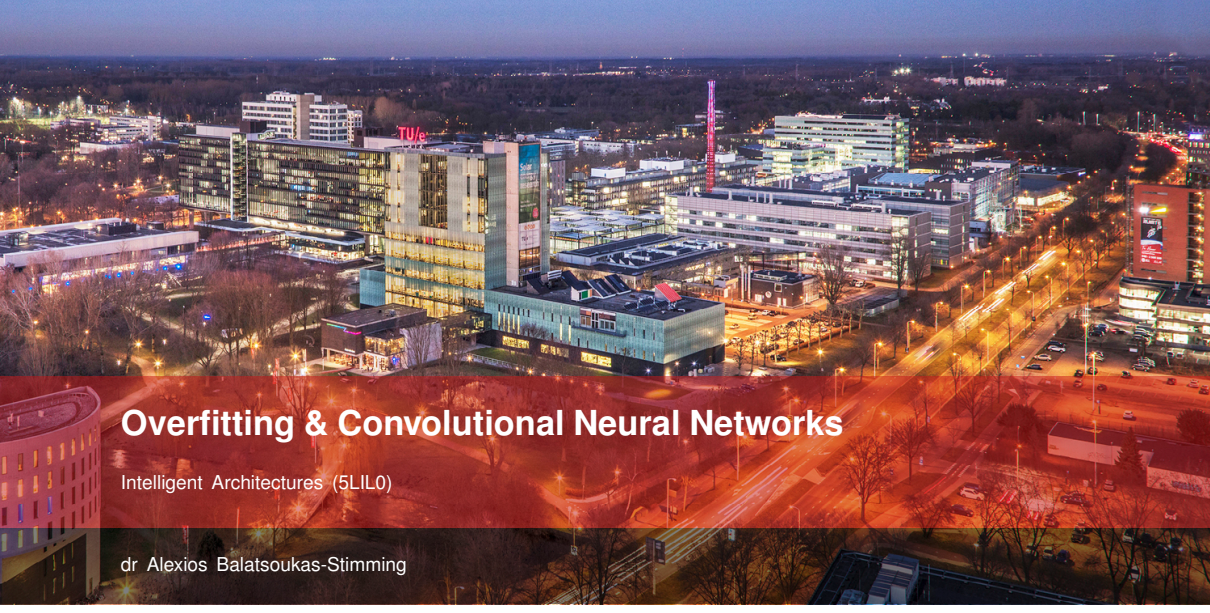

Overfitting & Convolutional Neural Networks

Intelligent Architectures (5LIL0)

dr Alexios Balatsoukas-Stimming

Department of Electrical Engineering, Electronic Systems Group

TU/e EINDHOVEN UNIVERSITY OF TECHNOLOGY

Last Time

- **Loss functions**, e.g., squared error:

$$L(\mathbf{y}, \hat{\mathbf{y}}) = |\mathbf{y} - \hat{\mathbf{y}}|_2^2 = \sum_{i=1}^{M} (y_i - \hat{y}_i)^2$$

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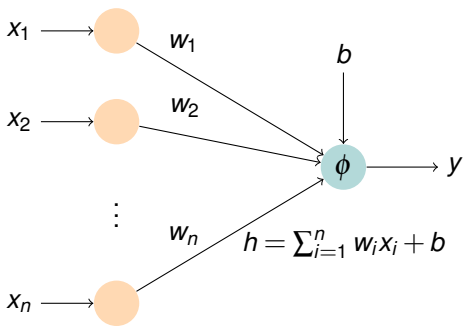

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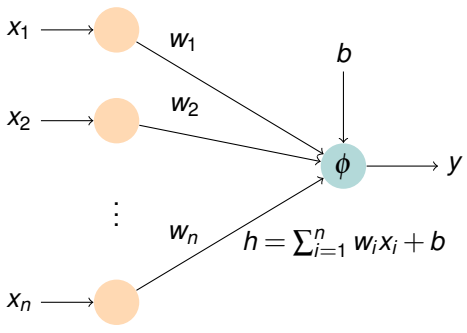
- **Weight initialization**: Xavier and He



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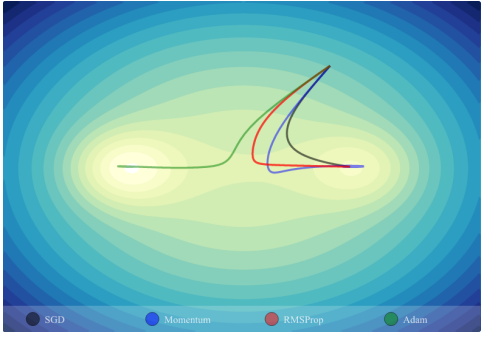

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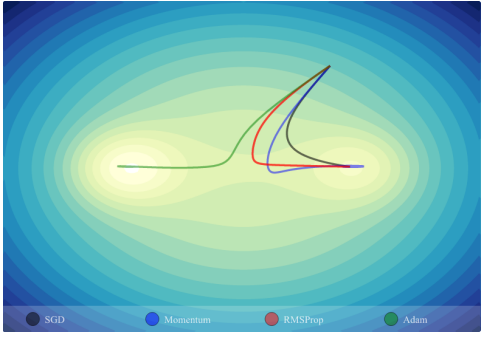

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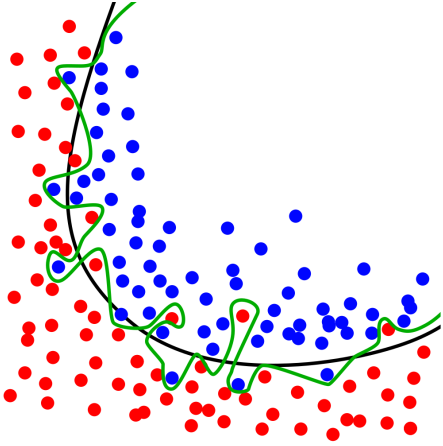

Chabacano, CC BY-SA 4.0, via Wikimedia Commons

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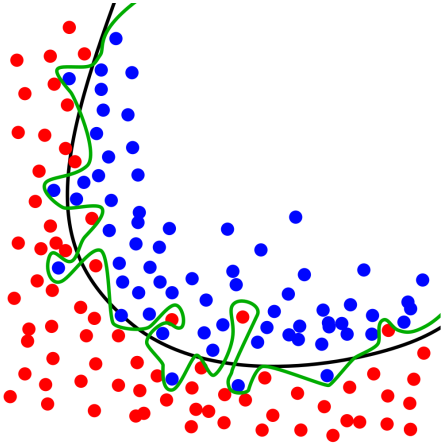

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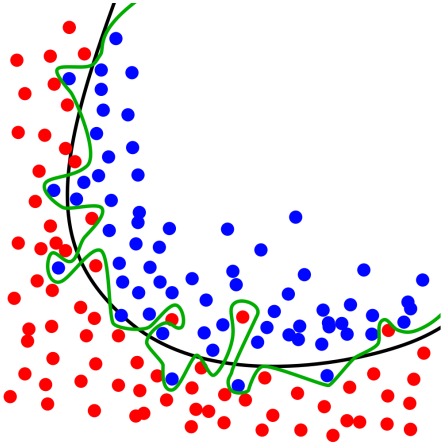

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Learning a Curve

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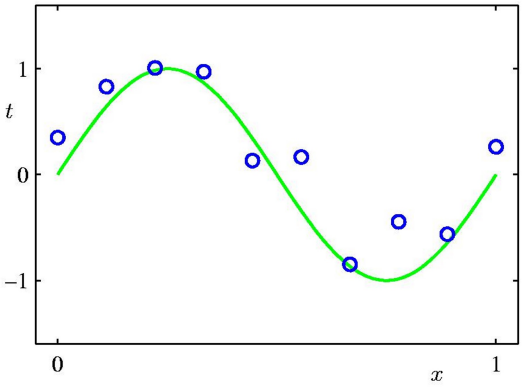

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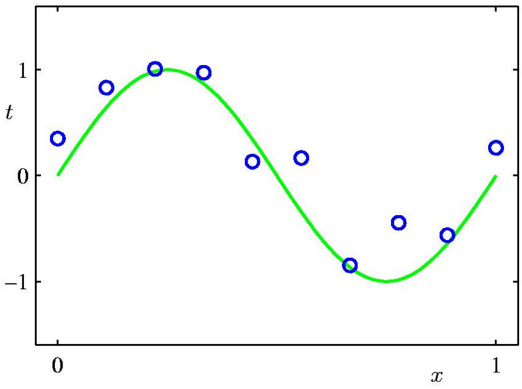

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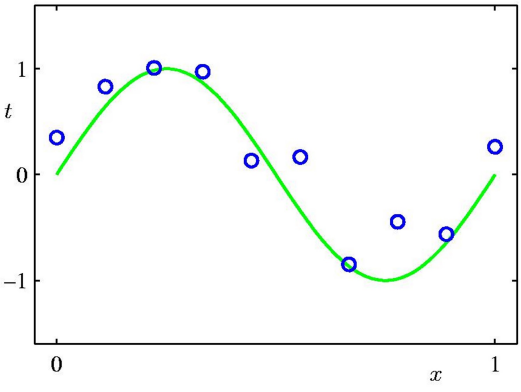

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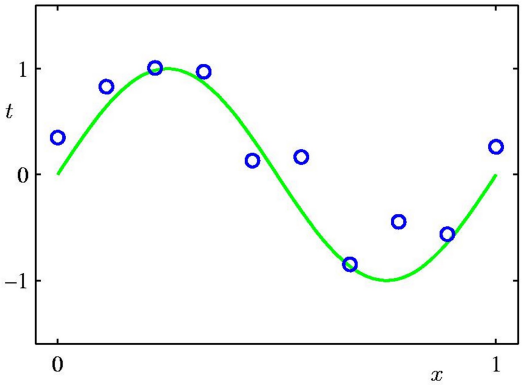

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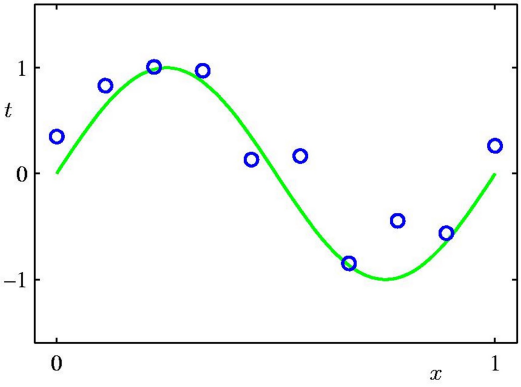

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- Can be trained with gradient descent, but closed-form solution exists (**least squares**).

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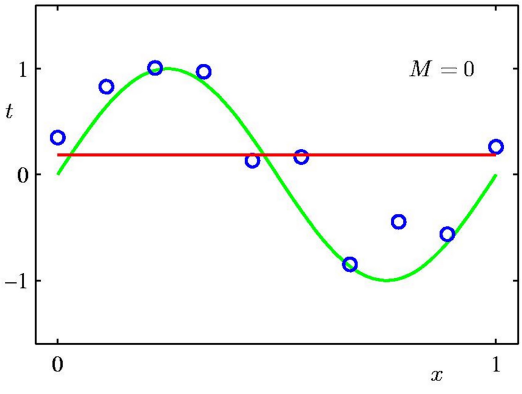
Learning a Curve ($M = 0$)

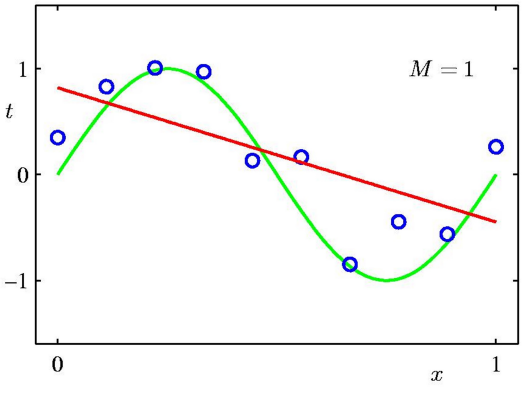
Parameter	Value
w_0	0.19



- **Model:** $\hat{t}(x, \mathbf{w}) = 0.19$

Learning a Curve ($M = 1$)

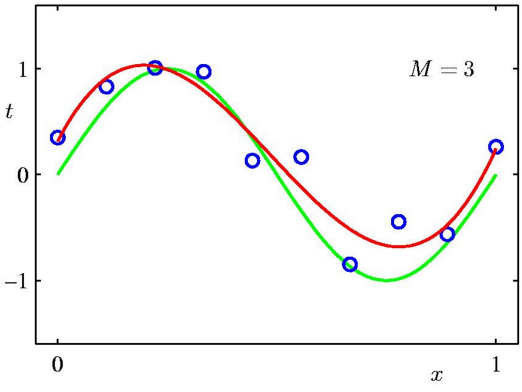
Parameter	Value
w_0	0.82
w_1	-1.27



- **Model:** $\hat{t}(x, \mathbf{w}) = 0.82 - 1.27x$

Learning a Curve ($M = 3$)

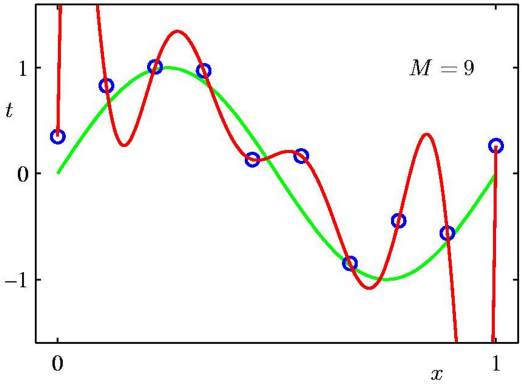
Parameter	Value
w_0	0.31
w_1	−7.99
w_2	−25.43
w_3	17.37



- **Model:** $\hat{t}(x, \mathbf{w}) = 0.31 - 7.99x - 25.43x^2 + 17.37x^3$

Learning a Curve ($M = 9$)

Parameter	Value
w_0	0.35
w_1	232
w_2	−5321
w_3	45688
w_4	−231630
w_5	640042
w_6	−1061800
w_7	1042400
w_8	−557682
w_9	125201

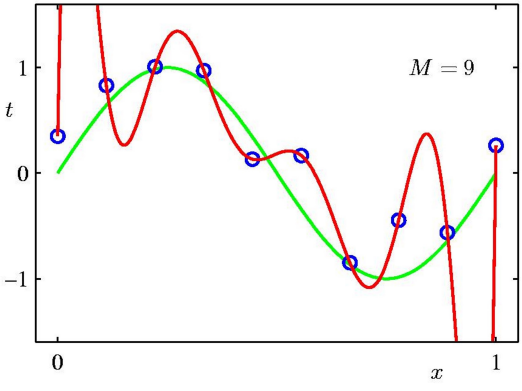


- **Model:** $\hat{t}(x, \mathbf{w}) = 0.35 + 232x - 5321x^2 + 45688x^3 - 231630x^4 + 640042x^5 - \ldots$

Overfitting

The overfitting problem:

1. The model fits dataset perfectly.
2. **BUT** its predictions are horrible almost everywhere else!



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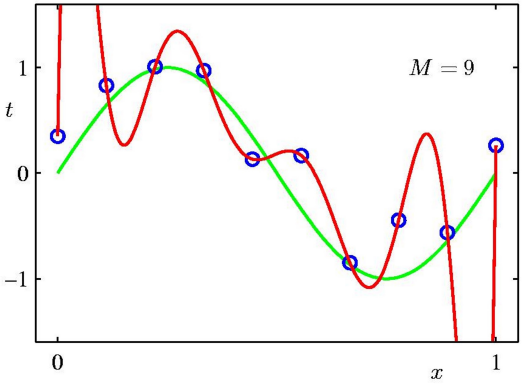

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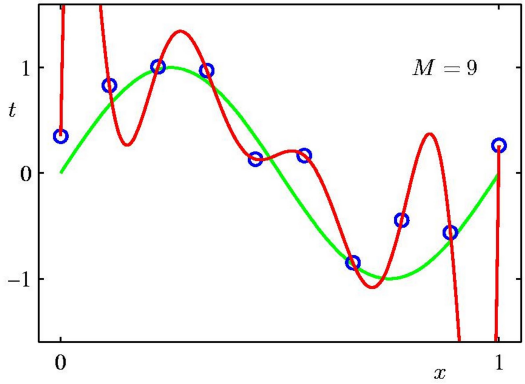

A word of caution

Identifying and dealing with overfitting is potentially more art than science!

Identifying Overfitting

- Split dataset:
  1. **Training set**: only used for training model
  2. **Test set**: only used for testing performance

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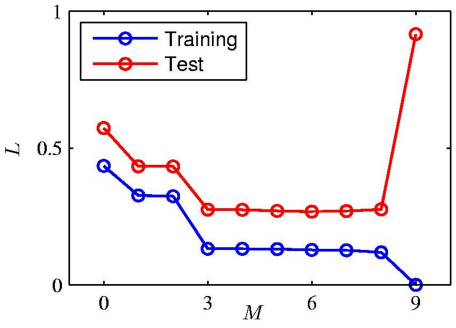

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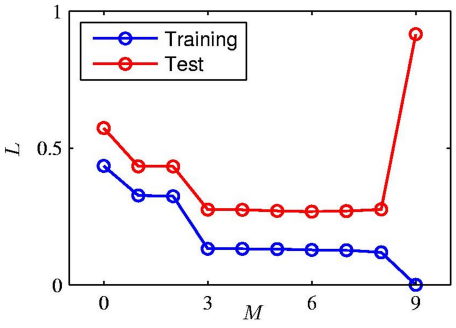

How to deal with overfitting?

The general idea is to **constrain** the model.

Dealing with Overfitting: Models & Training Set

Solution 1: Use a smaller model

Pros:

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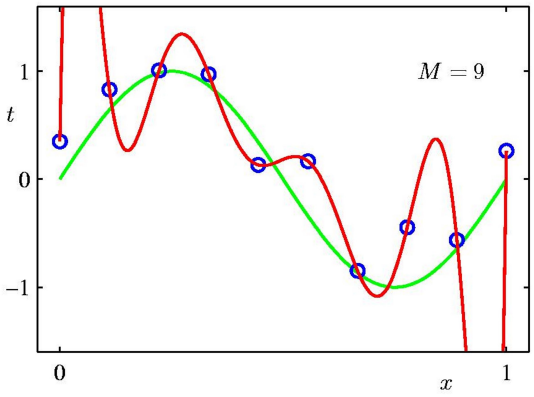

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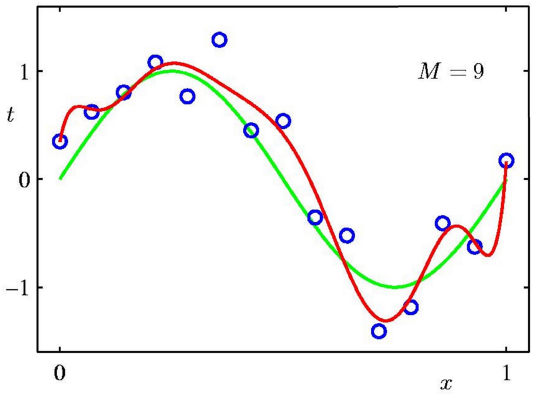

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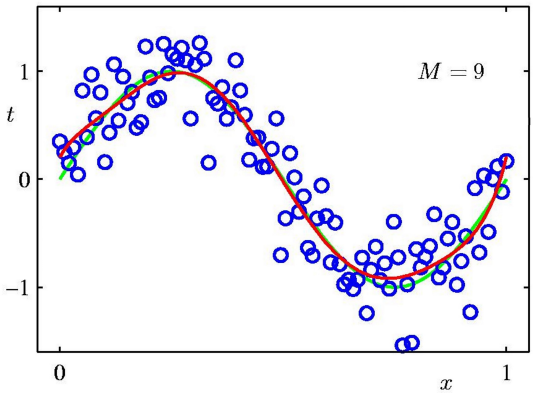

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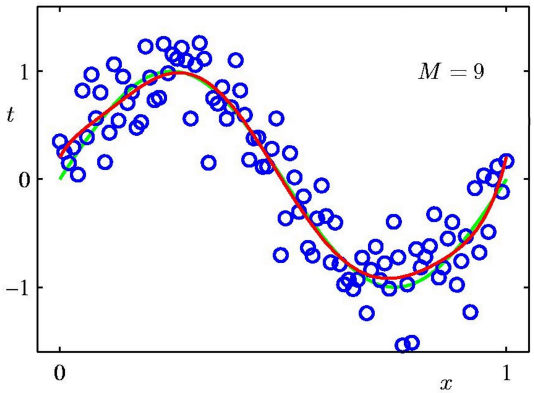

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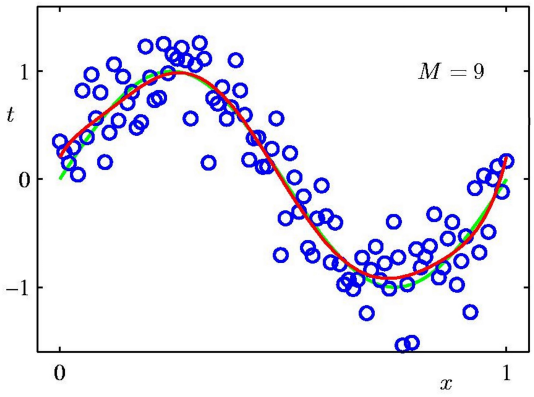

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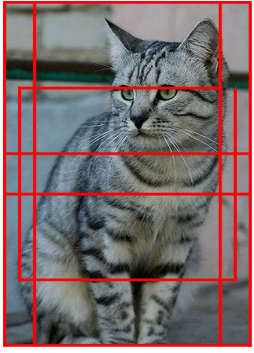

Crop & Resize

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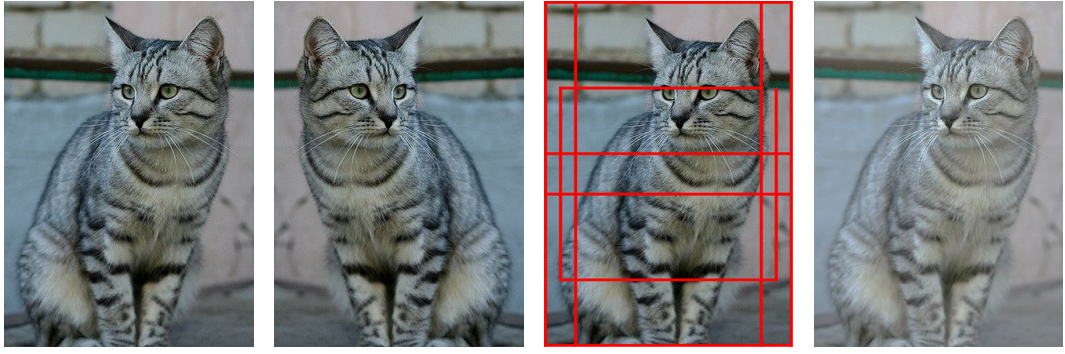

Original | Flip | Crop & Resize | Brightness & Contrast

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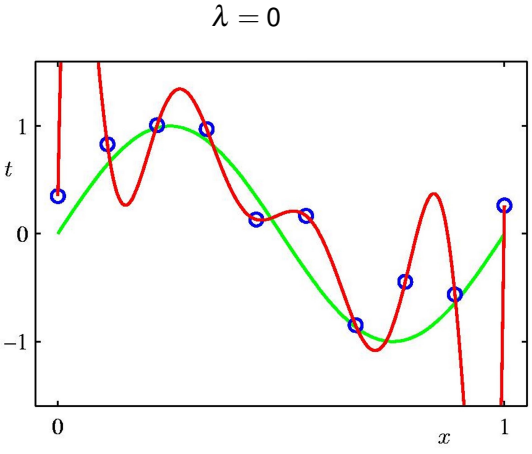

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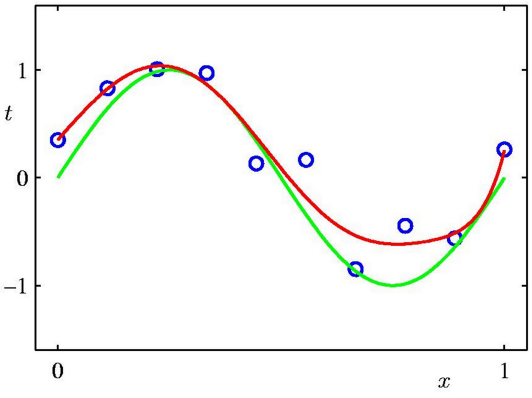

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Pros: effective, same model & dataset.

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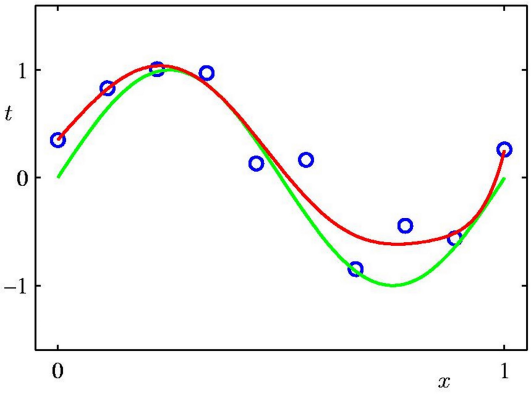

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- Model values fluctuate wildly due to **very large weights**.

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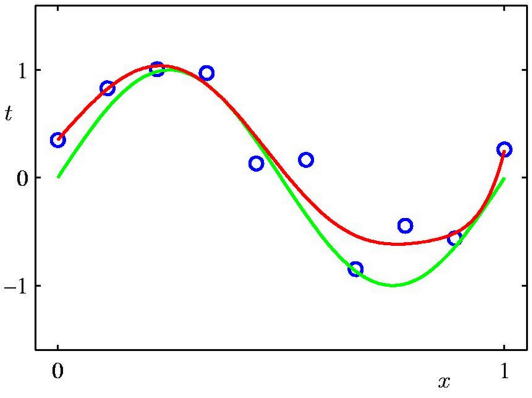
Modify loss function ($\lambda \geq 0$):

$$L(\mathbf{t}, \hat{\mathbf{t}}, \mathbf{w}) = \sum_{i=1}^{N} \left(t^{(i)} - \hat{t}^{(i)} \right)^2 + \lambda |\mathbf{w}|_2^2$$

Pros: effective, same model & dataset.
Cons: more complex training, λ tuning.

$\lambda = e^{-18}$



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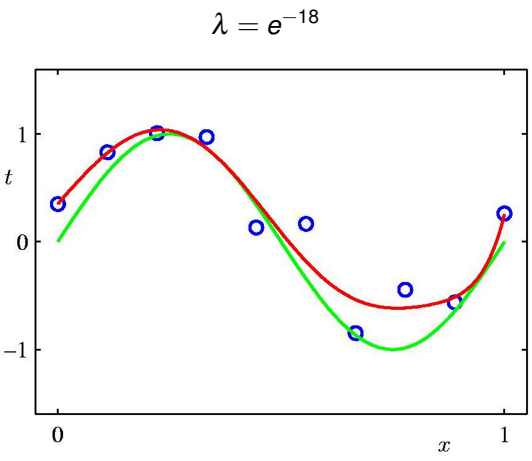
Alternative: add $\lambda |\mathbf{w}|_1$ to encourage sparse weights (see "Pruning" lecture).



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Remove neurons with probability p during the training process.

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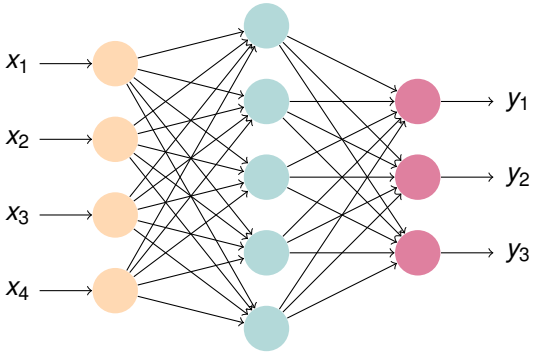

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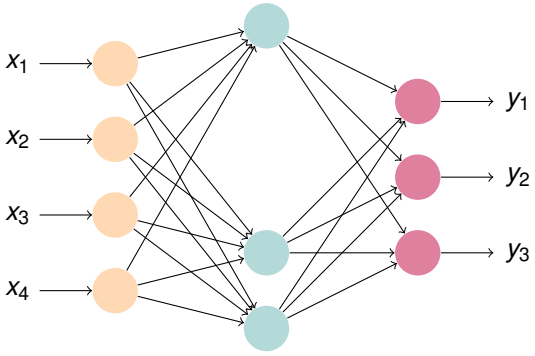

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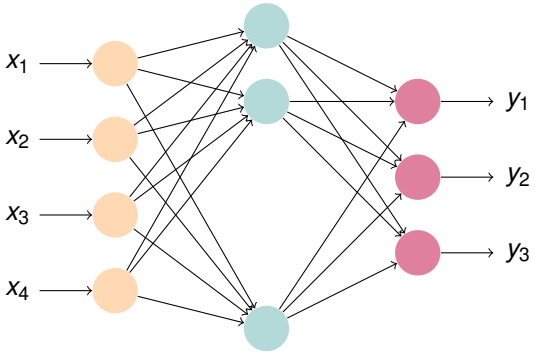

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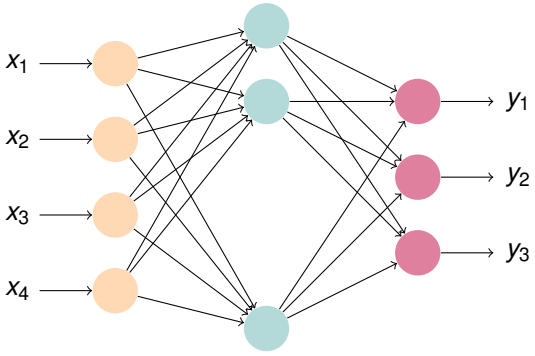

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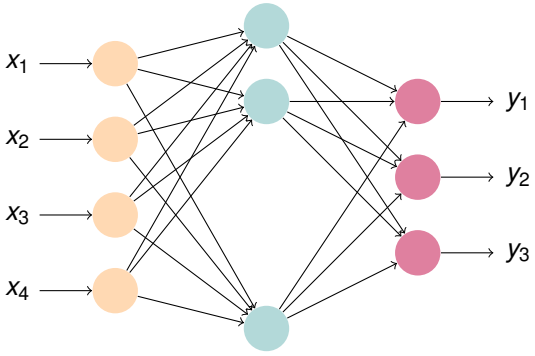

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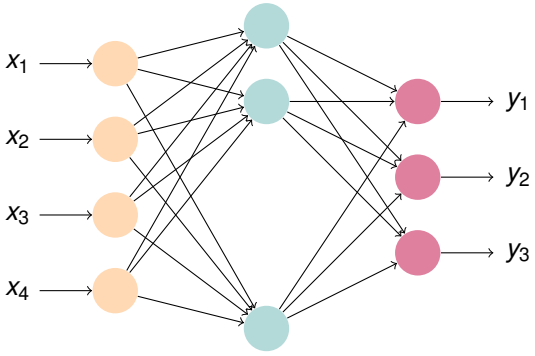

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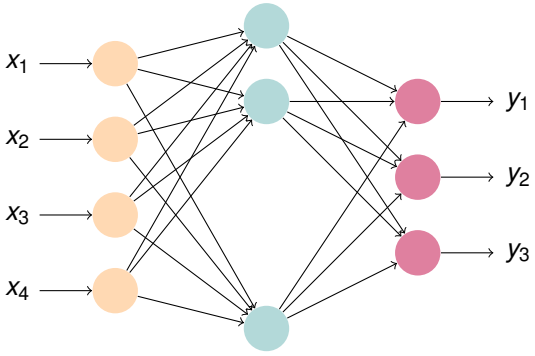

- Previous methods are general, this method is specific to neural networks!

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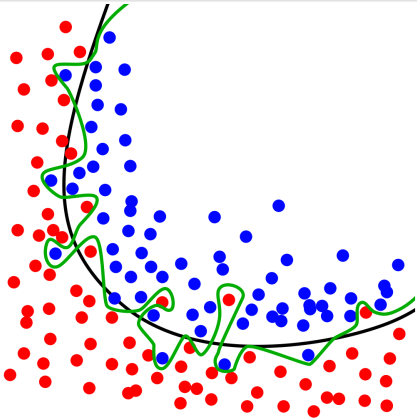

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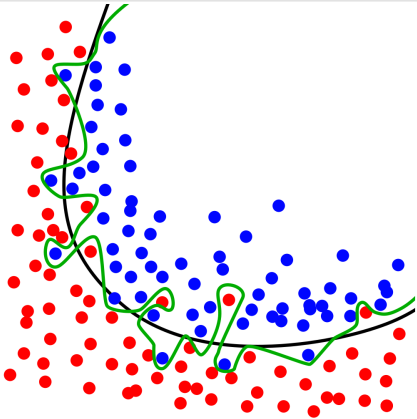

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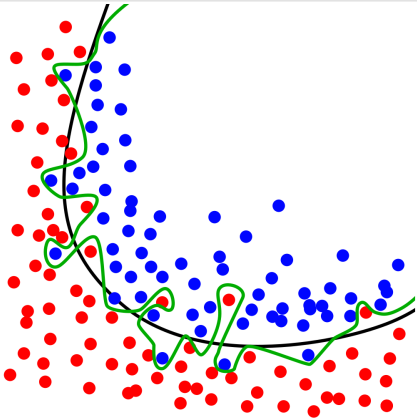

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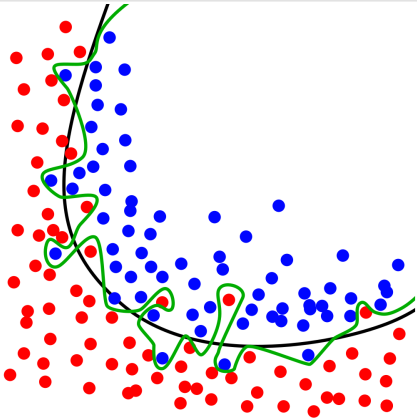

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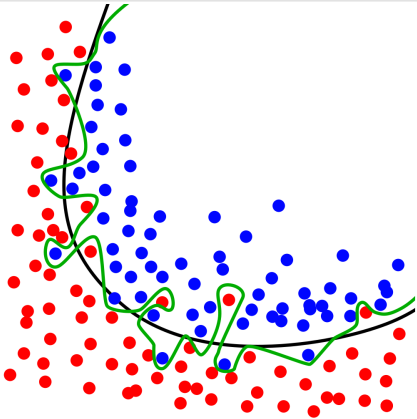

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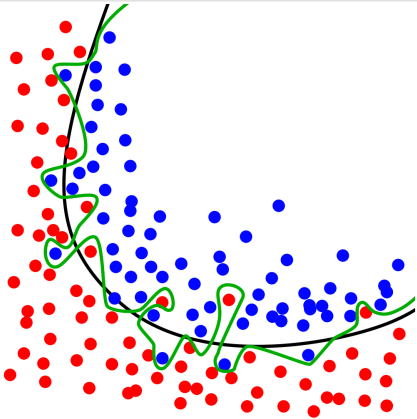
5. ...and many more (ensembling, remove features, early stopping)!



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4. Mini-batch size B
5. Type of weight initialization
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Selecting good hyperparameter values is **critical**!

Problem

The search space is **huge**. With 10 hyperparameters and 5 options for each: **almost 10 million trainings**!

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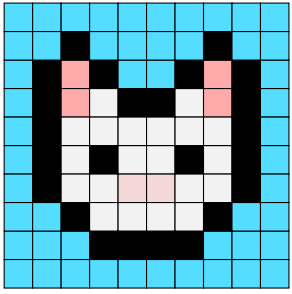
More details: “Neural architecture search” lecture.

Time For A Break

"*Running the same system harder or faster will not change the pattern as long as the structure is not revised.*"

– Dennis Meadows, "The Limits to Growth: The 30-Year Update," 2004.

Issues With Feedforward Neural Networks



- So far, we **vectorize** images to input to a NN.

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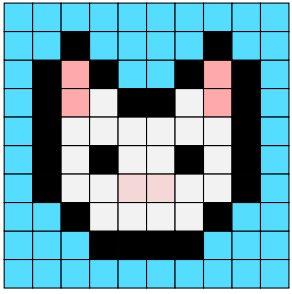

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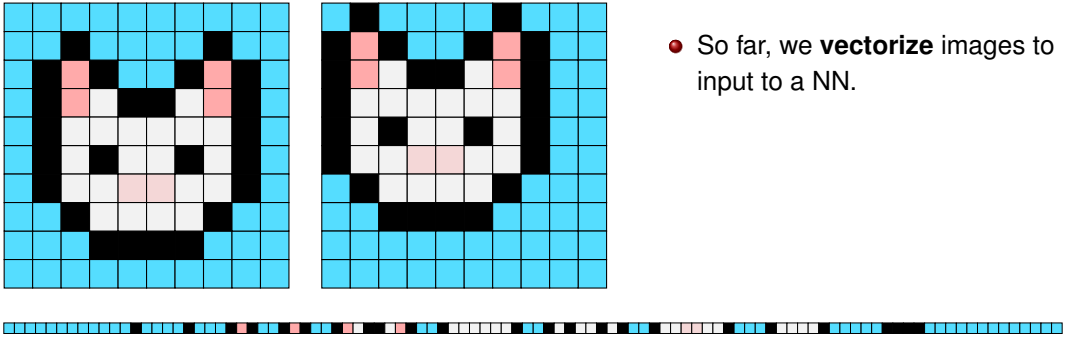

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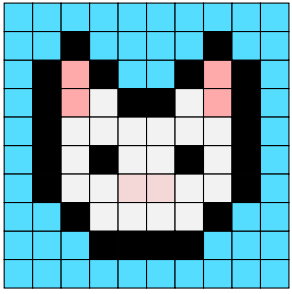

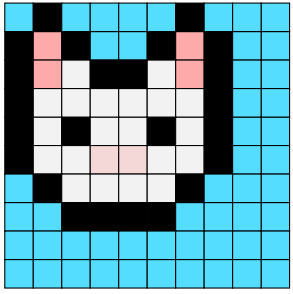

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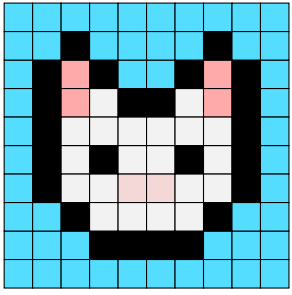

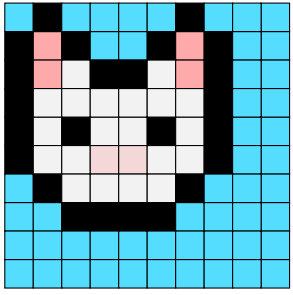

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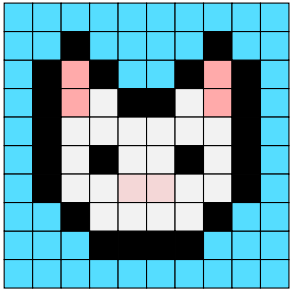

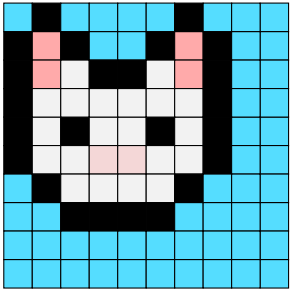

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- Using RGB, the first hidden layer alone has $10 \times 10 \times 3 = 300$ **weights per neuron!**

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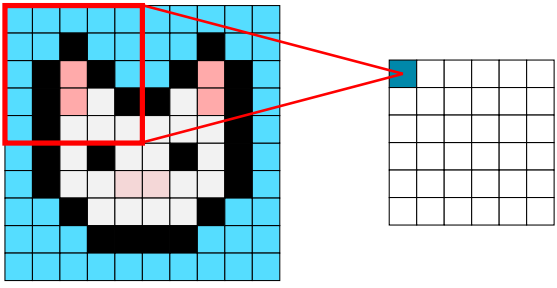

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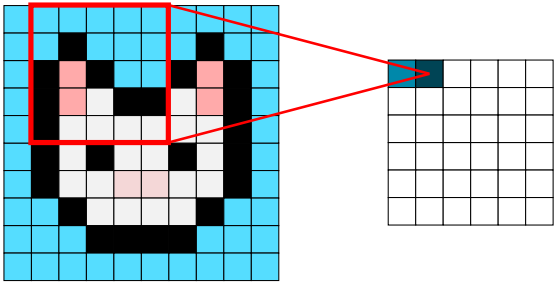

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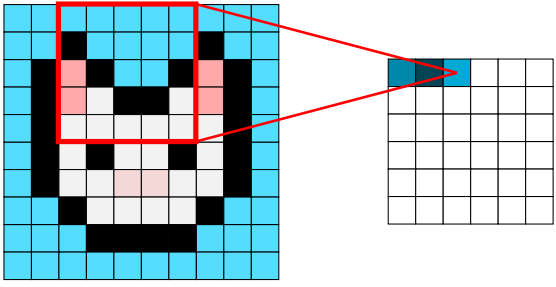

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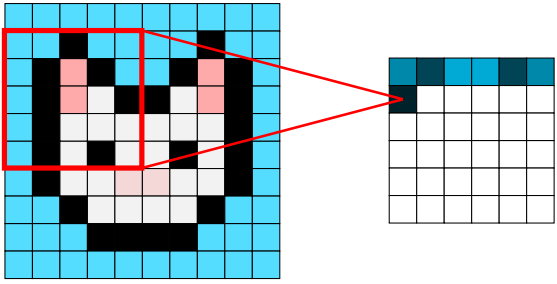

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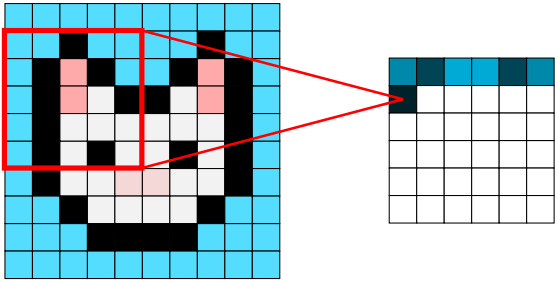

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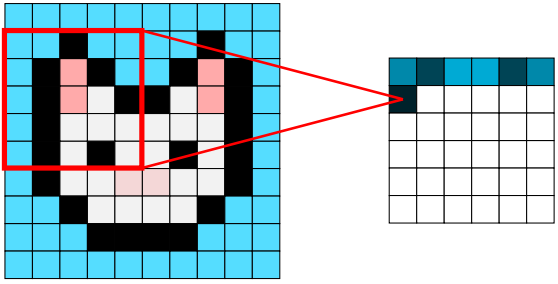

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Advantages

1) **Fewer weights** due to sparse connectivity and 2) **translation equivariance**

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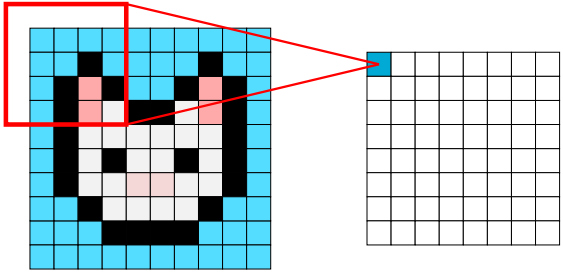

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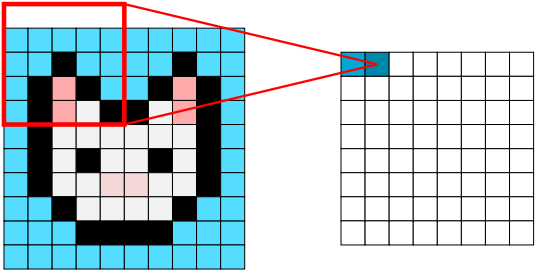

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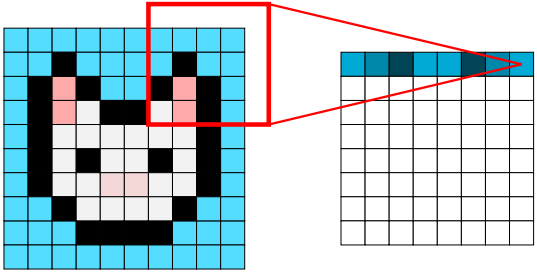

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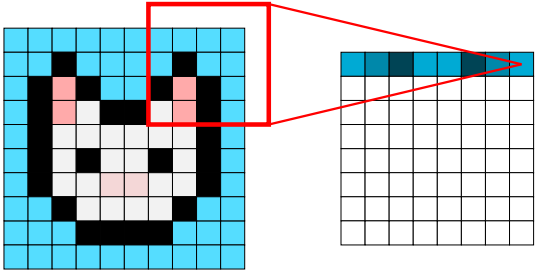
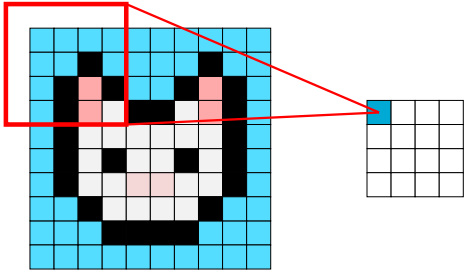


- **Padding:** use P pixels outside input
- **Input:** $W \times H$
- **Filter:** $S \times R$
- **Output:** $(W-S+2P+1) \times (H-R+2P+1)$

Stride



- **Stride:** steps of T pixels

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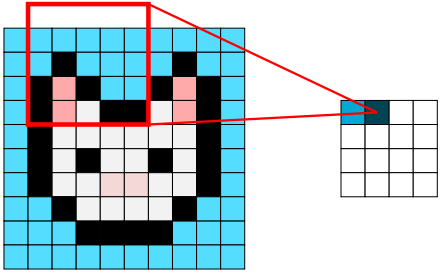

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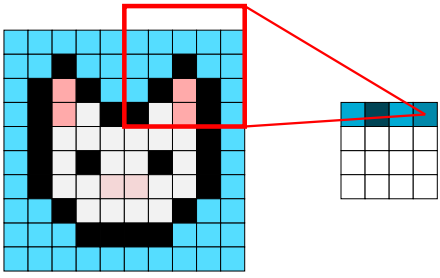

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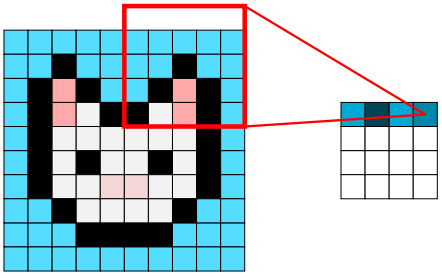
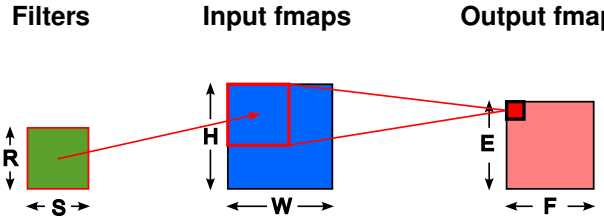


- **Stride:** steps of T pixels
- **Input:** $W \times H$
- **Filter:** $S \times R$
- **Output:** $(\lfloor \frac{W-S+2P}{T} \rfloor + 1) \times (\lfloor \frac{H-R+2P}{T} \rfloor + 1)$

The Convolutional Layer



- **Filters**: $S \times R$
- **Input fmaps**: $W \times H$
- **Output fmaps**: $F \times E$

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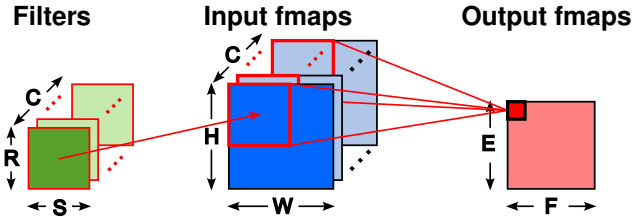
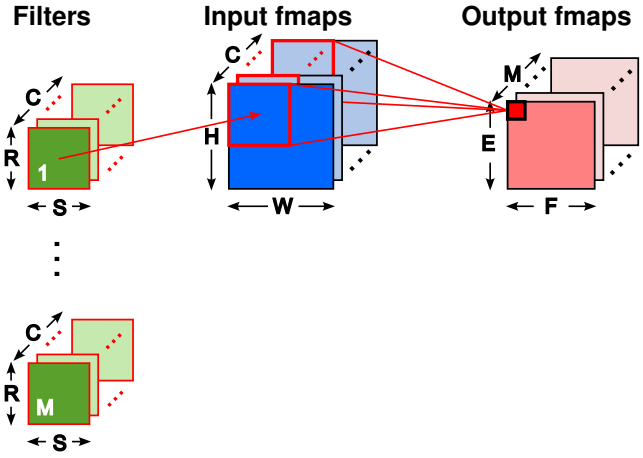


- **Filters**: $S \times R \times C$
- **Input fmaps**: $W \times H \times C$
- **Output fmaps**: $F \times E$

- **Input channels:** C

The Convolutional Layer



- **Filters**: $S \times R \times C \times M$
- **Input fmaps**: $W \times H \times C$
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- **Input channels:** C
- **Output channels:** M

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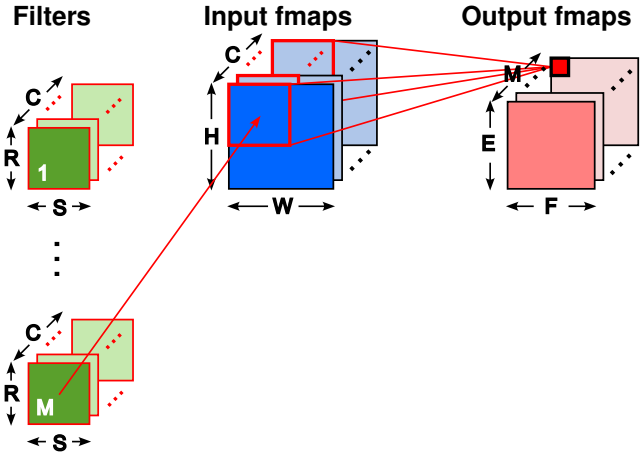

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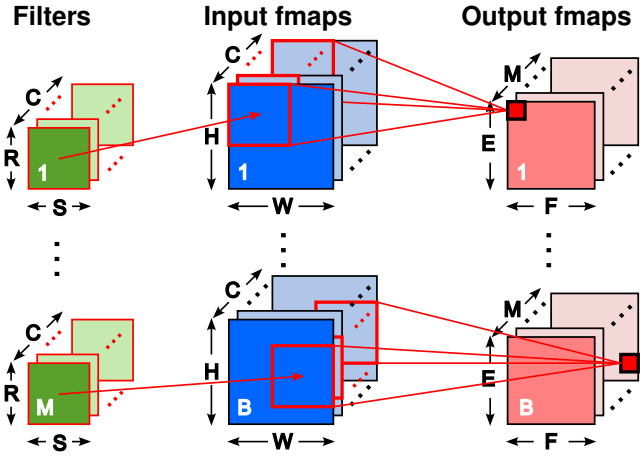
The Convolutional Layer



- **Filters**: $S \times R \times C \times M$
- **Input fmaps**: $W \times H \times C \times B$
- **Output fmaps**: $F \times E \times M \times B$

- **Input channels:** C
- **Output channels:** M
- **Batch size:** B

Pooling & Unpooling

Pooling is used between convolutional layers and **reduces the dimensions** of data.

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1	9	2	4
5	7	8	1
3	2	1	3
6	1	4	5

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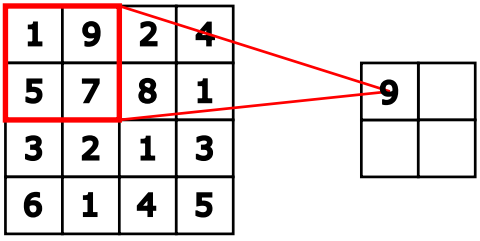

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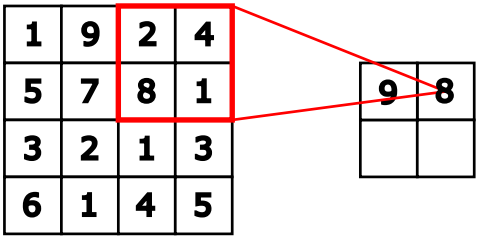

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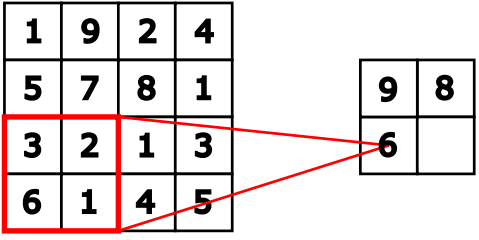

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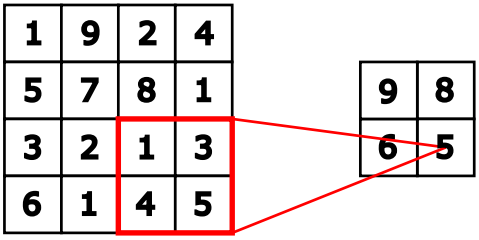

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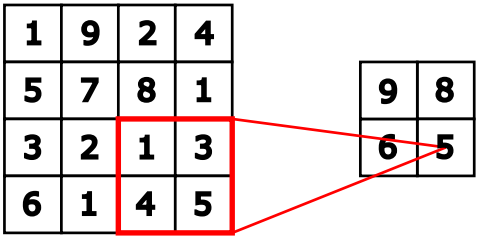

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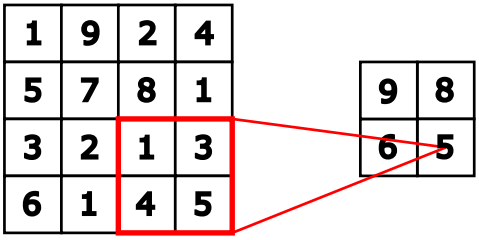

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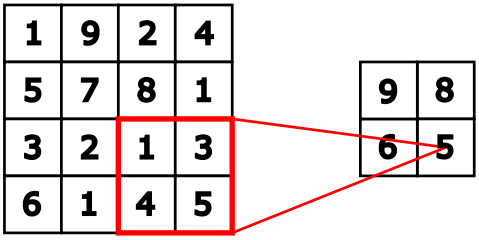

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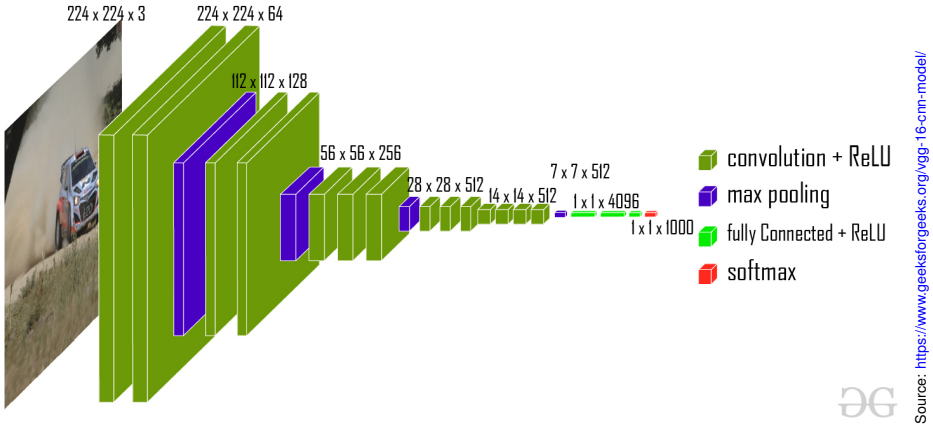
Unpooling can be used to **increase the dimensions** of data. Several options:

1. Nearest neighbor and max unpooling.
2. Learned transpose convolution.

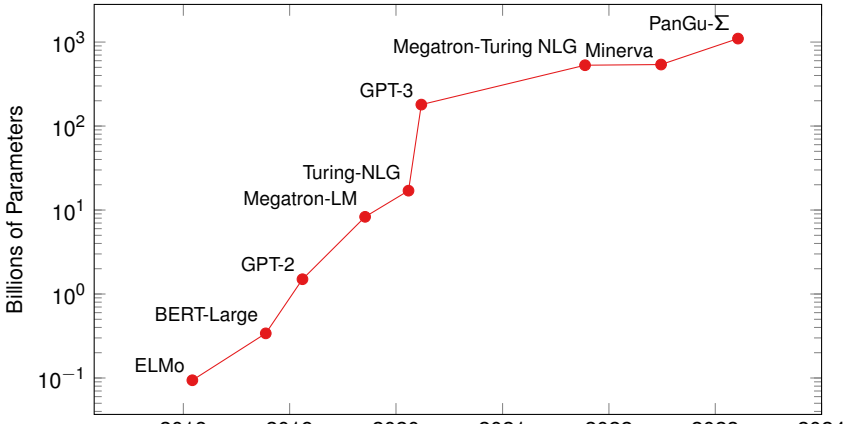
Putting It All Together: A Convolutional Neural Network (VGG-16)



Source: https://www.geeksforgeeks.org/vgg-16-cnn-model/

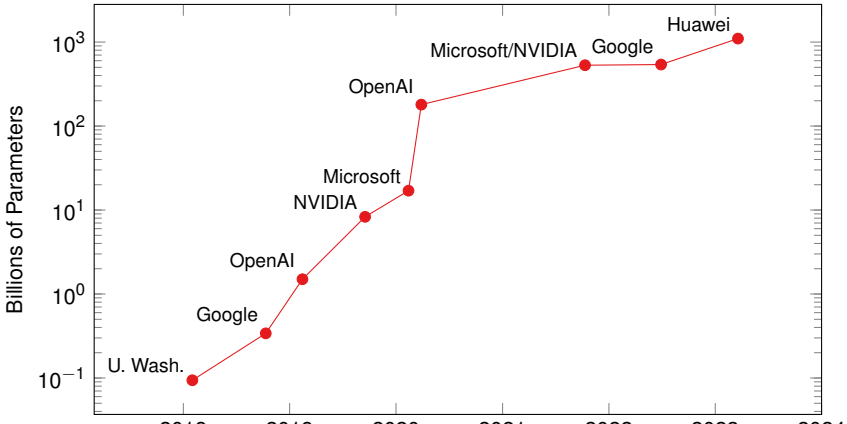
- The number of channels C equals the number of output feature maps M of the previous layer, so C is often omitted.

Model Size Is Exploding



Data source: https://epoch.ai/data/notable-ai-models

Model Size Is Exploding



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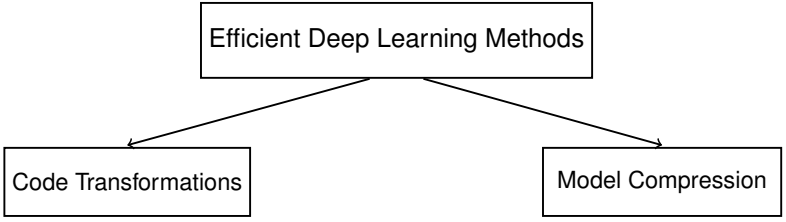

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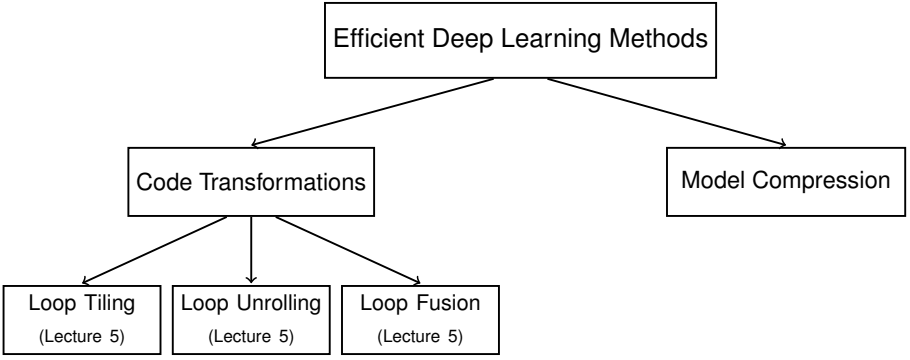

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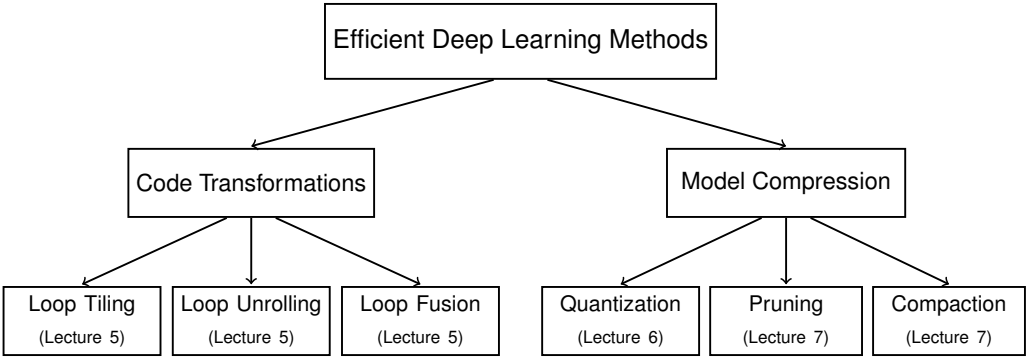

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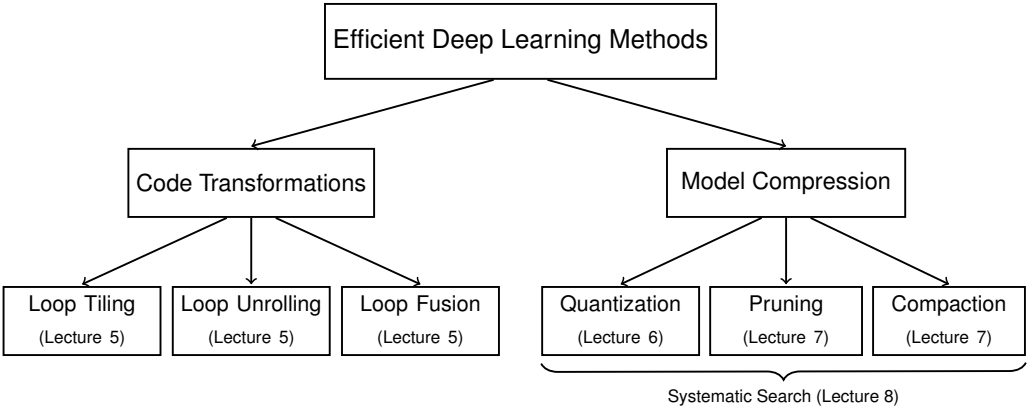

Time For A Break

"*Any intelligent fool can make things bigger, more complex, and more violent. It takes a touch of genius – and a lot of courage – to move in the opposite direction.*"

– Ernst F. Schumacher, "Small Is Beautiful: A Study of Economics As If People Mattered," 1973.

Conclusion

Summary:

1. Overfitting is an issue but can be overcome: **constrain the model**.
2. Convolutional neural networks exploit spatial image properties to reduce complexity.
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Next time:

1. Loop transformations.
2. Quantization.