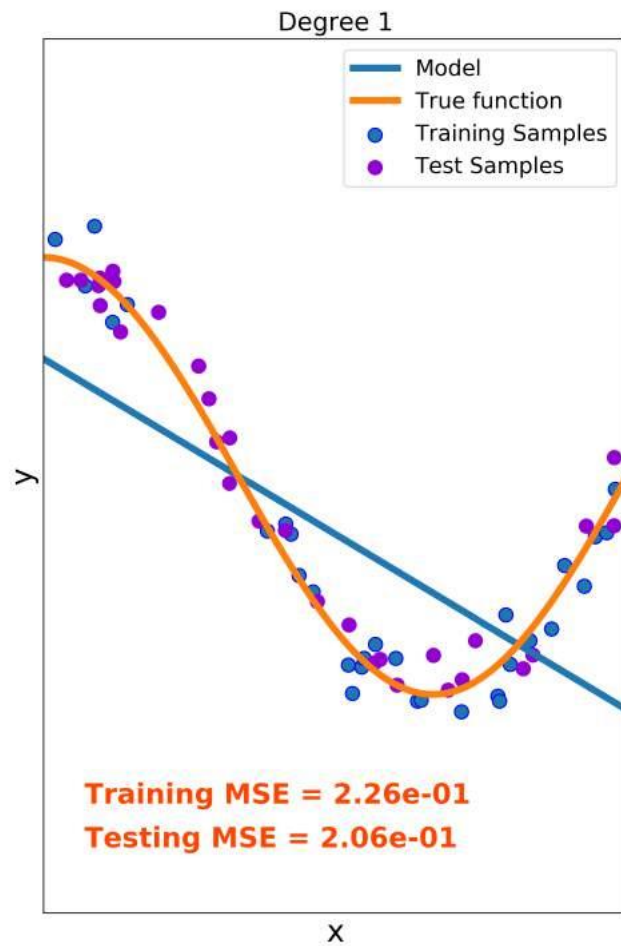


Regularisation

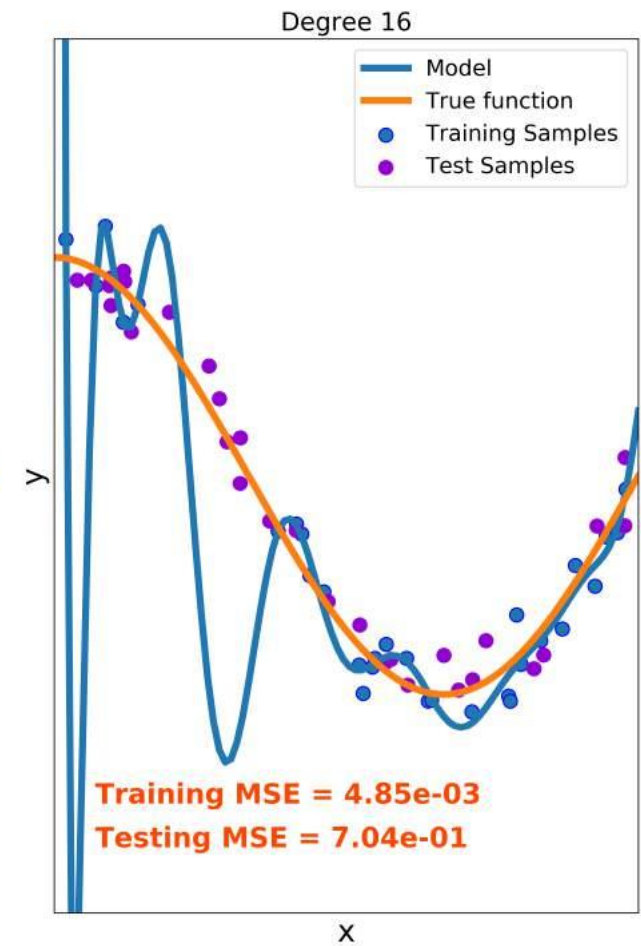
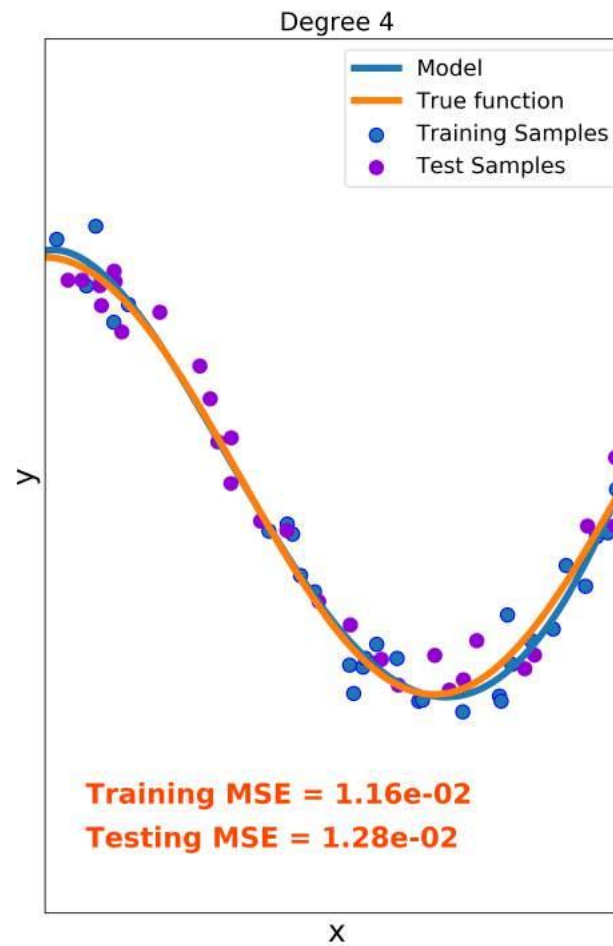
Overfitting/Underfitting



Overfitting/Underfitting



High Bias



High Variance

Bias-Variance Tradeoff

Assuming the true function is y and the learned function approximation is \hat{y} the error \mathcal{L} for a given input x is:

$$\mathcal{L}(x) = E[(\hat{y} - y)^2]$$

The error can be decomposed to:

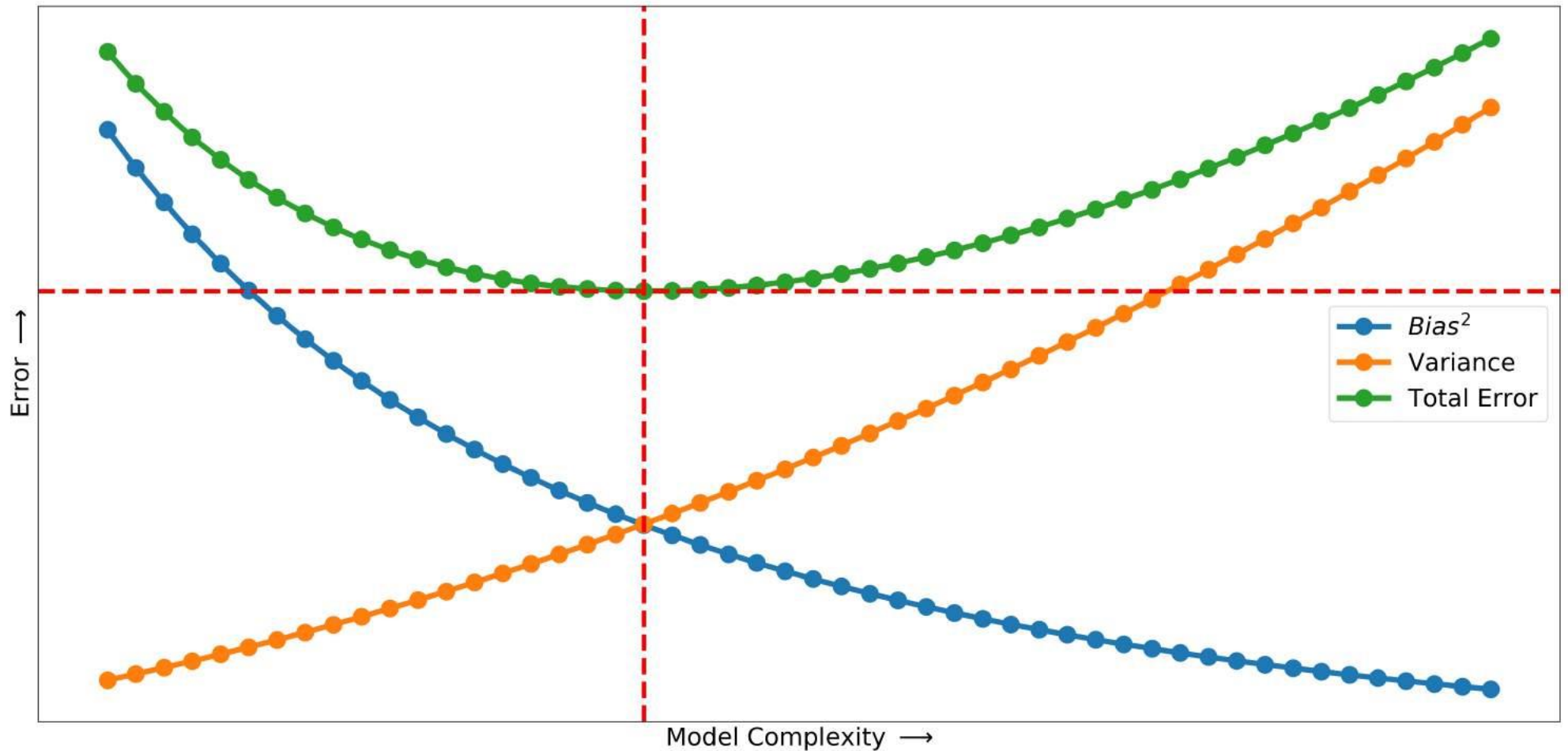
$$\mathcal{L}(x) = \text{Bias}^2 + \text{Var} + \text{Irreducible Error}$$

$$\text{Bias}^2 = (E[\hat{y}] - y)^2$$

$$\text{Var} = E[(\hat{y} - E[\hat{y}])^2]$$

$$\sigma_e^2 = \text{constant}$$

Bias-Variance Tradeoff

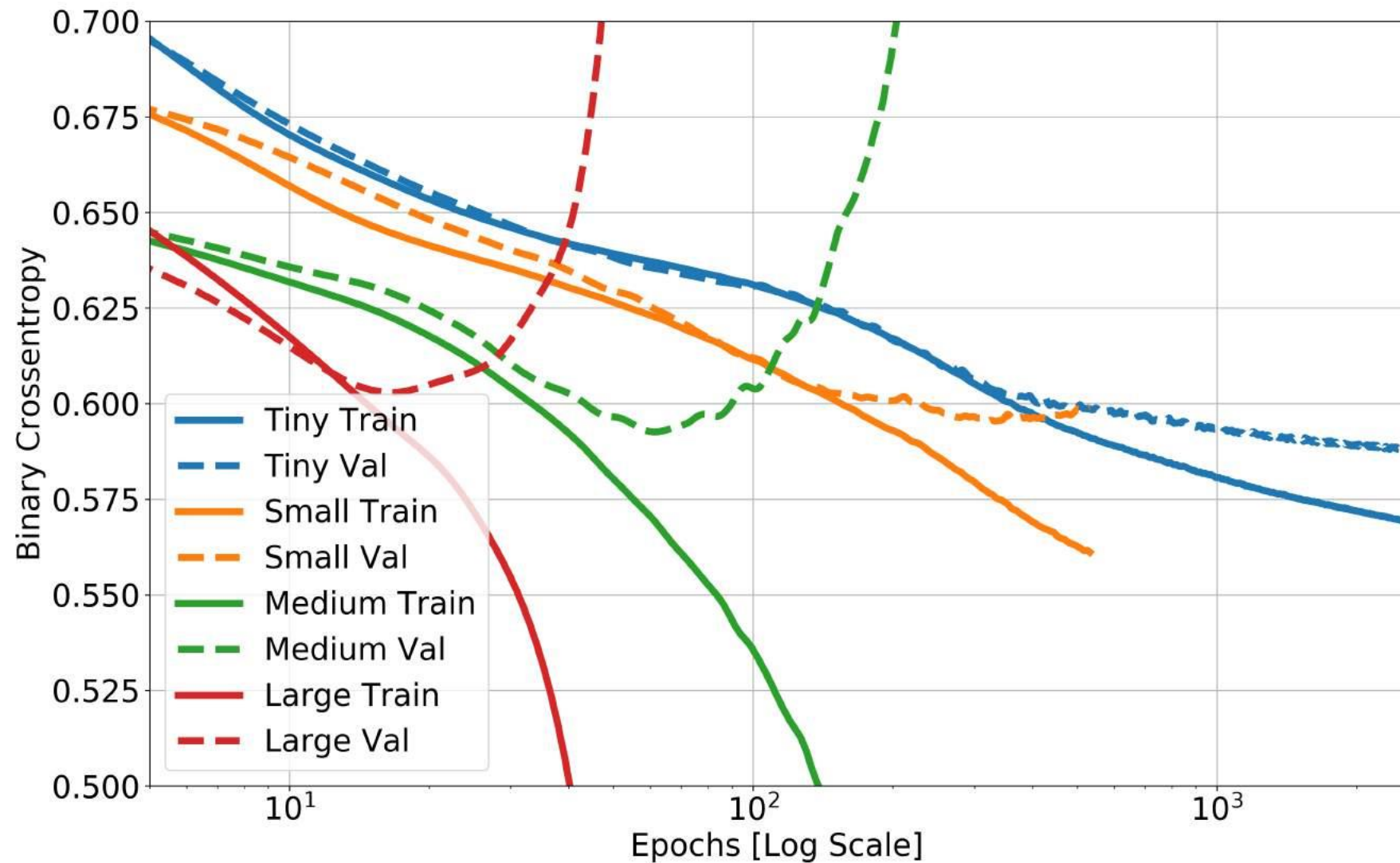


← Underfit

↑ Optimal

Overfit →

Underfitting/Overfitting



Regularisation

Modify Loss function \mathcal{L} to penalise complex models

$$\mathcal{L}(x) = E \left[\left(f(x) - \hat{f}(x) \right)^2 \right] + \lambda \|w\|_p^p$$

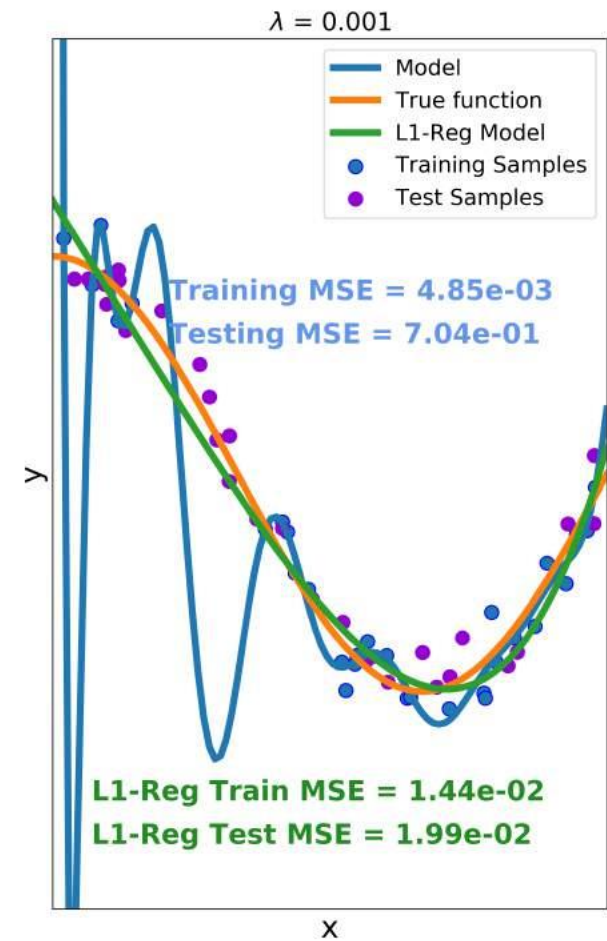
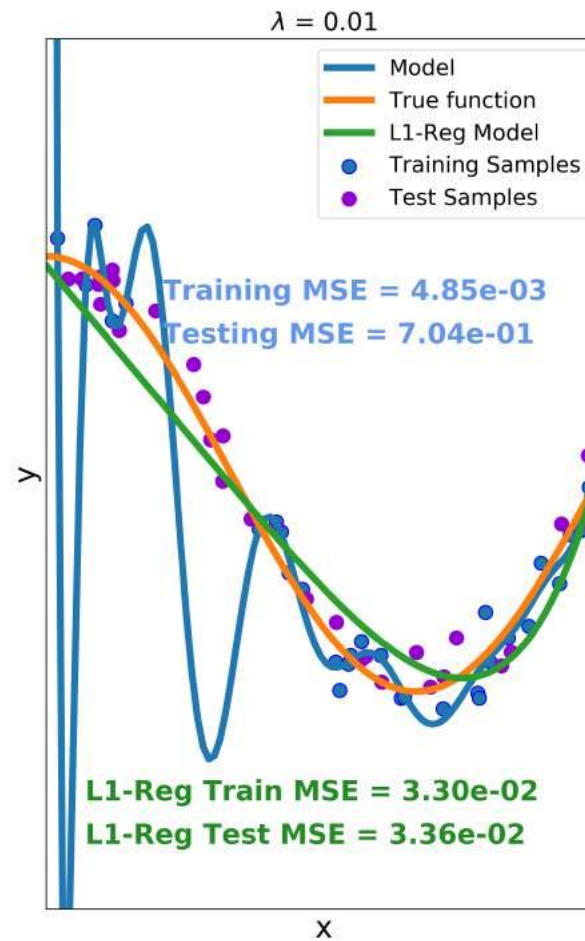
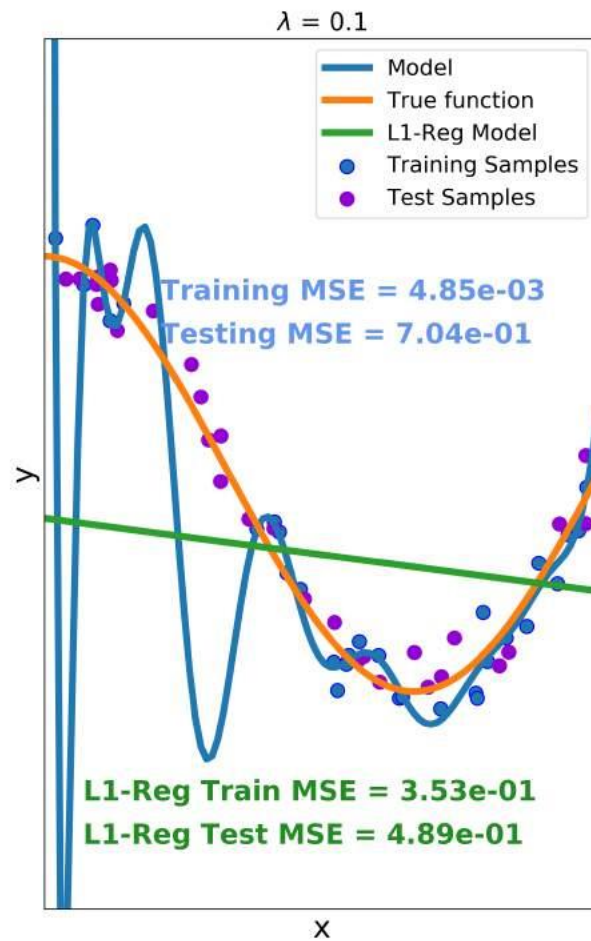
Where $\|w\|_p$ is the p norm of the model parameters:

- $p = 1$, L1 norm: $\|w\|_1 = \sum_{j=1}^p |w_j|$

- $p = 2$, L2 norm: $\|w\|_2 = \sqrt{\sum_{j=1}^p w_j^2}$

and λ the regularisation coefficient for $\lambda \rightarrow 0$ the loss function reduces to no regularisation and for $\lambda \rightarrow \infty$ error becomes large and all the weights will approach zero

Effect of λ



How to select λ ?

- λ is another hyperparameter
- To find the best λ run multiple iteration with random train/test splits and select the λ that minimises the variance

Weight Decay

Update rule for SGD:

$$w_{t+1} = w_t - \eta \frac{\partial L}{\partial w} - \eta \lambda w_t$$

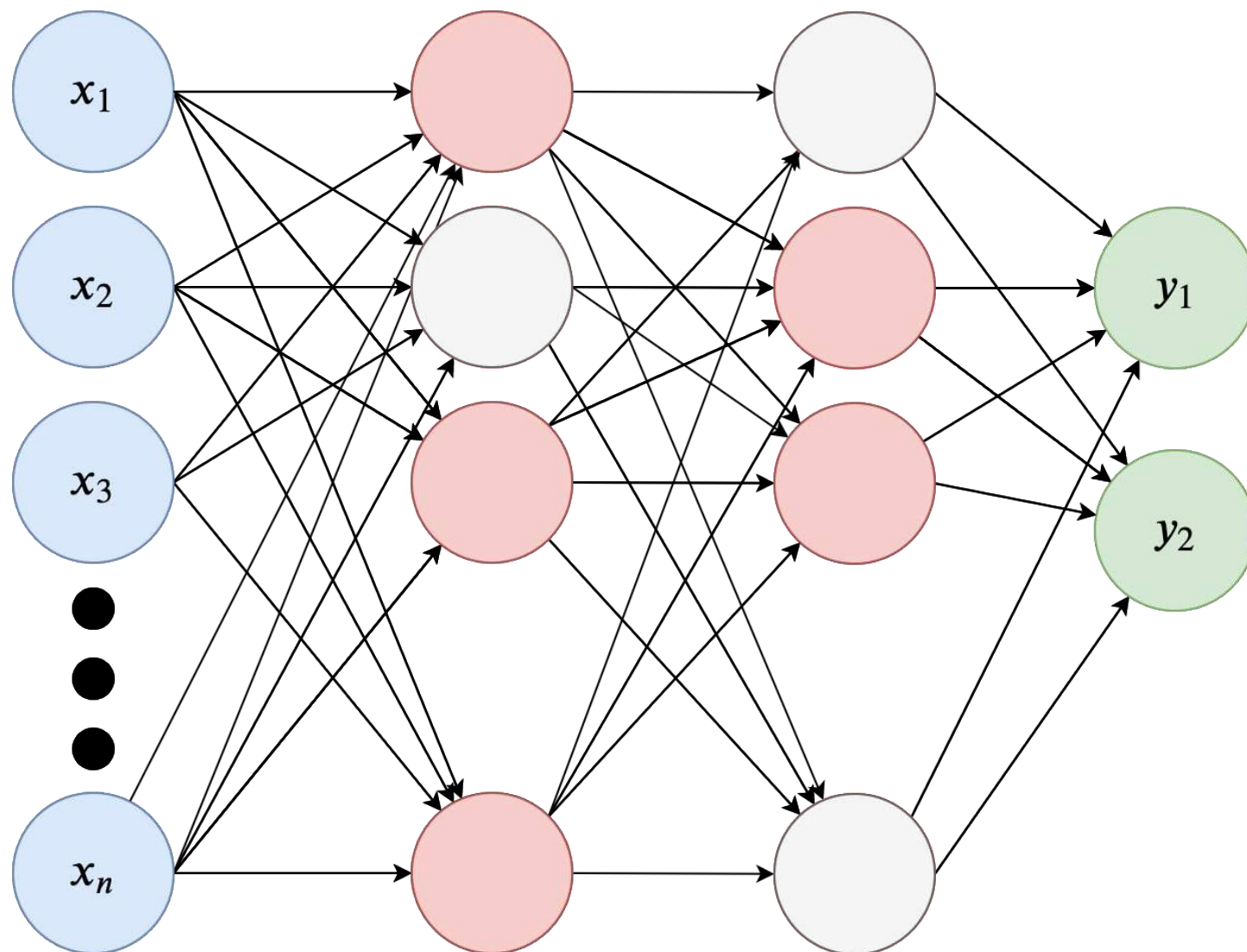
Every update we subtract $\eta \lambda w_t$ and we decay the weights

Equivalent to L2 Regularisation (**for vanilla SGD**)

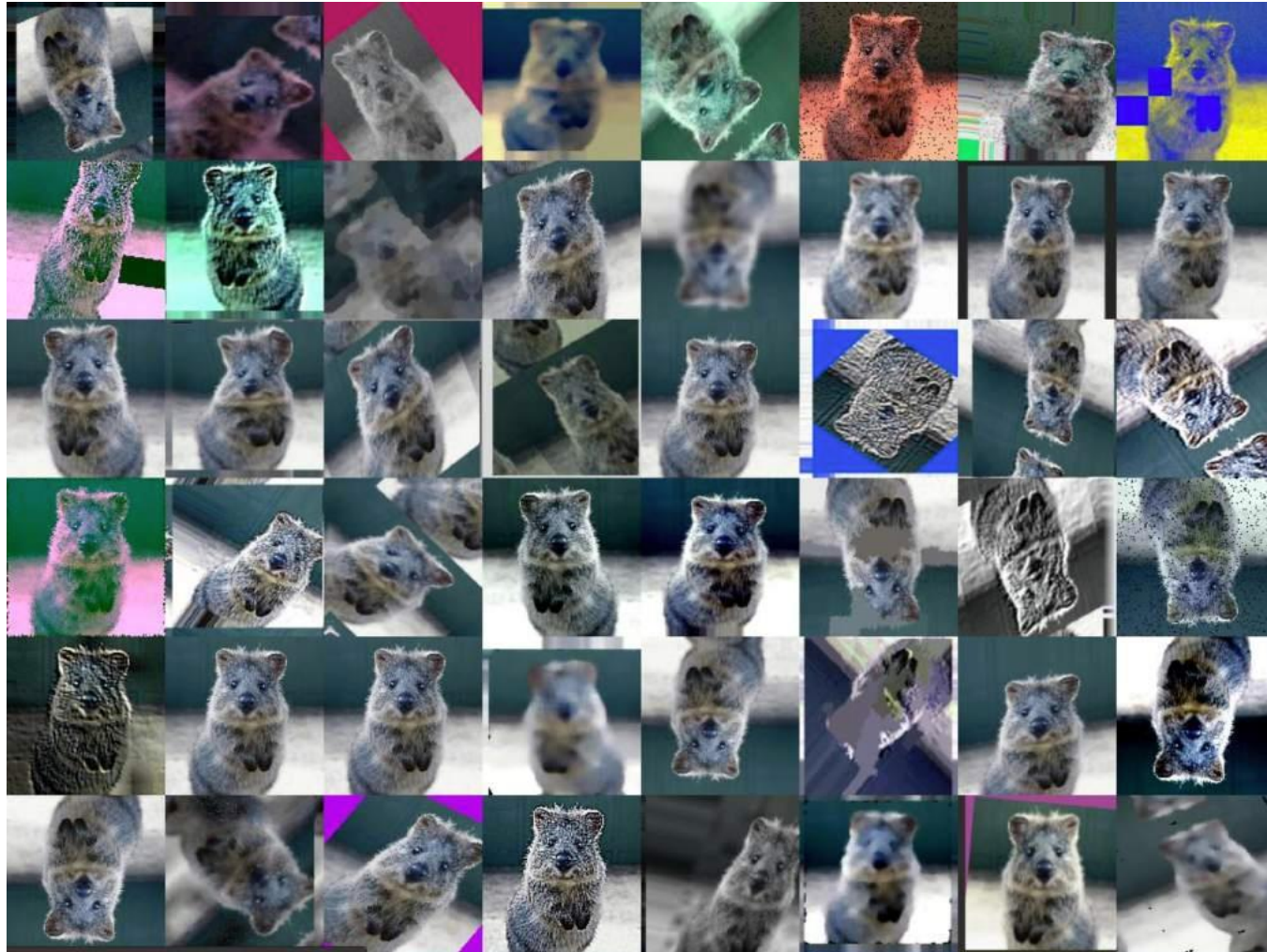
$$\mathcal{L}' = \mathcal{L} + \frac{\lambda}{2} \|w\|_2^2$$

(Note instead of λ we use $\frac{\lambda}{2}$ to make math easier)

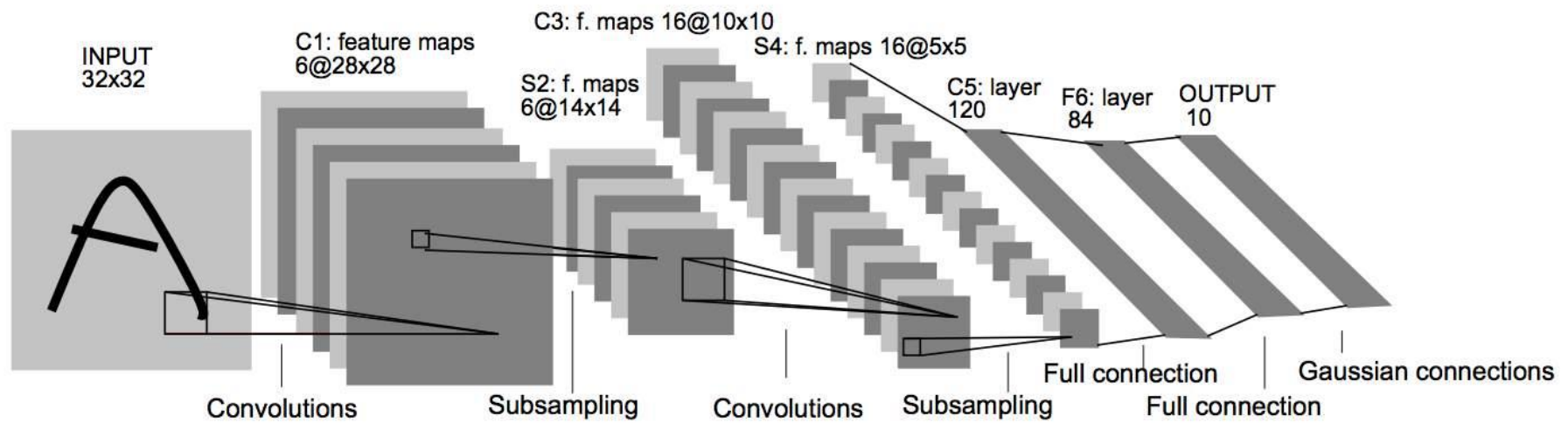
Dropout



Data Augmentation

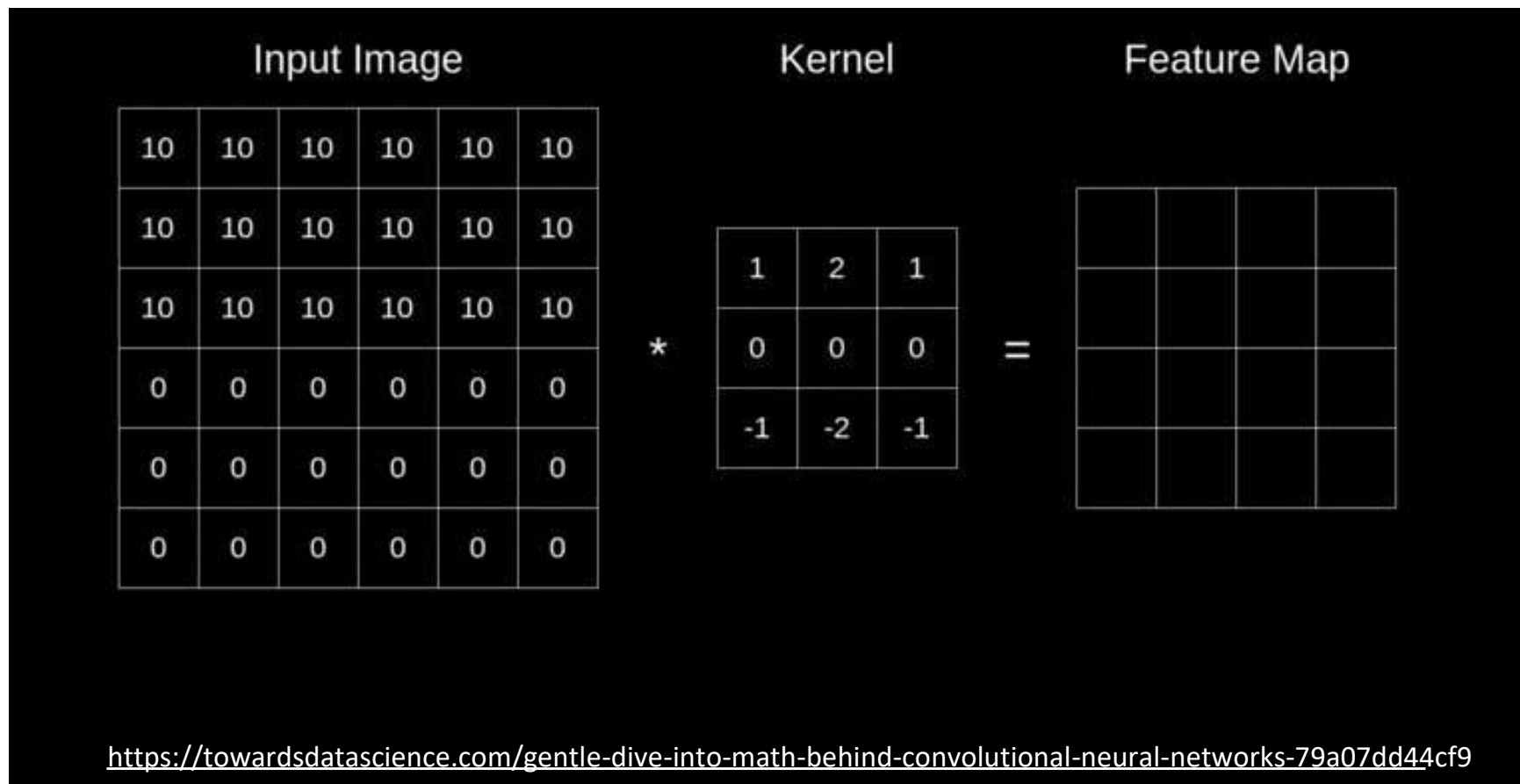


LeNet-5

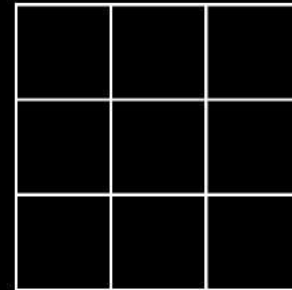


2D Convolution

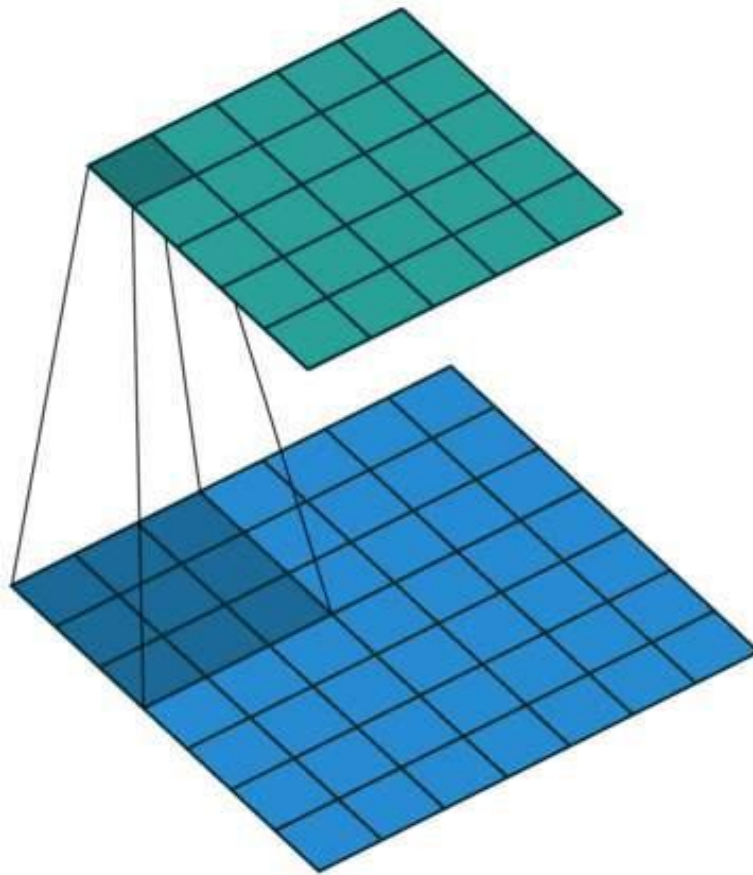
$$G[m, n] = (f * g)[m, n] = \sum_j \sum_k f[m - j, n - k] g[j, k]$$



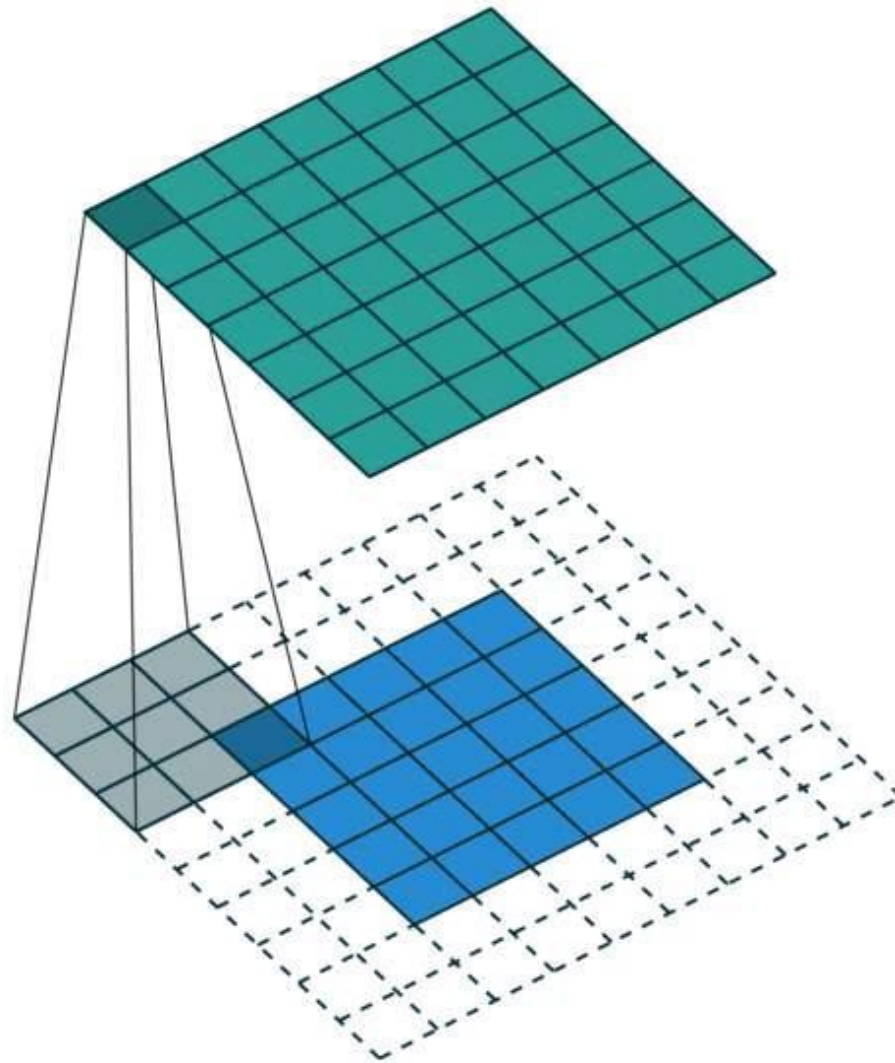
2D Convolution Examples for different Kernels



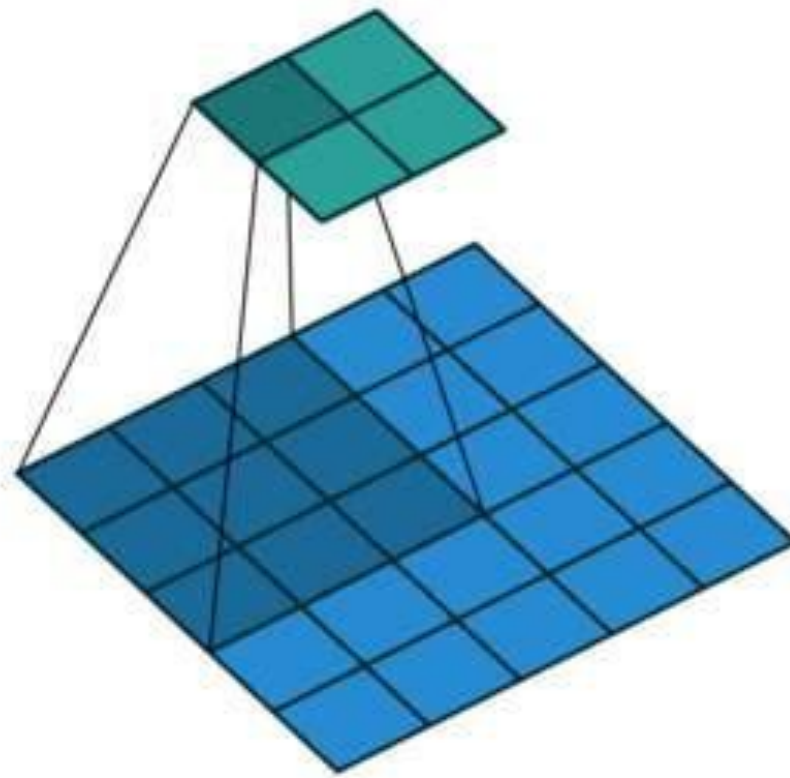
2D Convolution



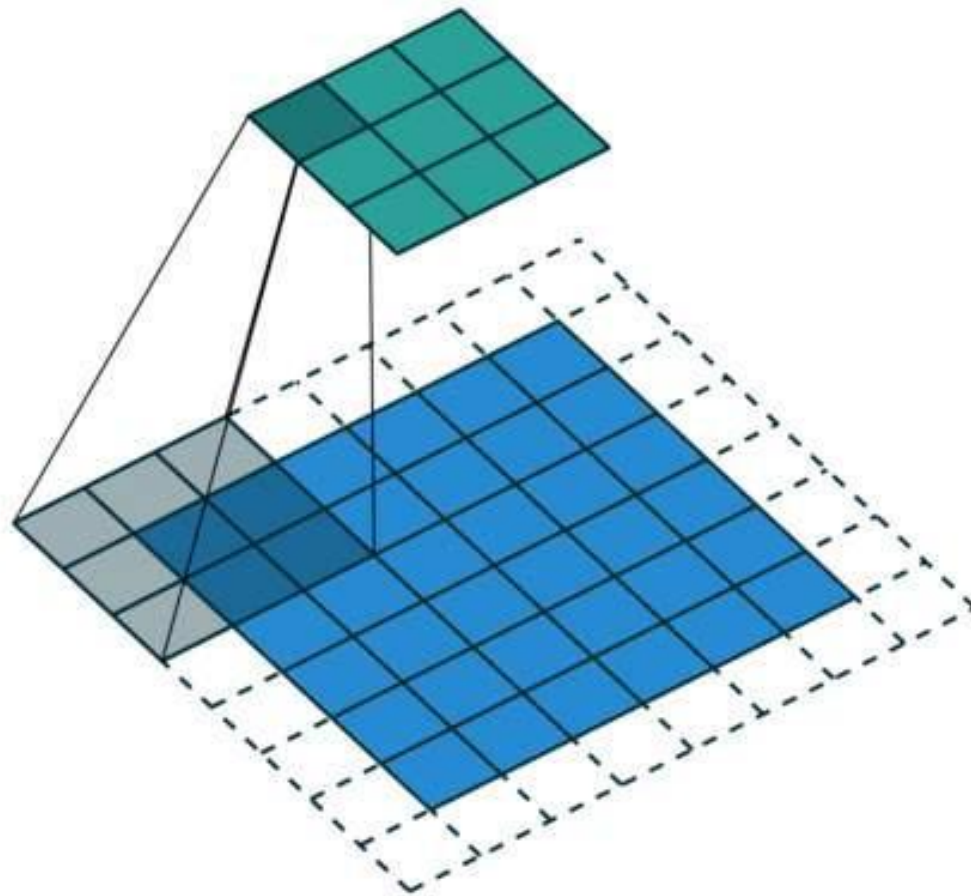
2D Convolution Padding



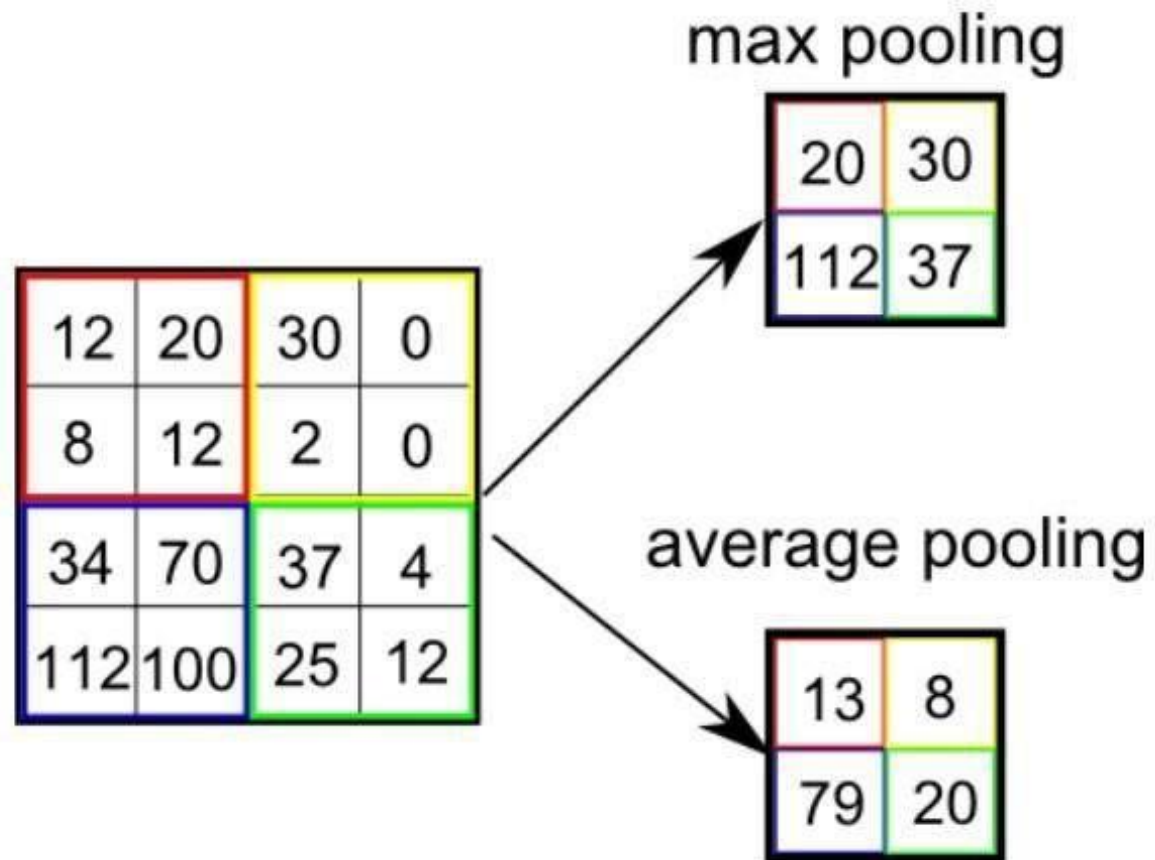
2D Convolution with Stride



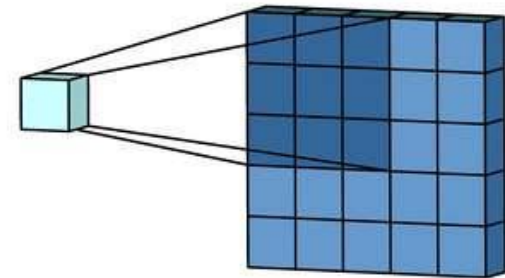
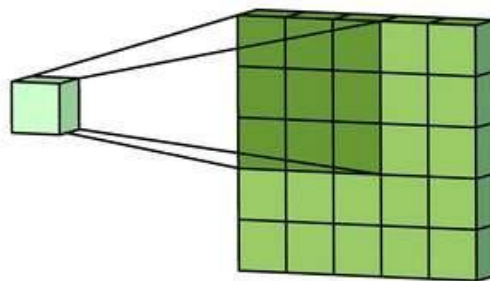
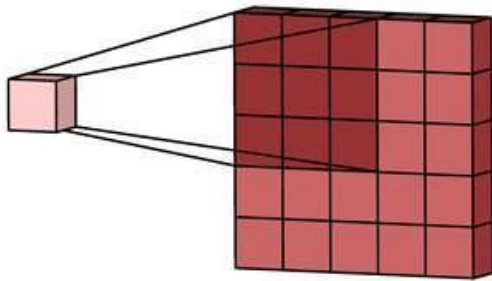
Combination of Strides and Padding



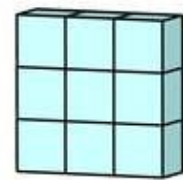
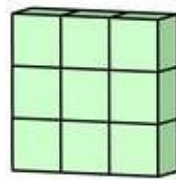
Pooling

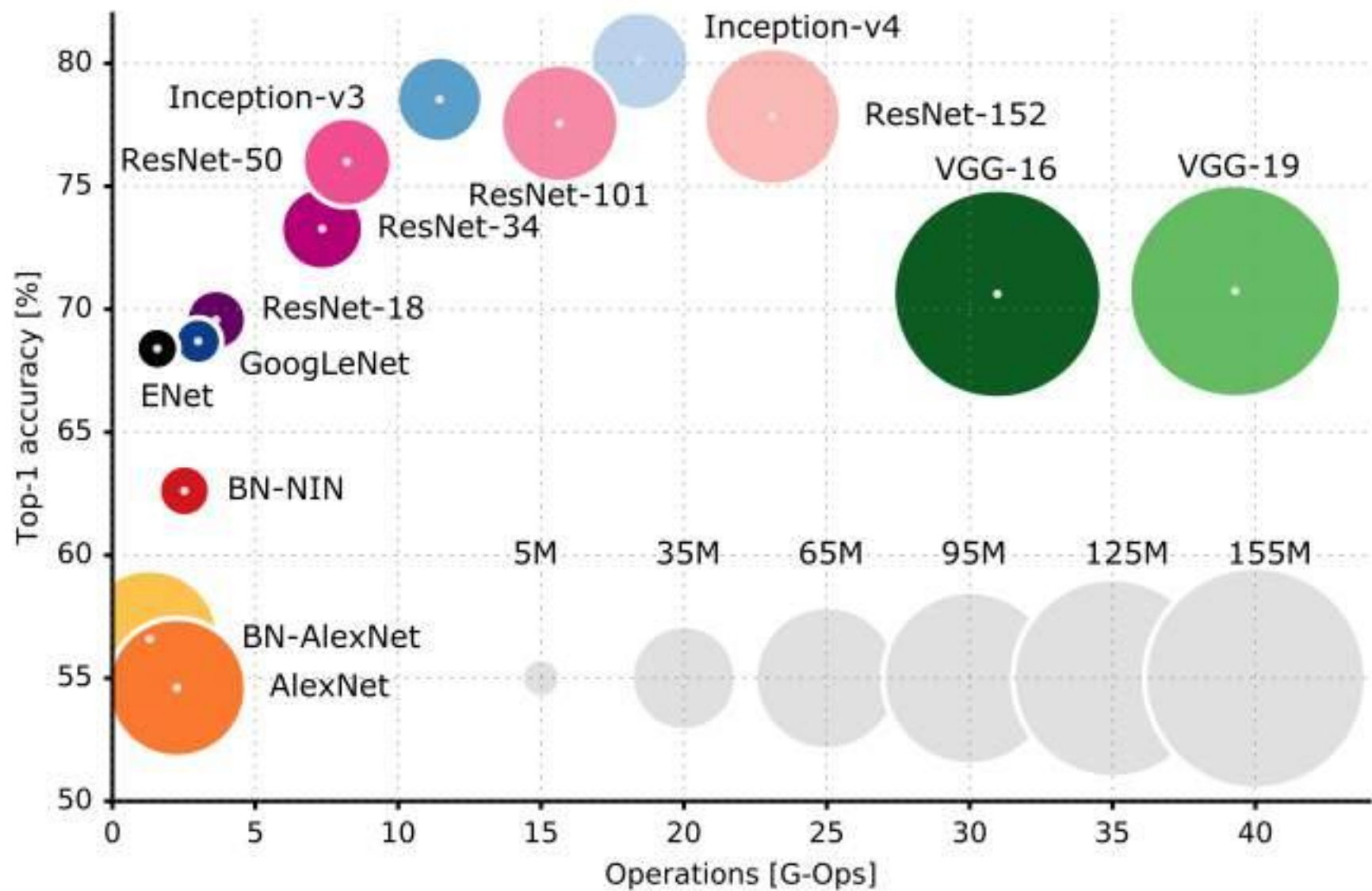


Convolutions on RGB Image

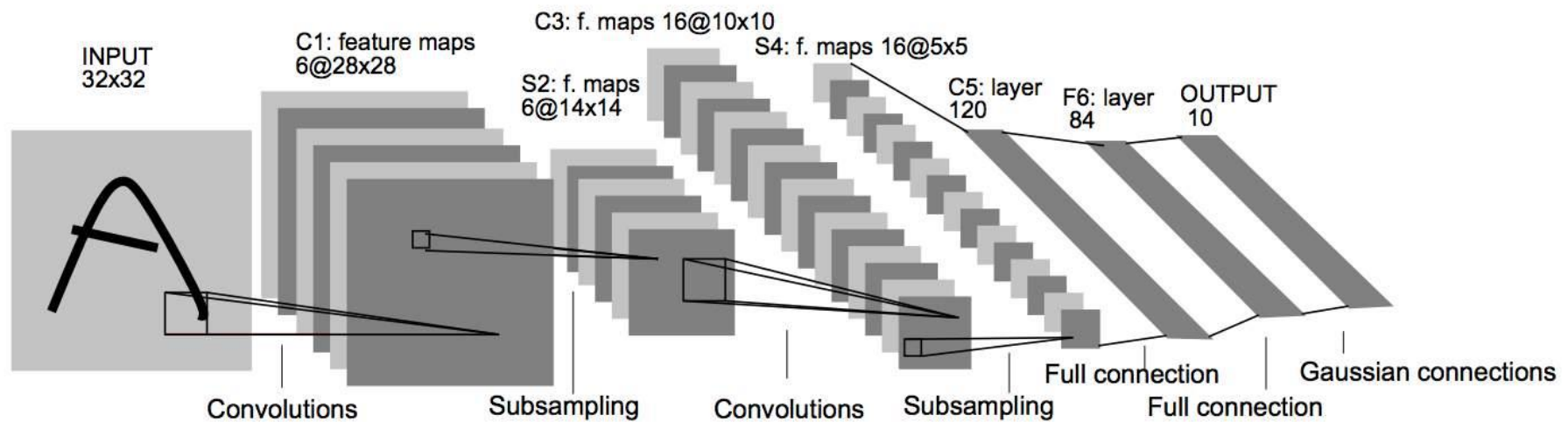


Convolutions on RGB Image

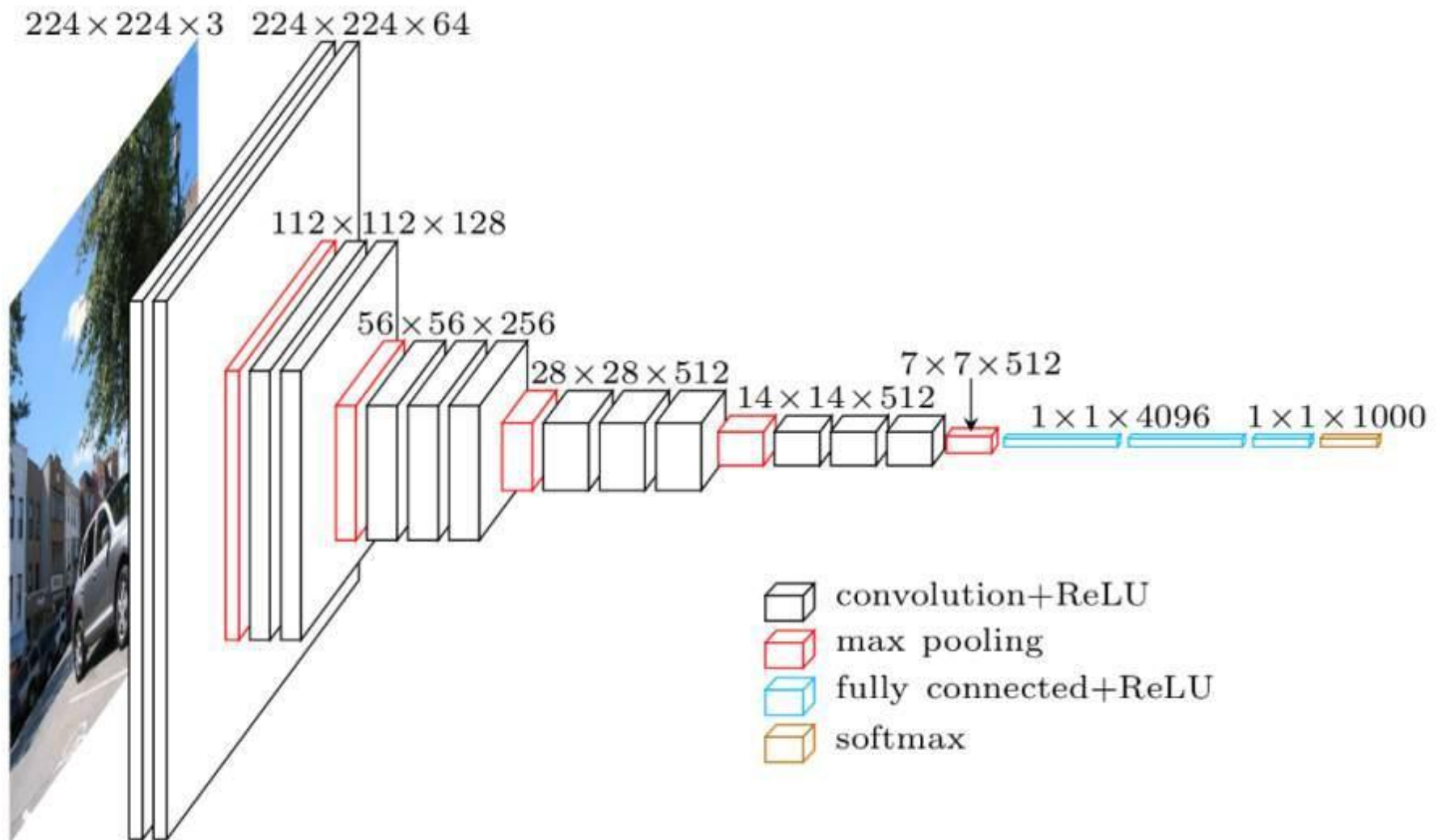




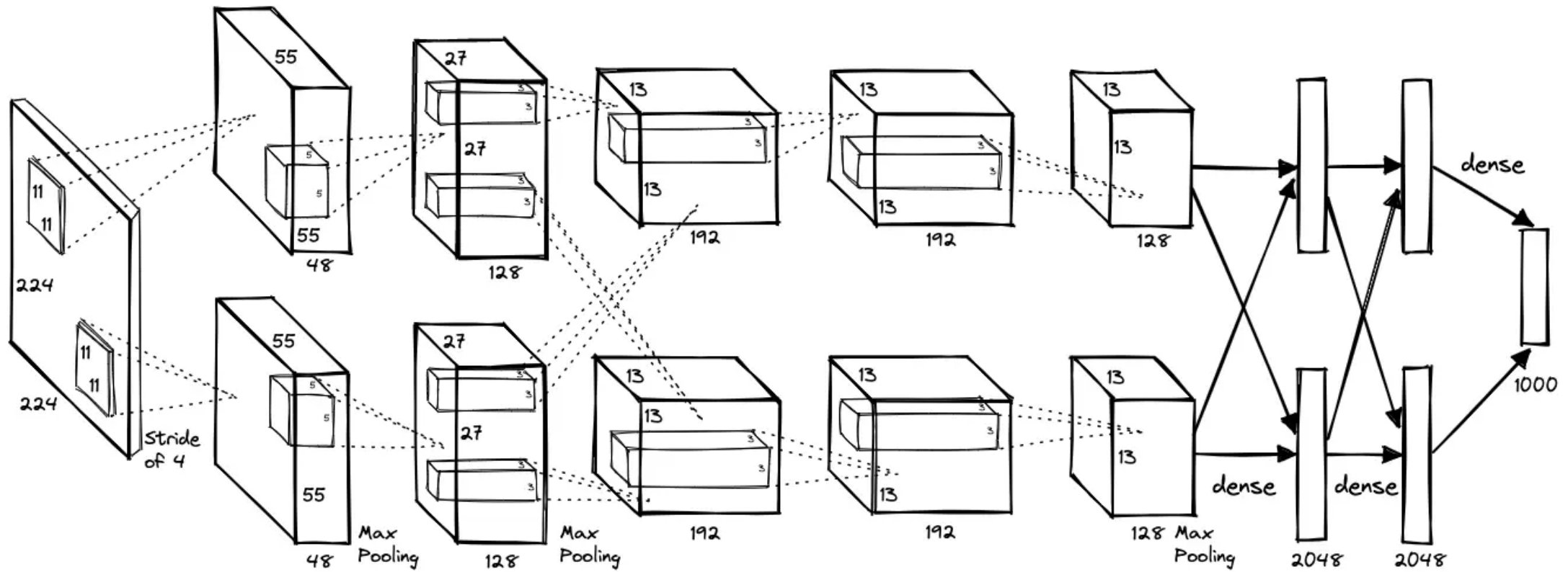
Convolutional Neural Networks (LeNet-5)



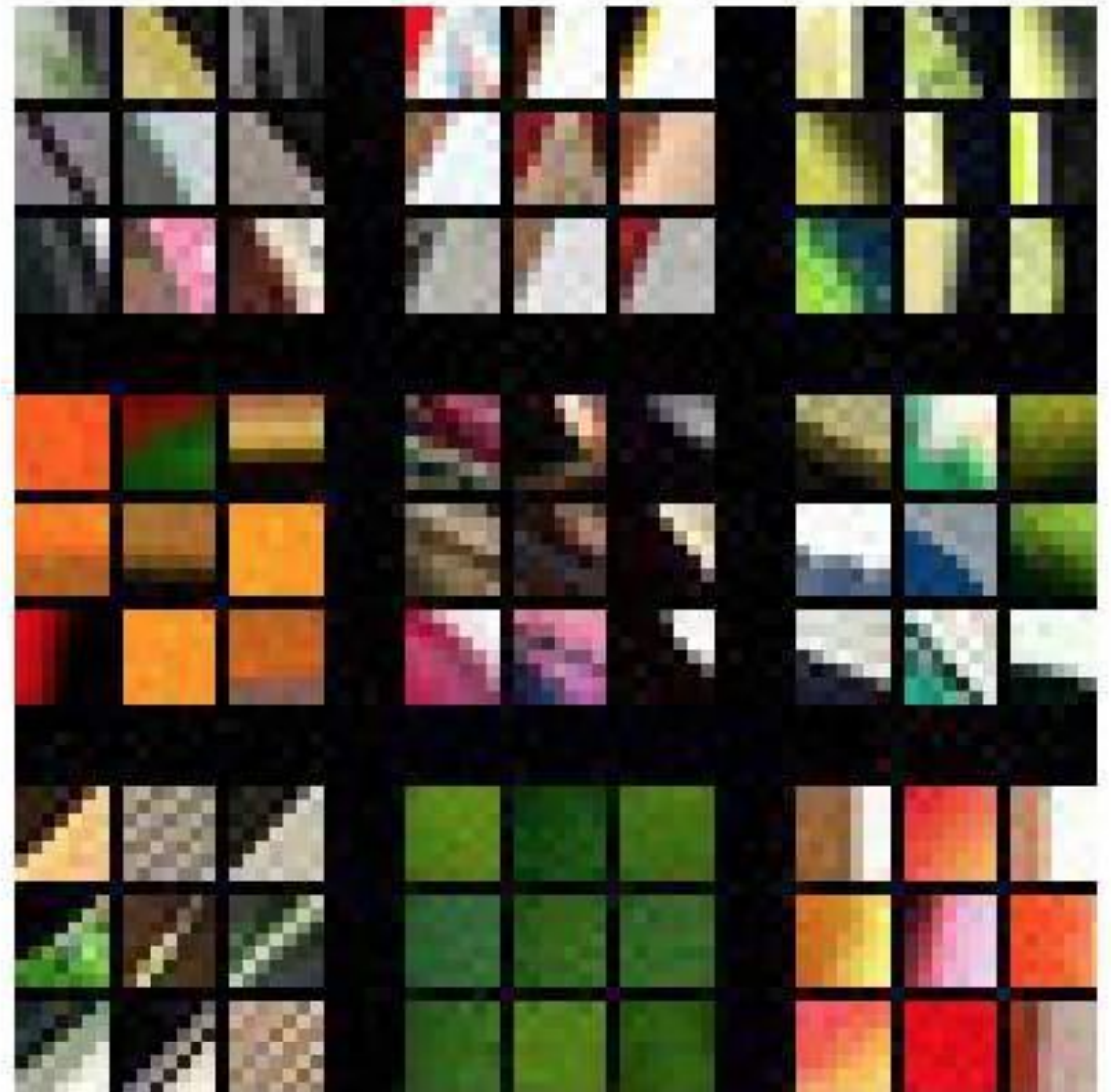
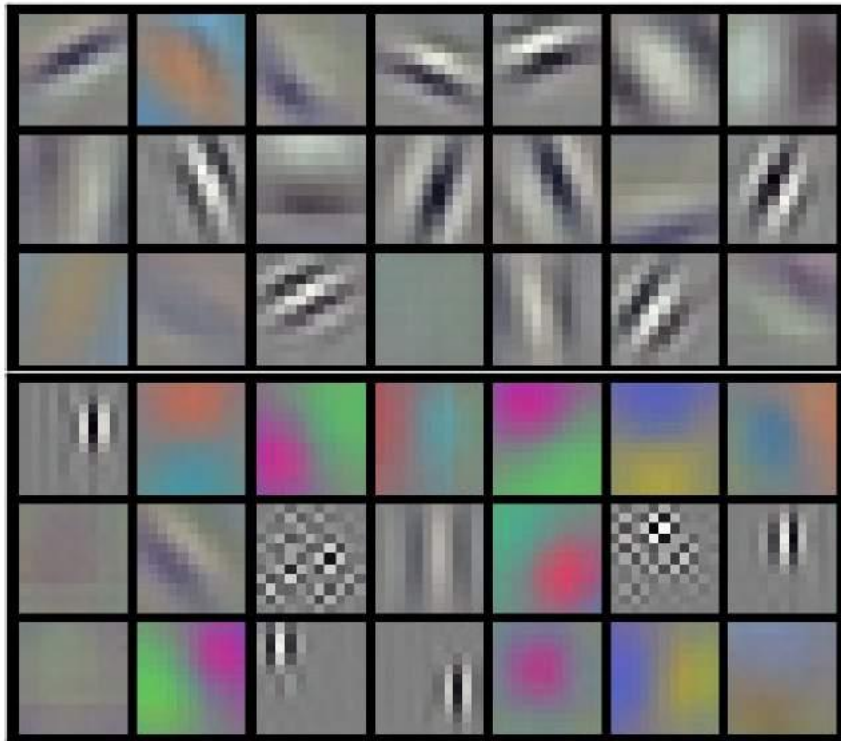
VGG-16



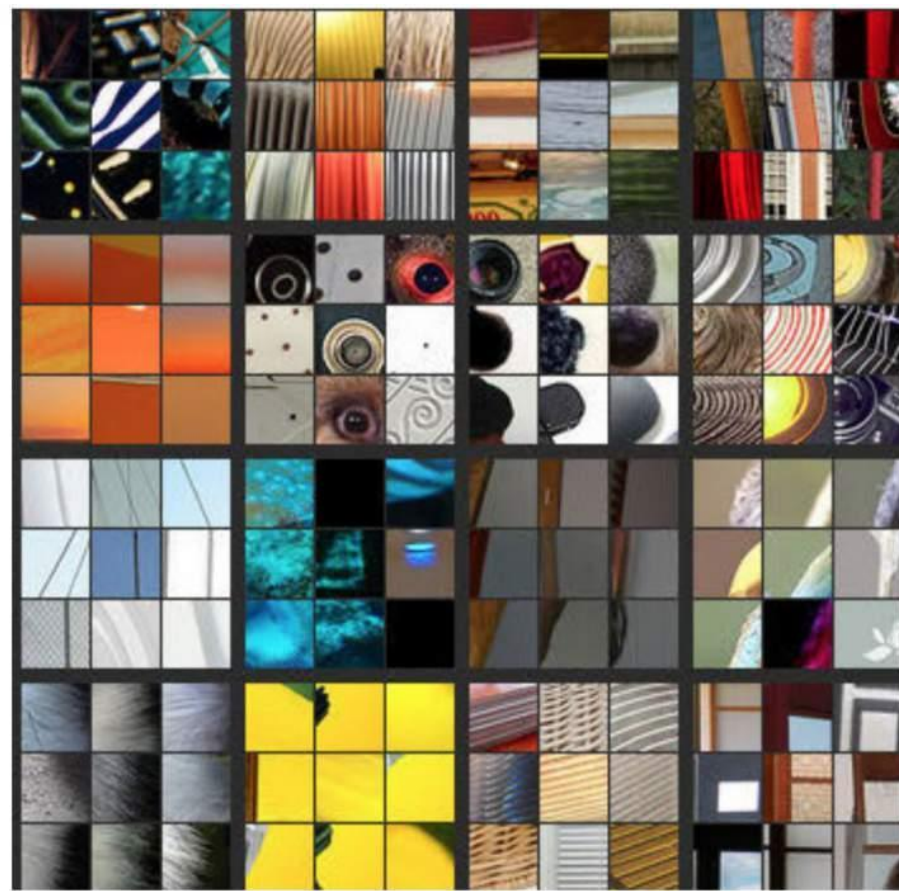
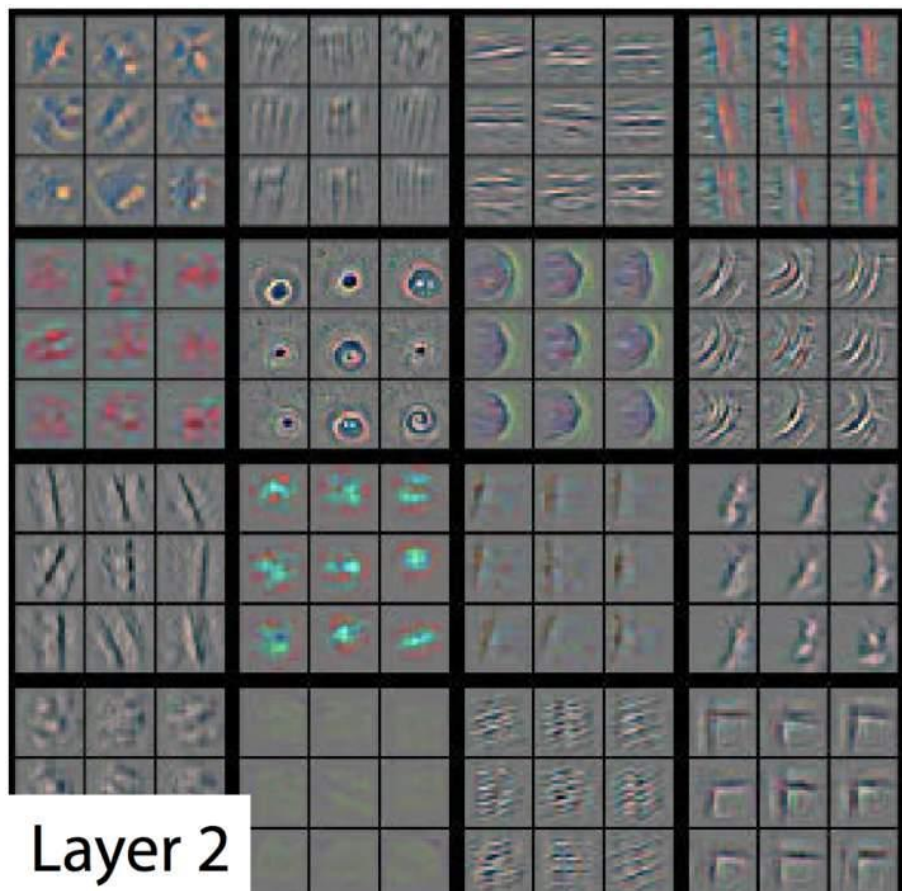
AlexNet



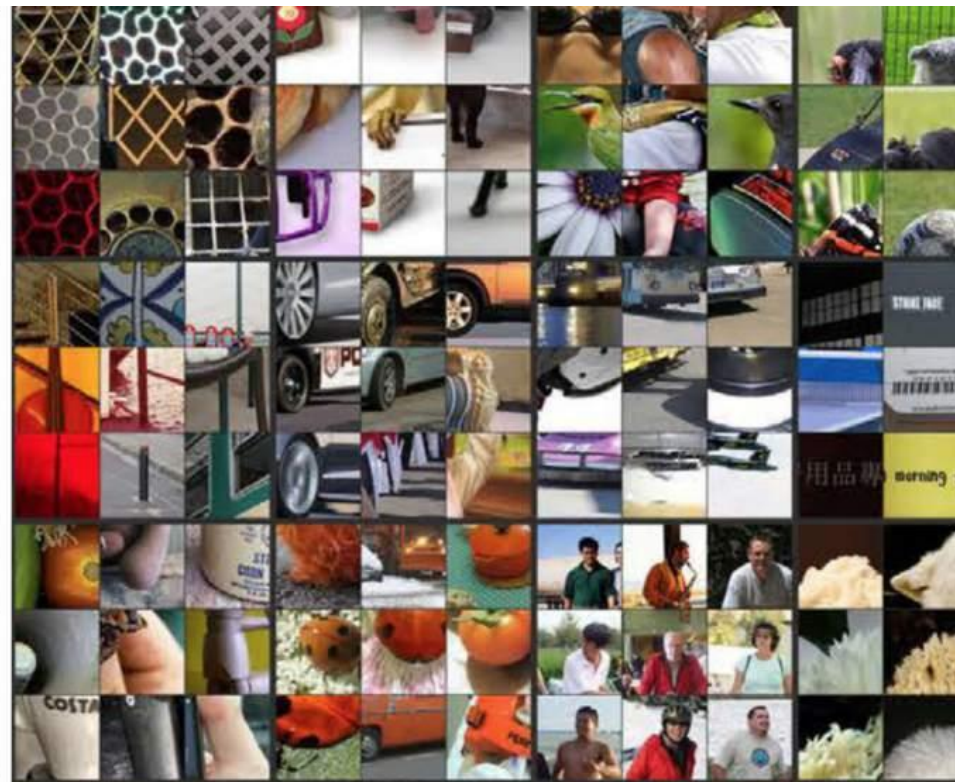
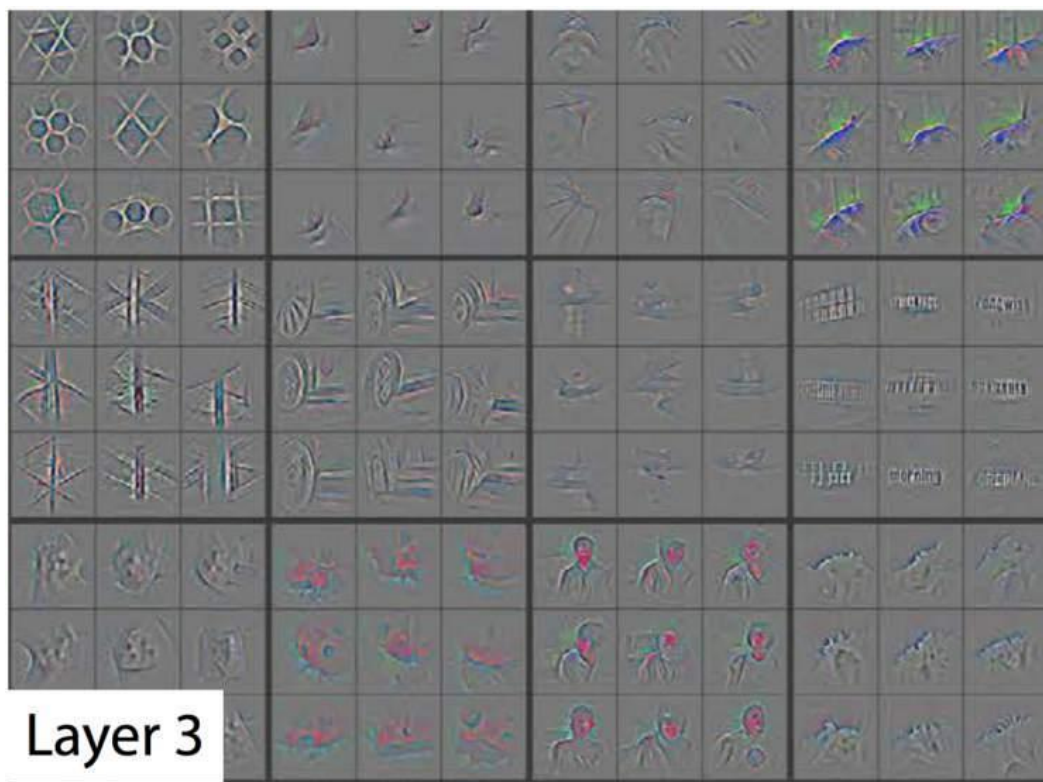
Layer 1



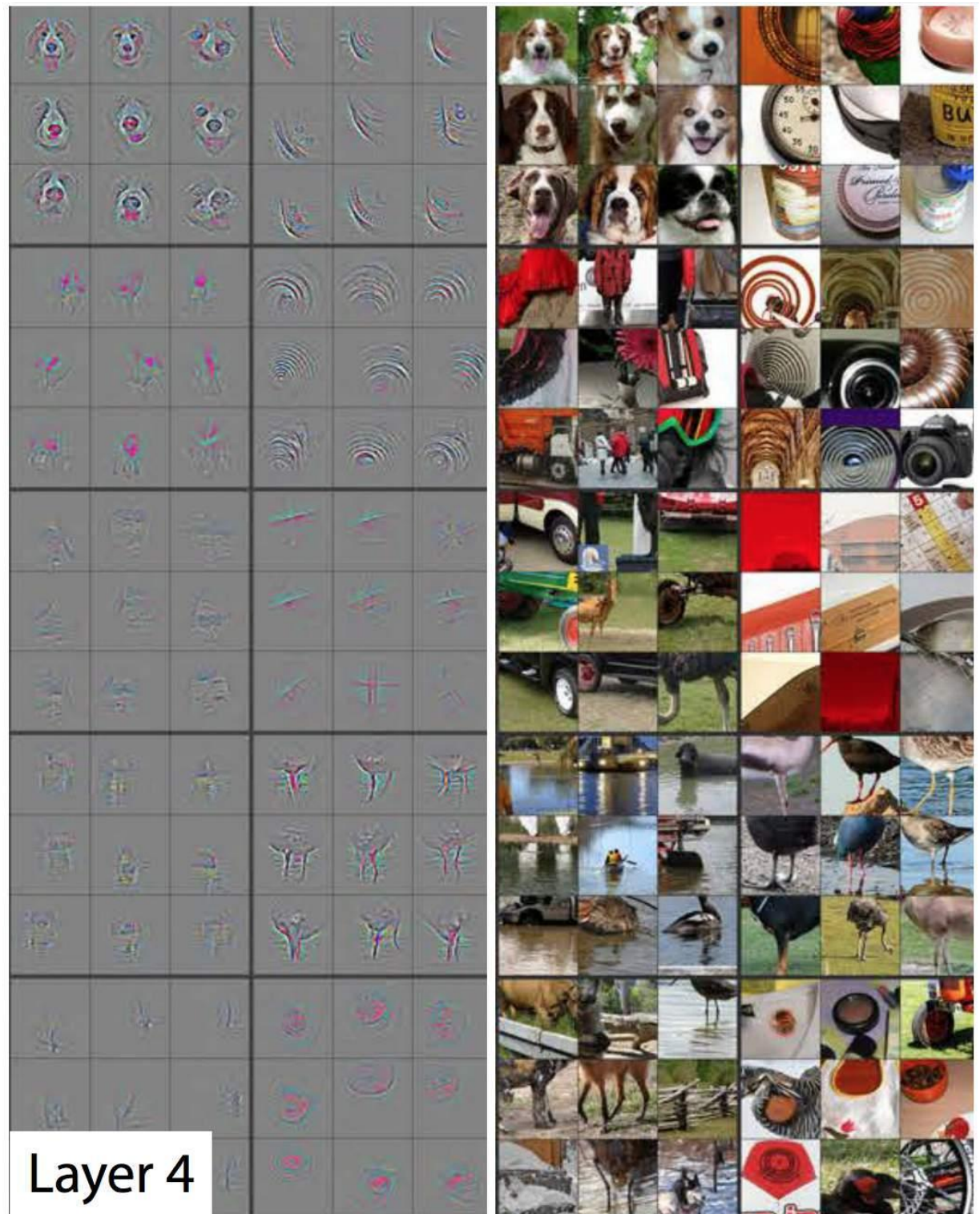
Layer 2



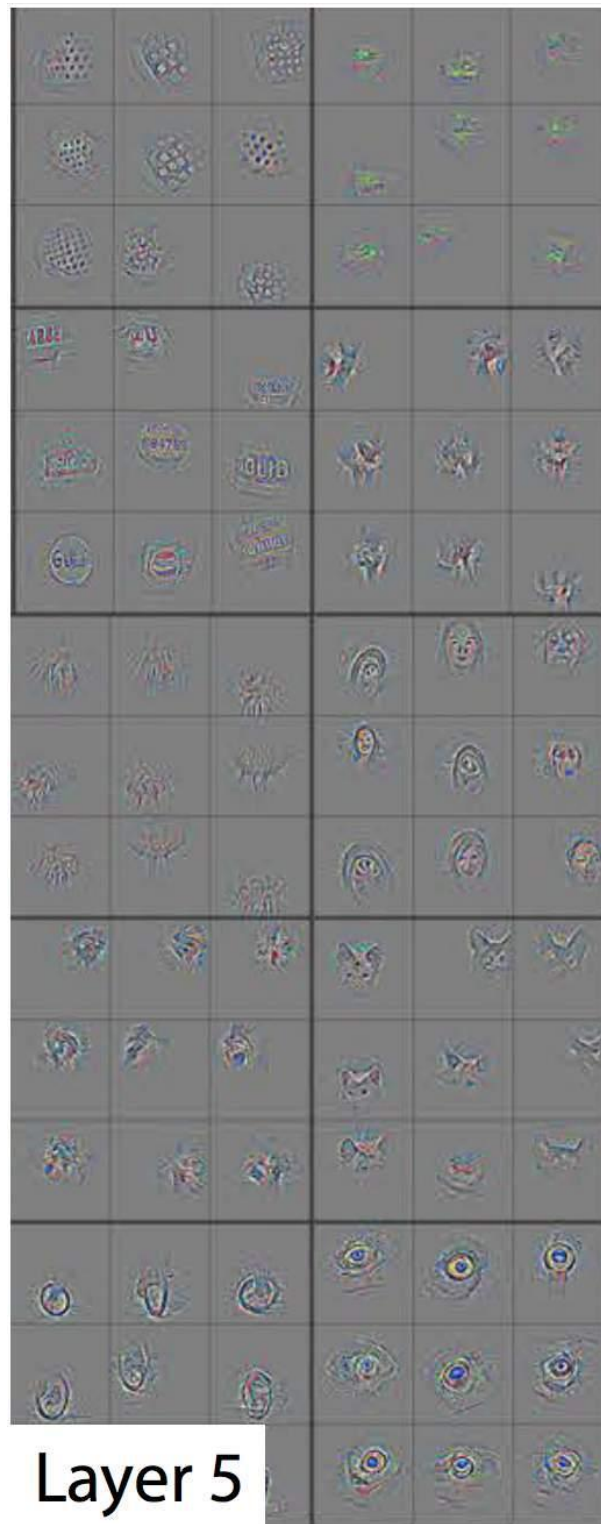
Layer 3



Layer 4



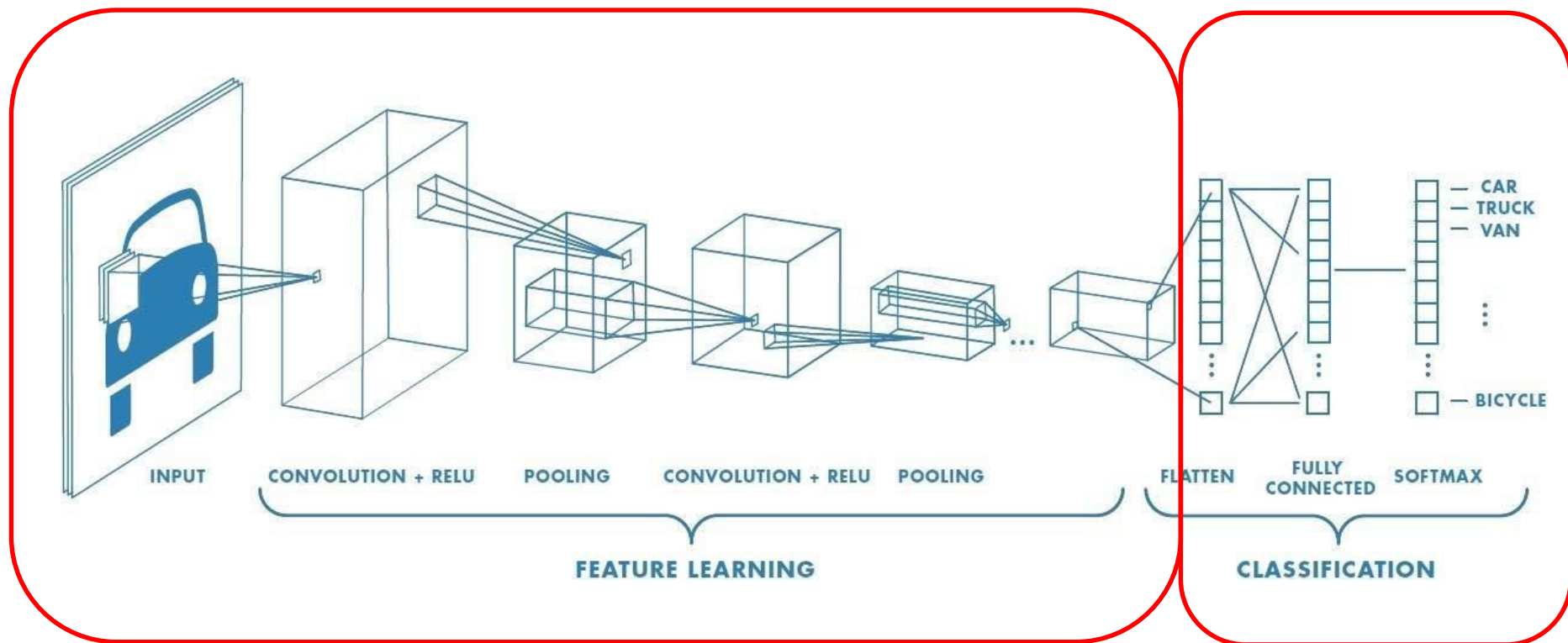
Layer 5



Layer 5



Transfer Learning



ResNet

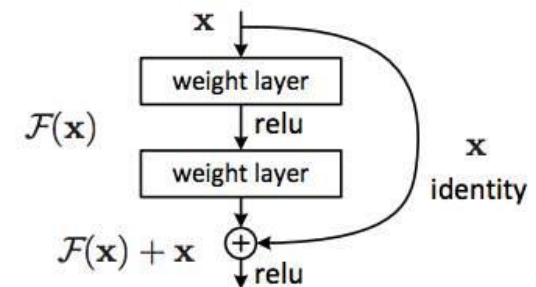
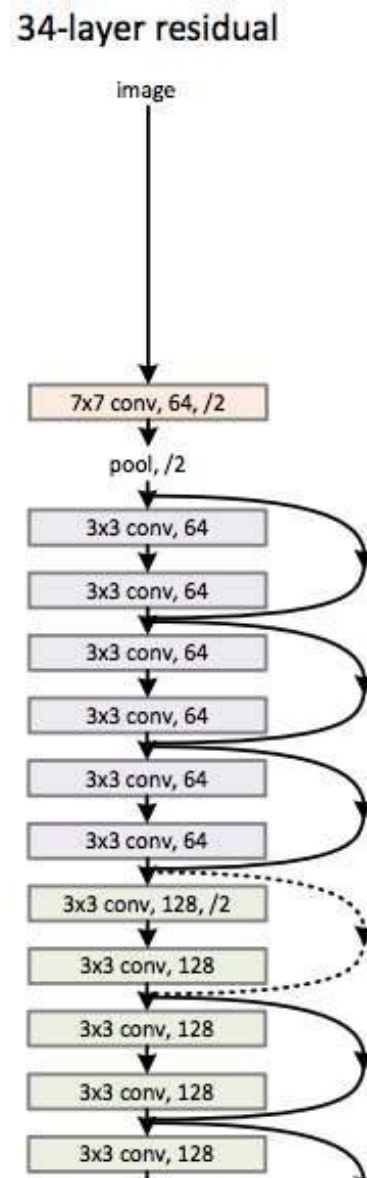
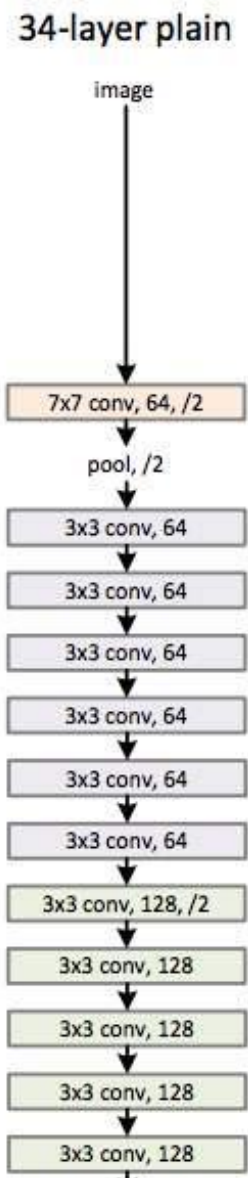
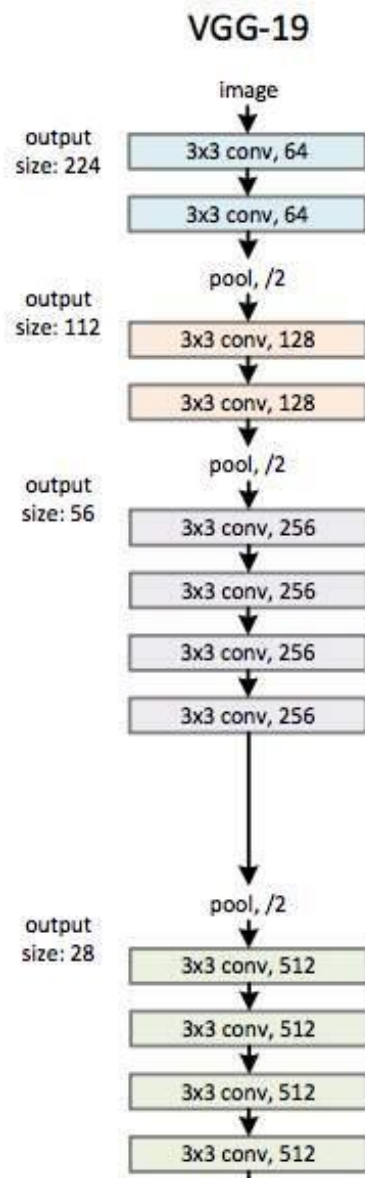
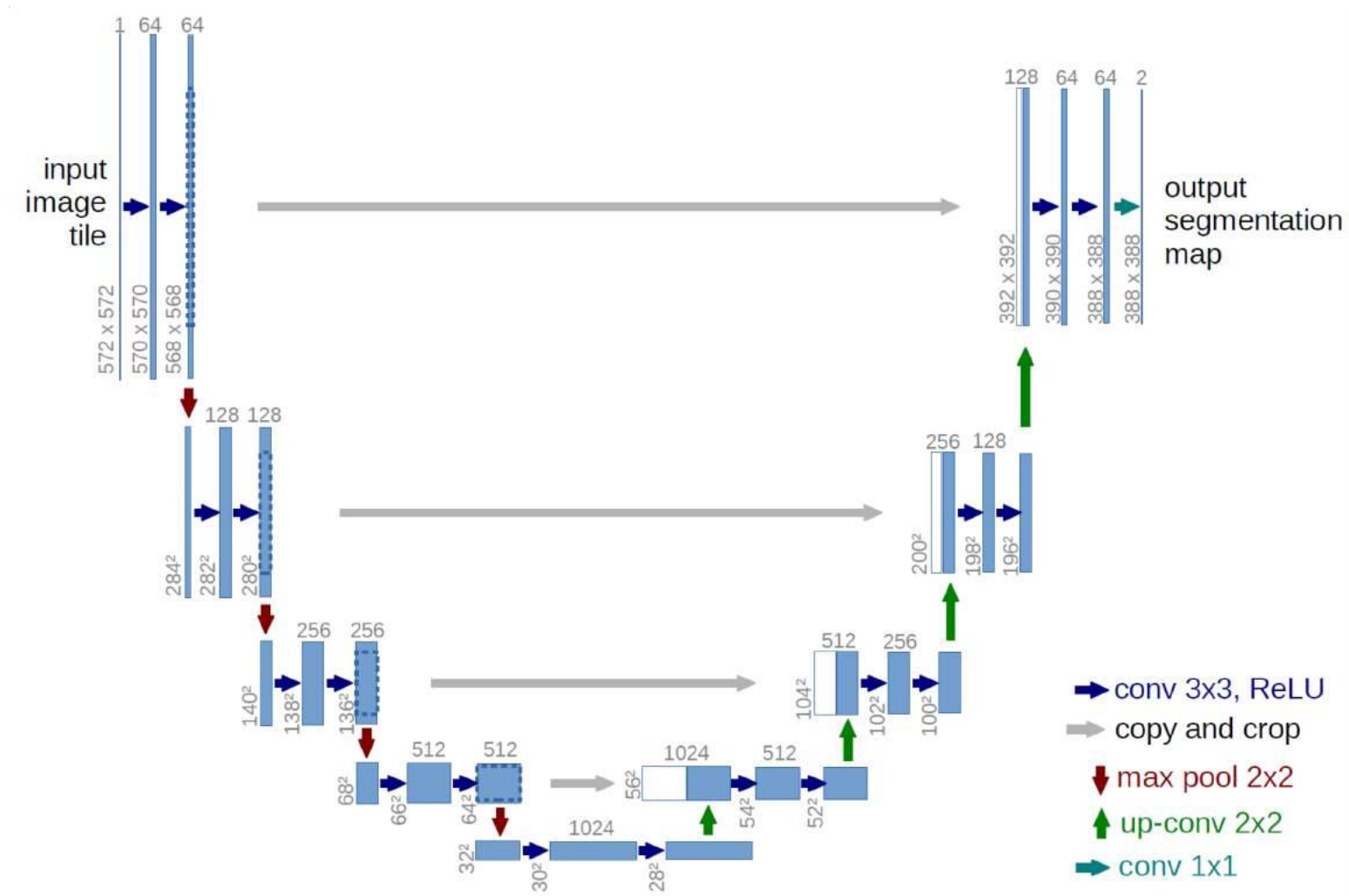


Figure 2. Residual learning: a building block.

UNet



HPC-Enabled Precision Agriculture

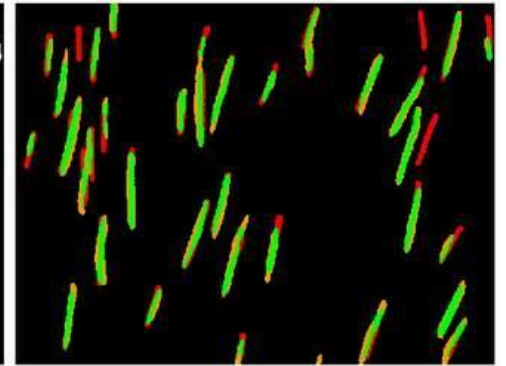
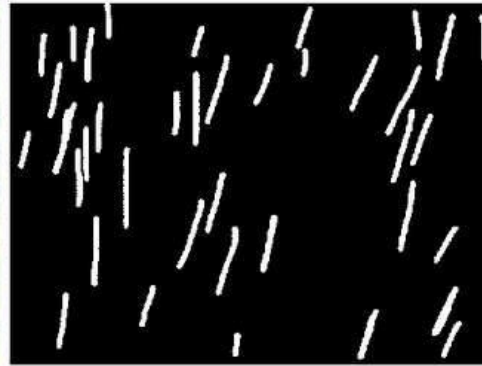
Automatic counting of wheat ears

Input

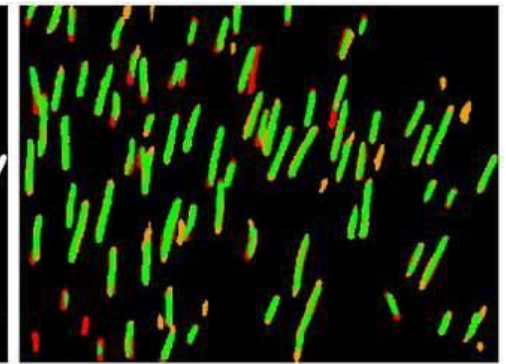
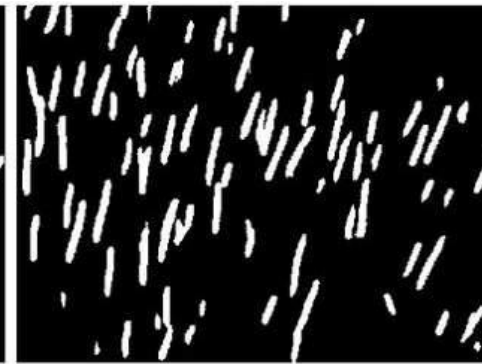
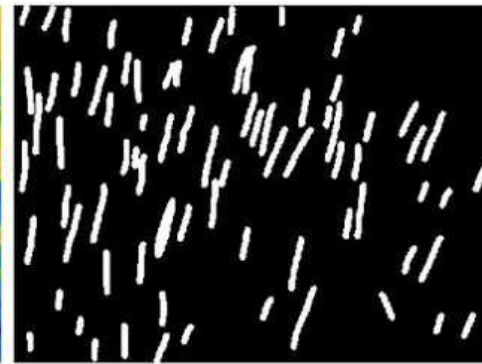
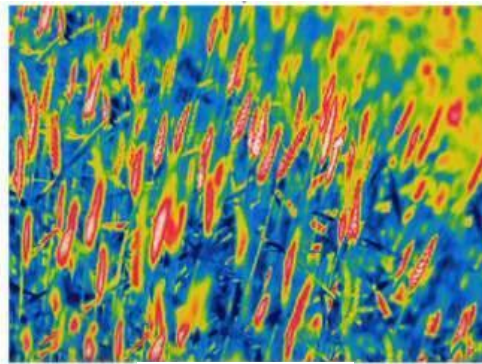
Ground truth

Prediction

Prediction (overlay)

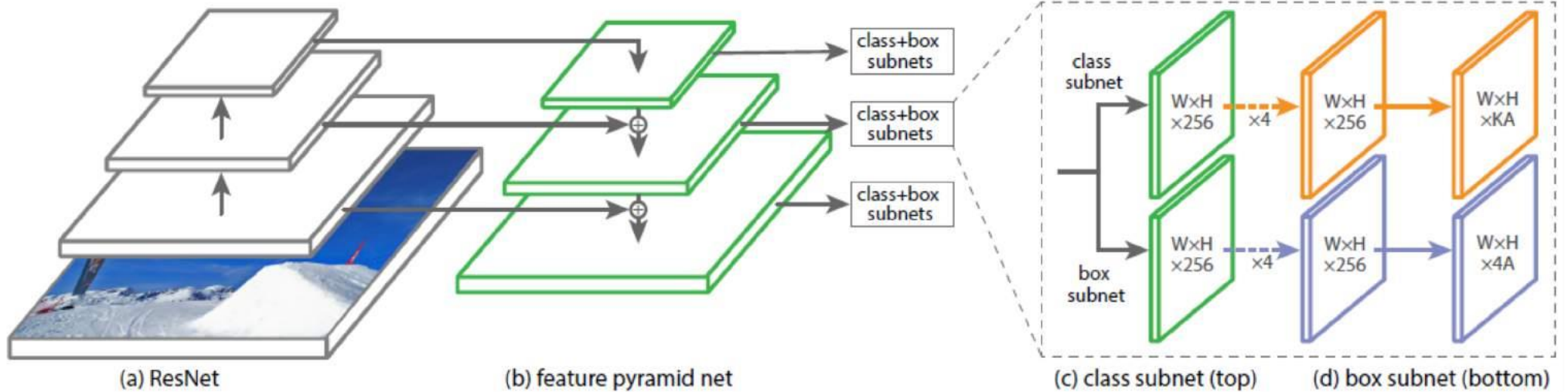


RGB



Thermal

RetinaNet



Mask-RCNN

