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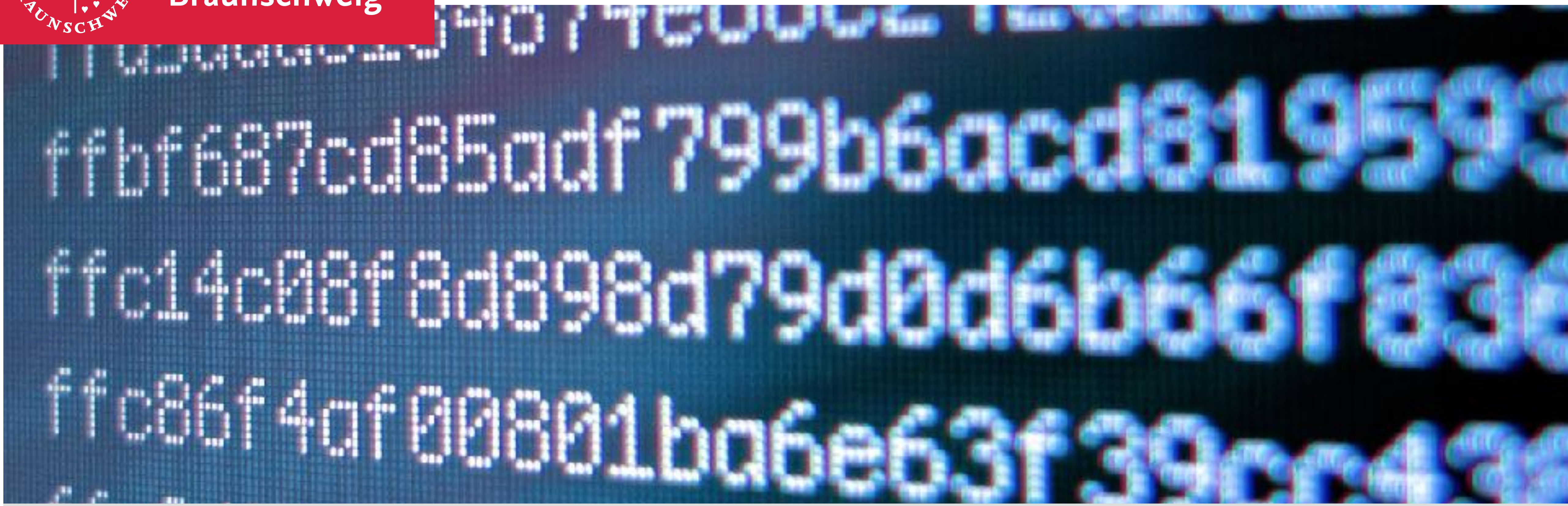


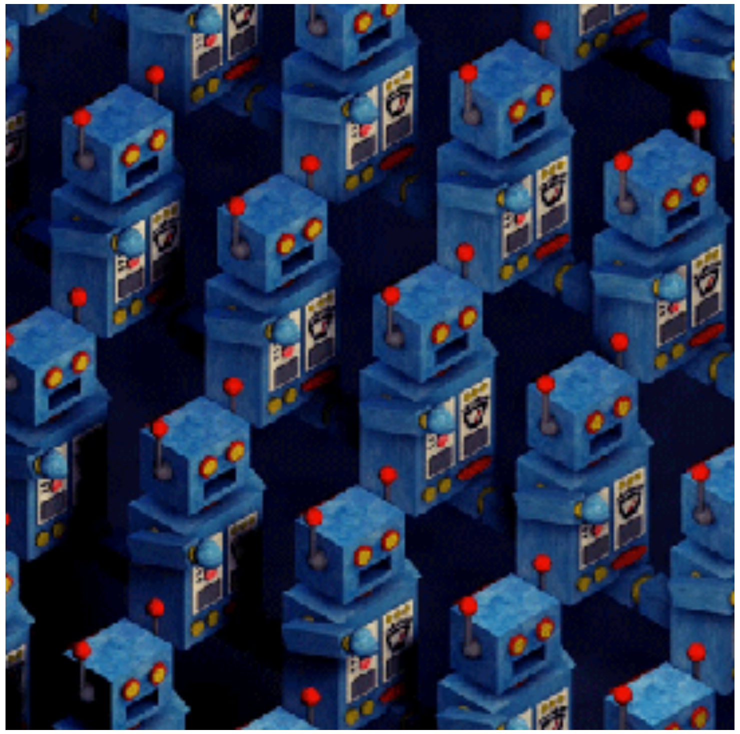
Deep Learning for Malware Analysis

Machine Learning for Computer Security

Hugo Gascón

Overview

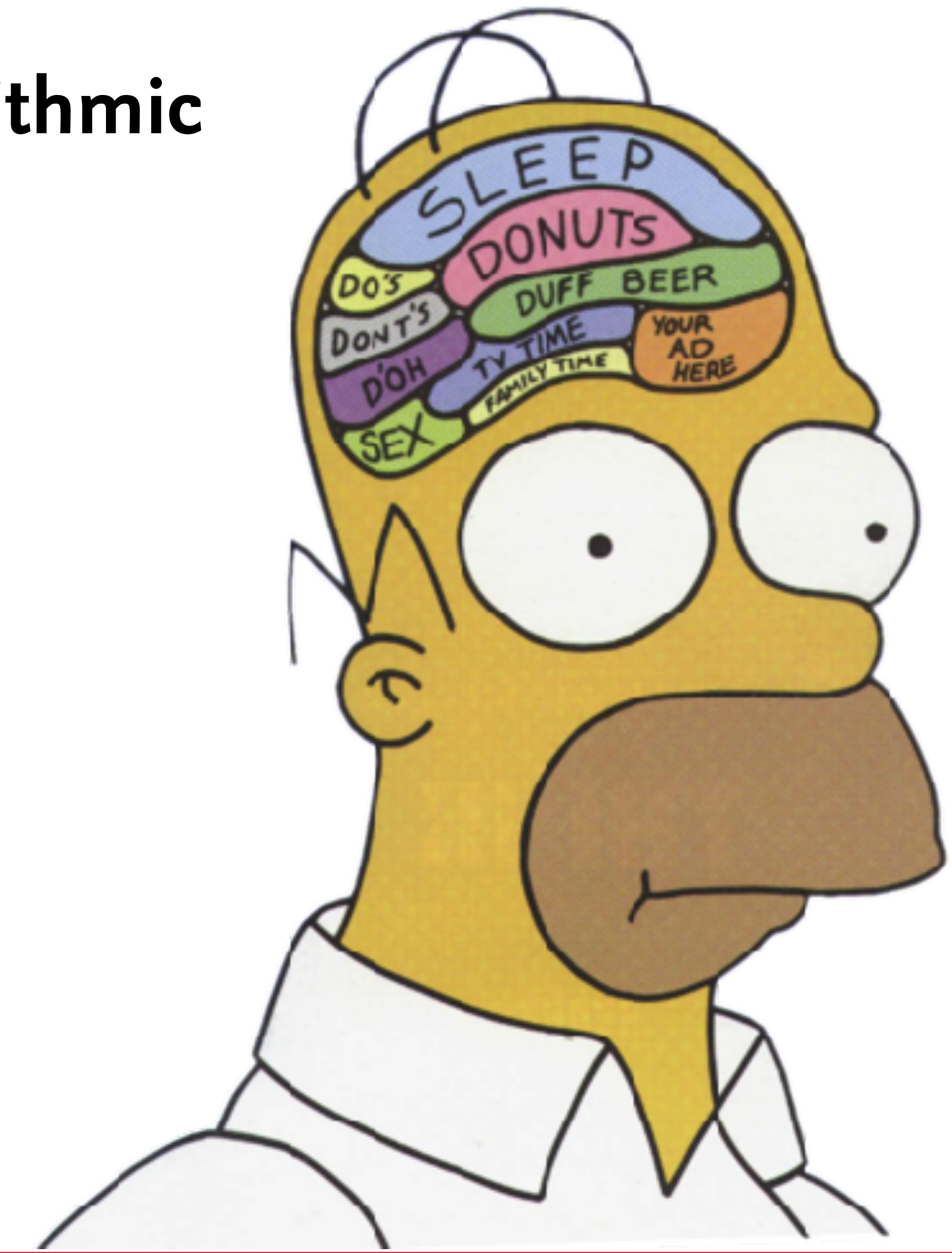
- **What you will learn today**
  - A primer on artificial neural networks
  - Deep network architectures
  - Applications to malware analysis



A Primer on Neural Networks

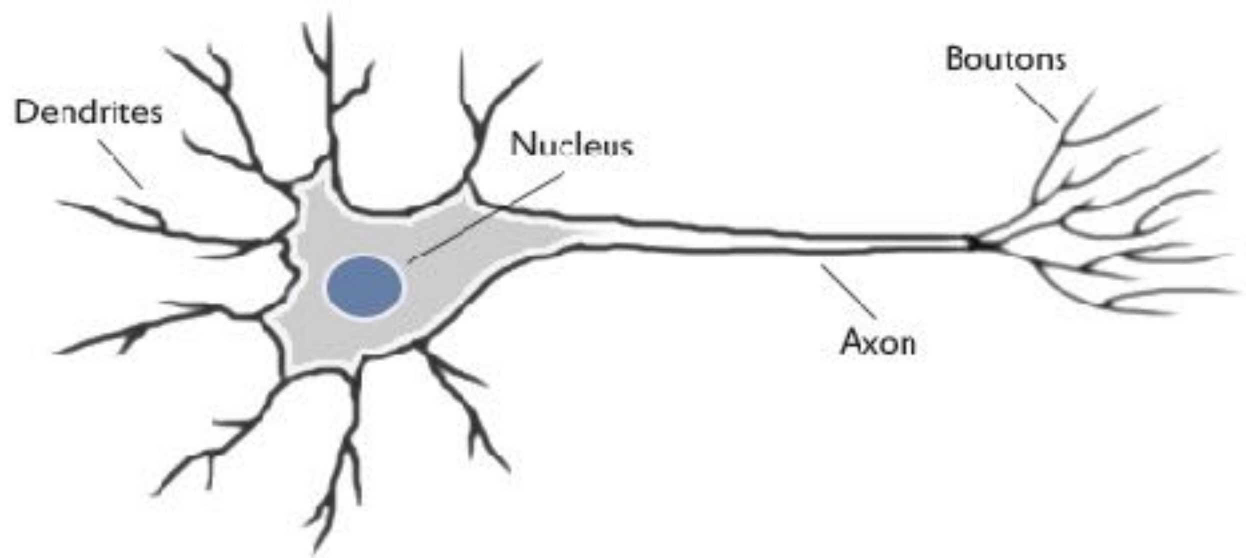
What is an Artificial Neural Network?

- **Computers are great at solving algorithmic and math problems**
- **Real world task difficult to define mathematically, e.g.:**
  - Recognising faces
  - Understanding language
- **Artificial neural networks model information like the brain does**



How does the brain work?

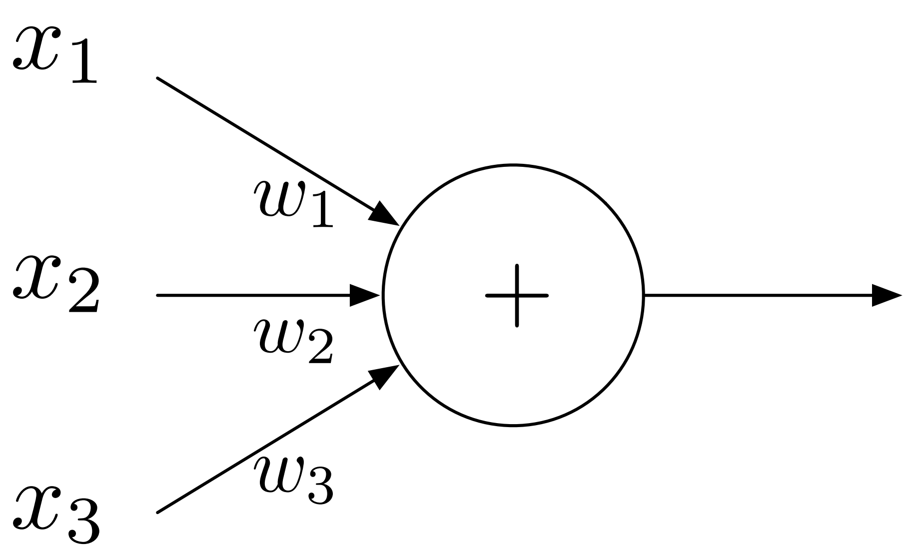
- Extremely large interconnected networks of ~10^{11} neurones
- Output a weighted sum of inputs when triggered



- The artificial model of a neurone is called perceptron

Perceptron

- **Developed in the 50s and 60s by the Frank Rosenblatt**
- **Linear classifier on top of a simple feature extractor**



$$h(x) = \begin{cases} 0 & \text{if } \sum_i w_i x_i \leq threshold \\ 1 & \text{if } \sum_i w_i x_i > threshold \end{cases}$$

Perceptron

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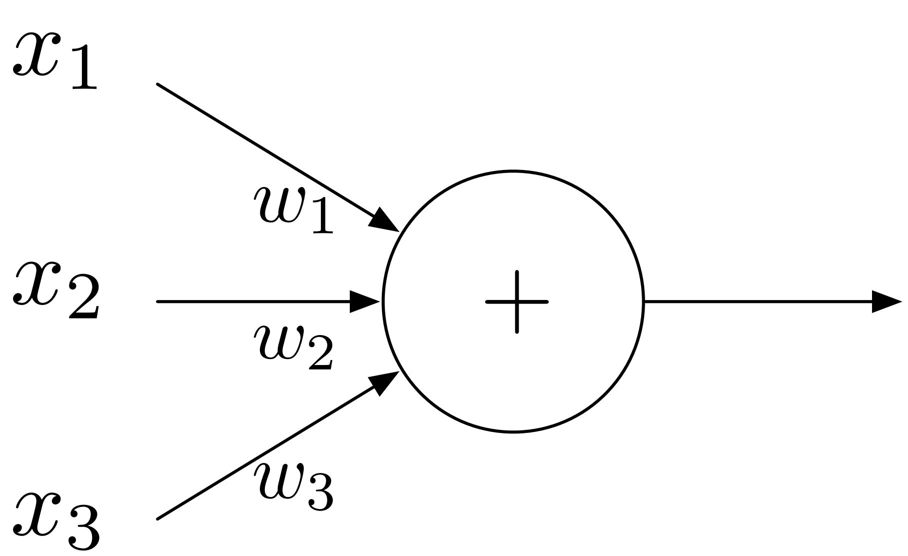


dot product

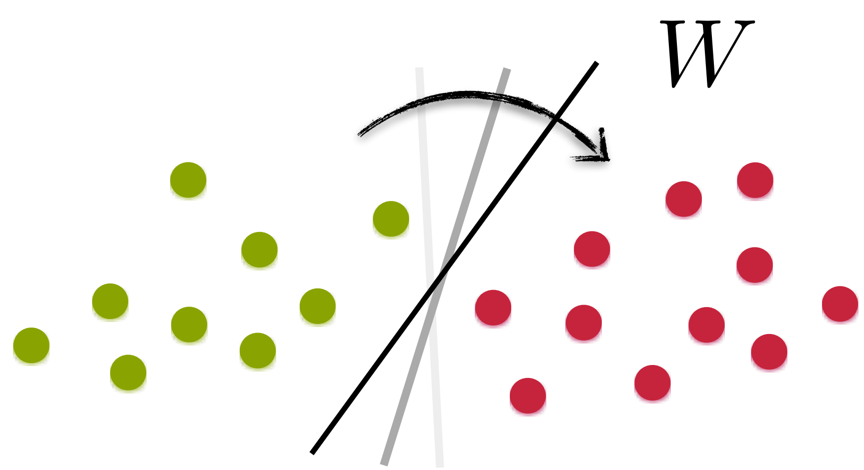
$$h(x) = \begin{cases} 0 & \text{if } \sum_i w_i x_i - b \leq 0 \\ 1 & \text{if } \sum_i w_i x_i - b > 0 \end{cases}$$

activation function

Perceptron as Classifier

- **The perceptron is the first learning machine**
  - Classic supervised learning algorithm for classification
- **Learning model**
  - Weight vector $W = \{w_1, w_2, w_3\}$ defines a hyperplane

$$\sum_i w_i x_i - b \leq 0$$



$$\sum_i w_i x_i - b > 0$$

Perceptron Rule

- **Learning by iterative updates of weight vector W**
  - Pick x_i from training data and compute the output
  - Update weights following rule

$$w_i^{m+1} = w_i^m + \alpha(t_j - y_j^m)x_{j,i}$$

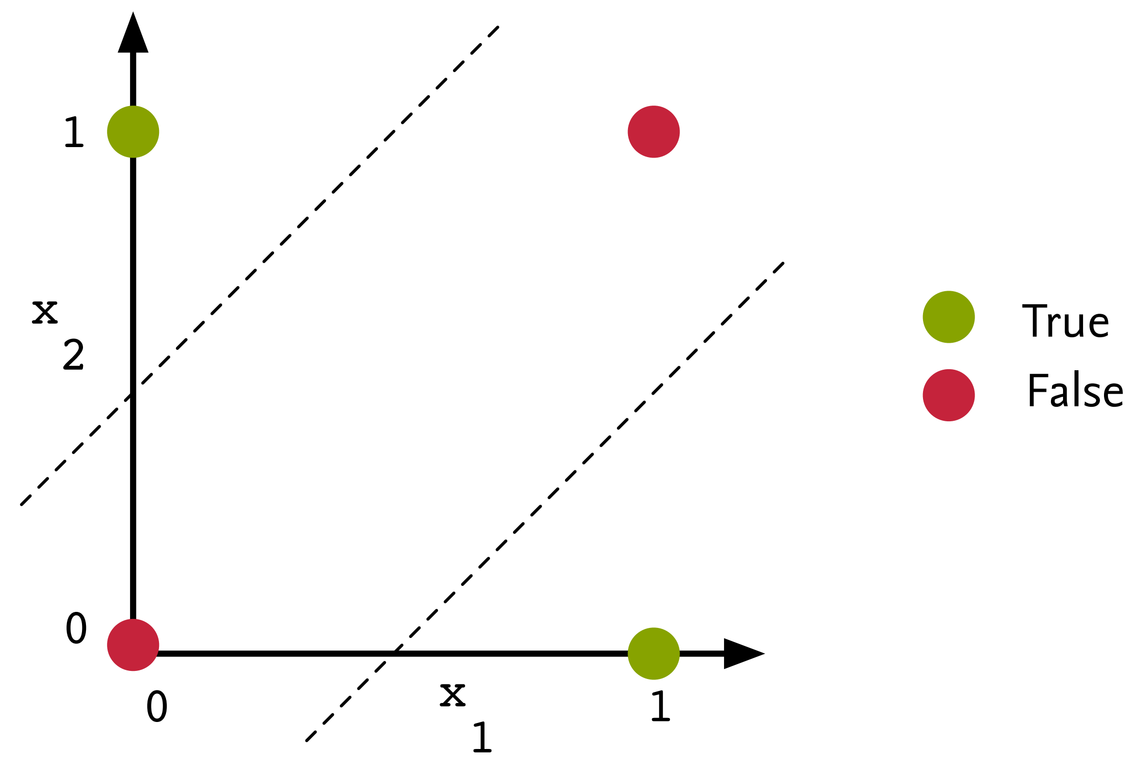
$$0 \leq i \leq n$$

- **Algorithm only converges if data is linearly separable**

Perceptron Limitations

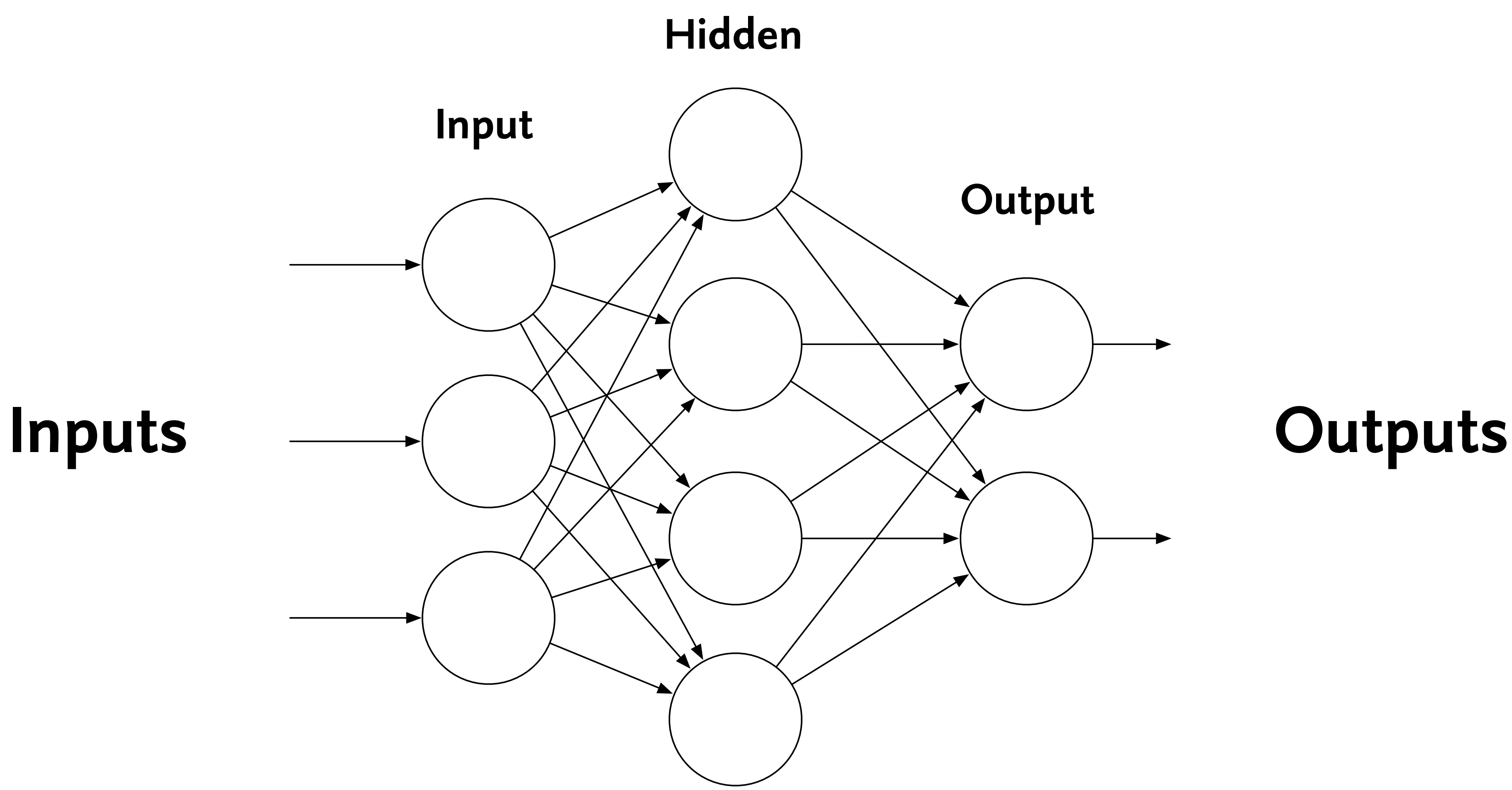
- **Simplest problem that can not be solved by a perceptron**

		x_1	
	XOR	0	1
x_2	0	0	1
	1	1	0



Feedforward Neural Network

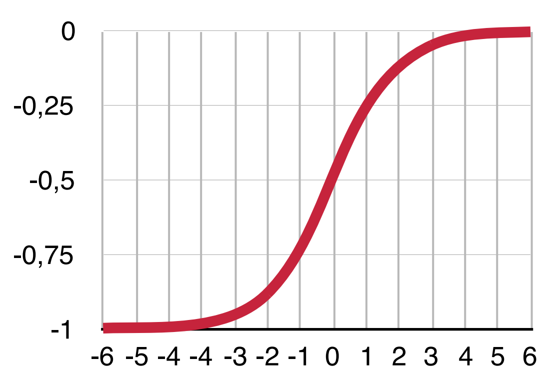
- **Perceptron basic building block of neural networks**
  - Each layer weights the decisions from the previous layer
  - Complex and abstract decision making at higher layers



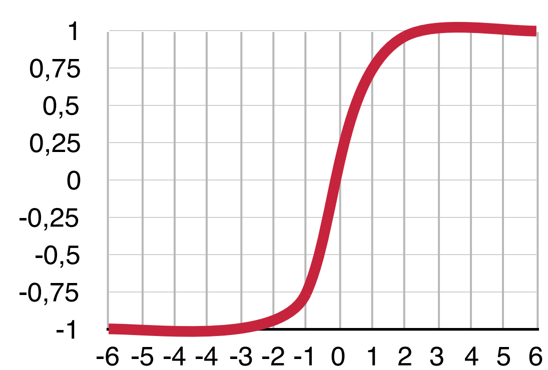
Beyond Linearity

- **A linear composition of several linear functions is still linear**
- **Alternative are non-linear activation functions or rectifiers**

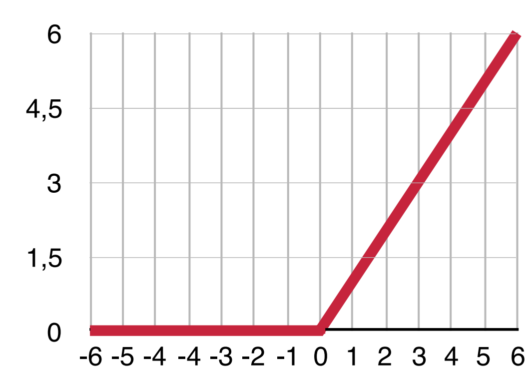
Logistic



Tanh



Rectifier



$$h(x) = \frac{1}{1 + e^{-x}}$$

$$h(x) = tanh(x)$$

$$h(x) = max(0, x)$$

Beyond Linearity

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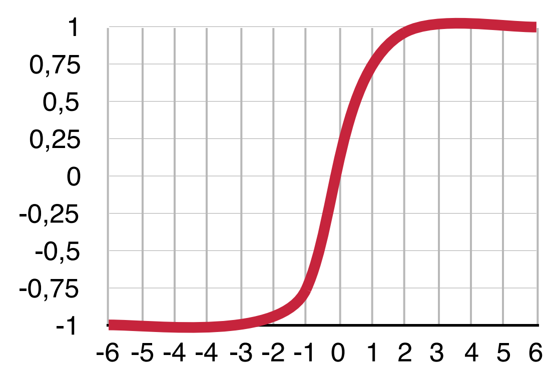

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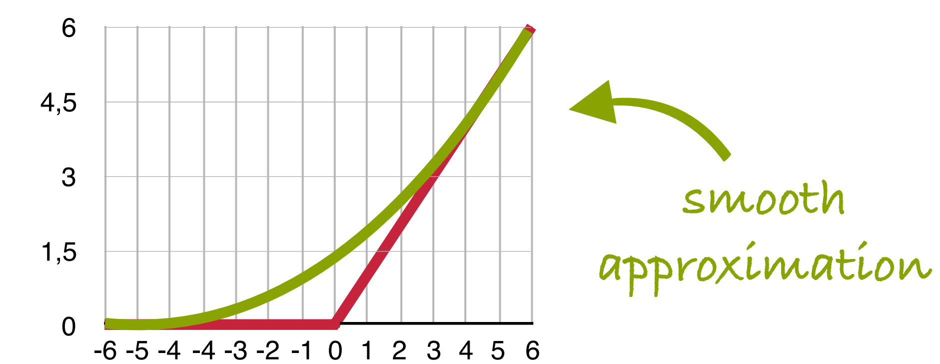
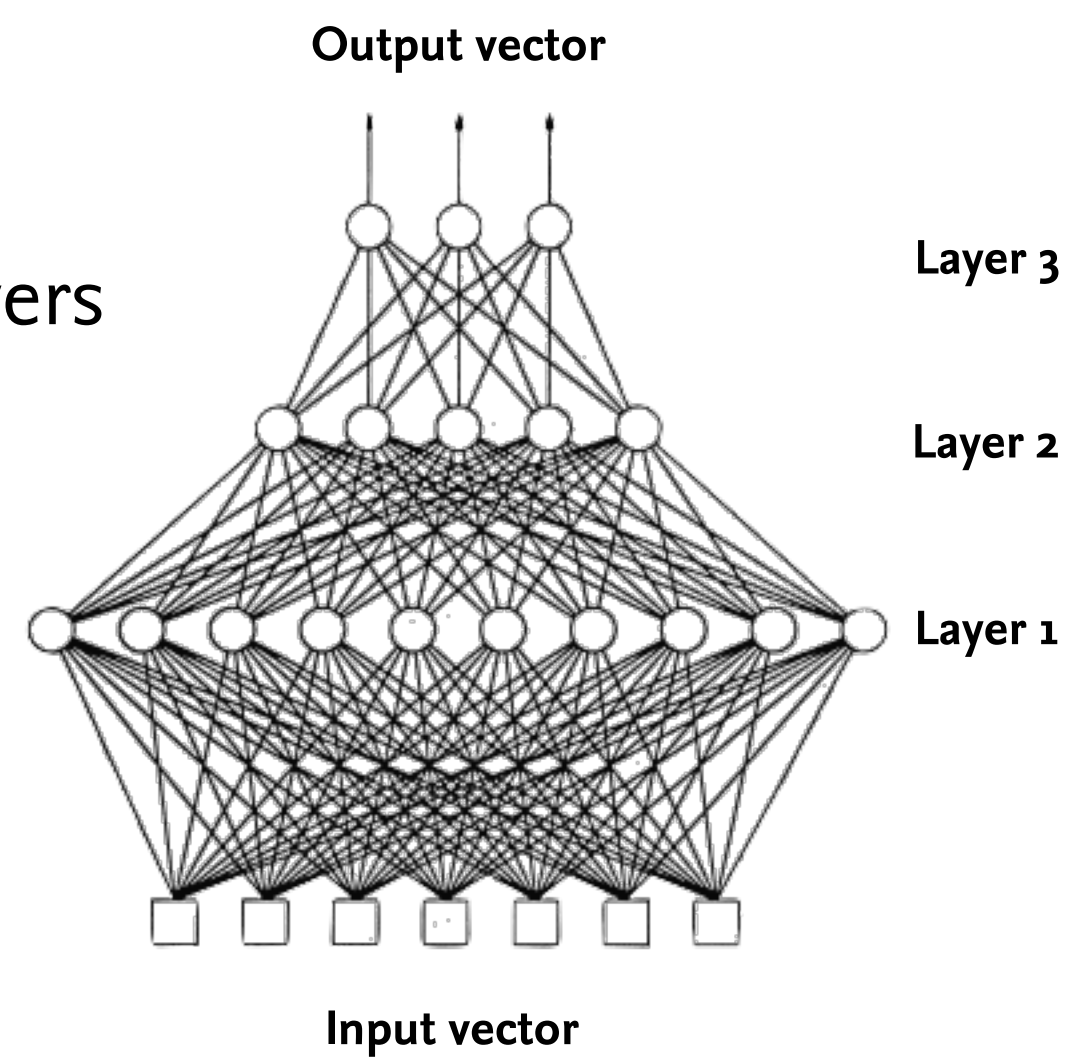


$$h(x) = max(0, x)$$

$$h(x) = ln(1 + e^{x})$$

Multilayer Perceptron

- **Feedforward neural network with** **sigmoid neurons**
  - Three or more fully connected layers
  - Can distinguish data that are not linearly separable
- **Supervised learning with** **backpropagation**



Backpropagation

- **Find internal representations to allow an arbitrary mapping**
- **Basic strategy**
  - Backward propagation of errors
  - Gradient of **loss function** respect to all weights
  - Update of weights

e.g. mean square error $E = \frac{1}{2}(t - y)^2$

- **Requires**
  - Known desired output value per input
  - **Differentiable** activation functions

Backpropagation Phases

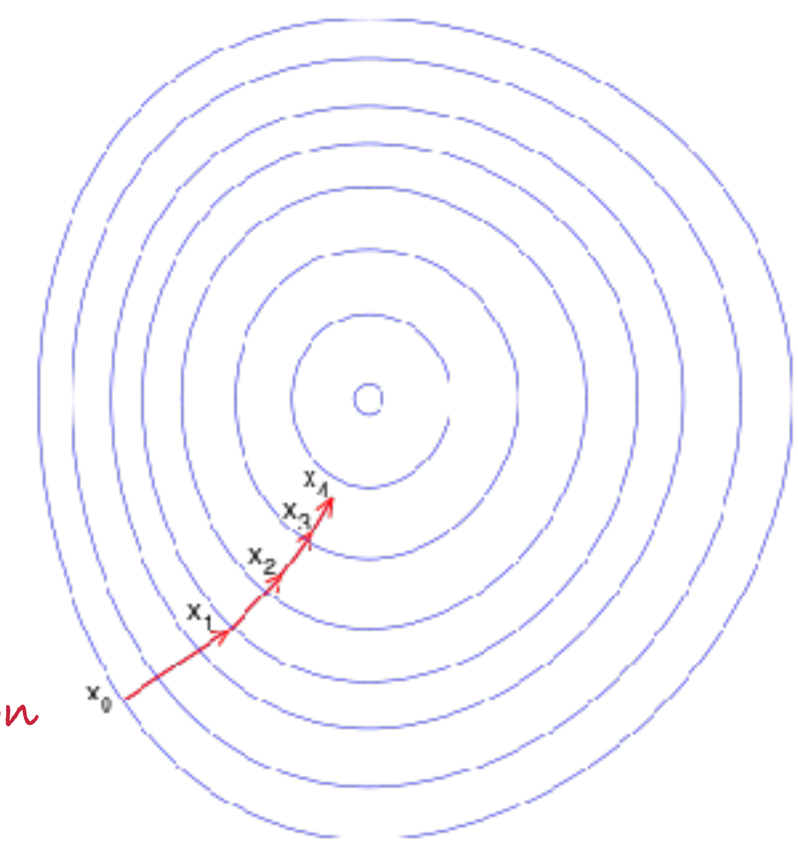
1. **Propagation**
   - Forward propagation of a training pattern's input
   - Backward propagation of outputs to compute deltas
2. **For each weight**
   - Multiply output delta and input activation to get gradient
   - Subtract a percentage of the gradient from the weight

Minimize error with stochastic gradient descent

Gradient Descent

- **Most common optimization algorithm for neural networks**
  - Iterative update of parameters to minimize E
  - All training samples required for a single weight update

$$w = w - \eta \sum_{i}^{n} \frac{\partial E(w)}{\partial w_i}$$

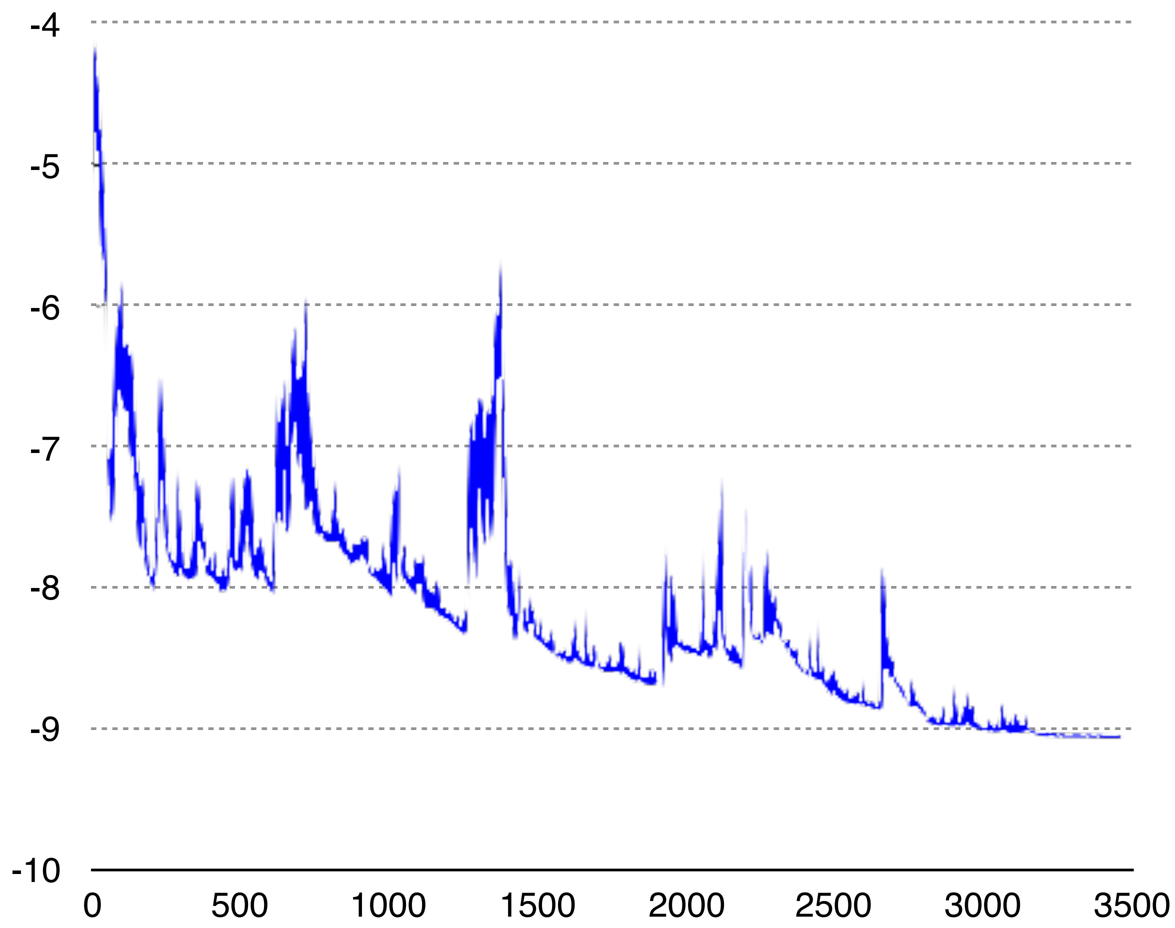


2-dimensional function

Stochastic Gradient Descent

- **Improvement over gradient descent**
  - One training sample and label per weight update
  - Much faster convergence

$$w = w - \eta \frac{\partial E(w)}{\partial w_i}$$



Stochastic Gradient Descent

- **Improvement over gradient descent**
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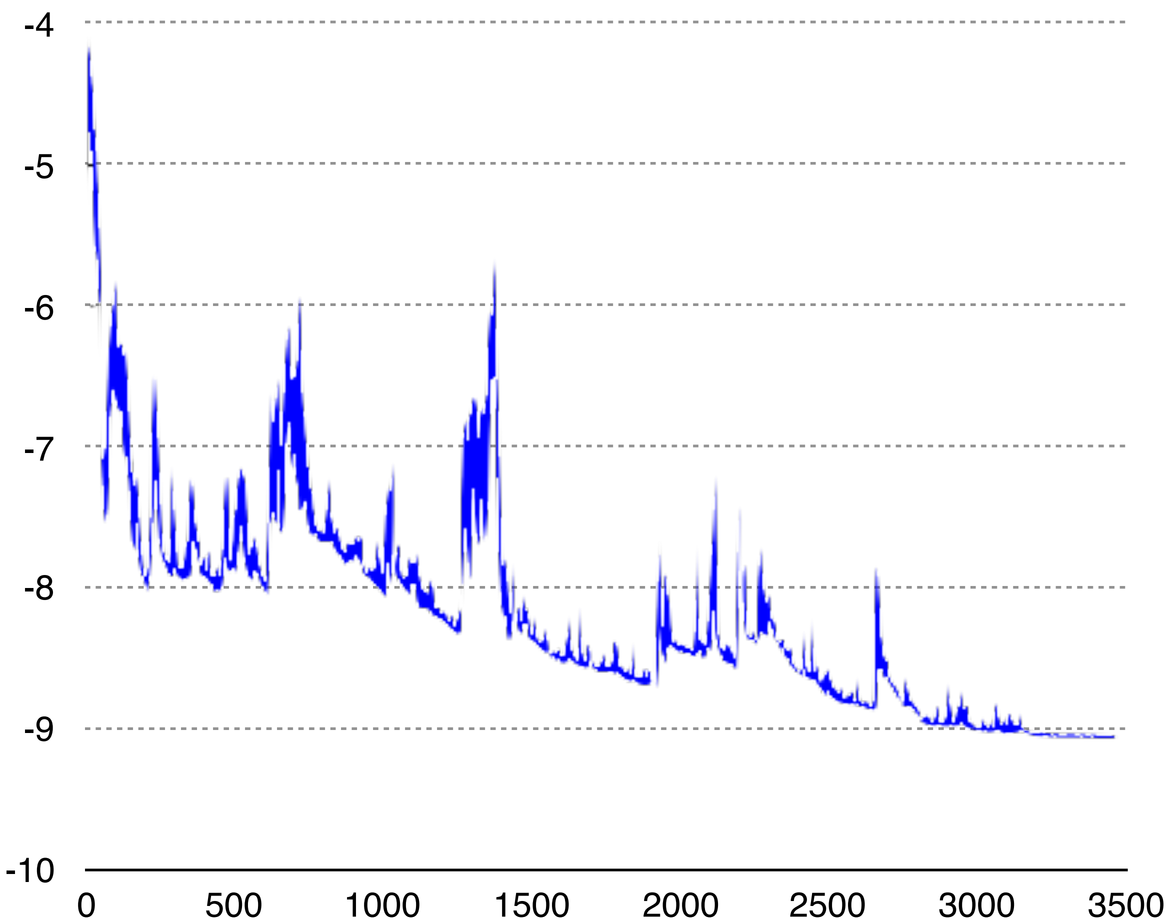
Thinking in code…

```
define w, rate
while E > e:
 shuffle training set
 for i in N:
   w = w – rate*dEi(w)
```



Stochastic Gradient Descent Example

- **Fit** $y = w_1 + w_2 x$ **to a set of points** $(x_1, y_2), \ldots, (x_n, y_n)$
- **Error function using least squares**

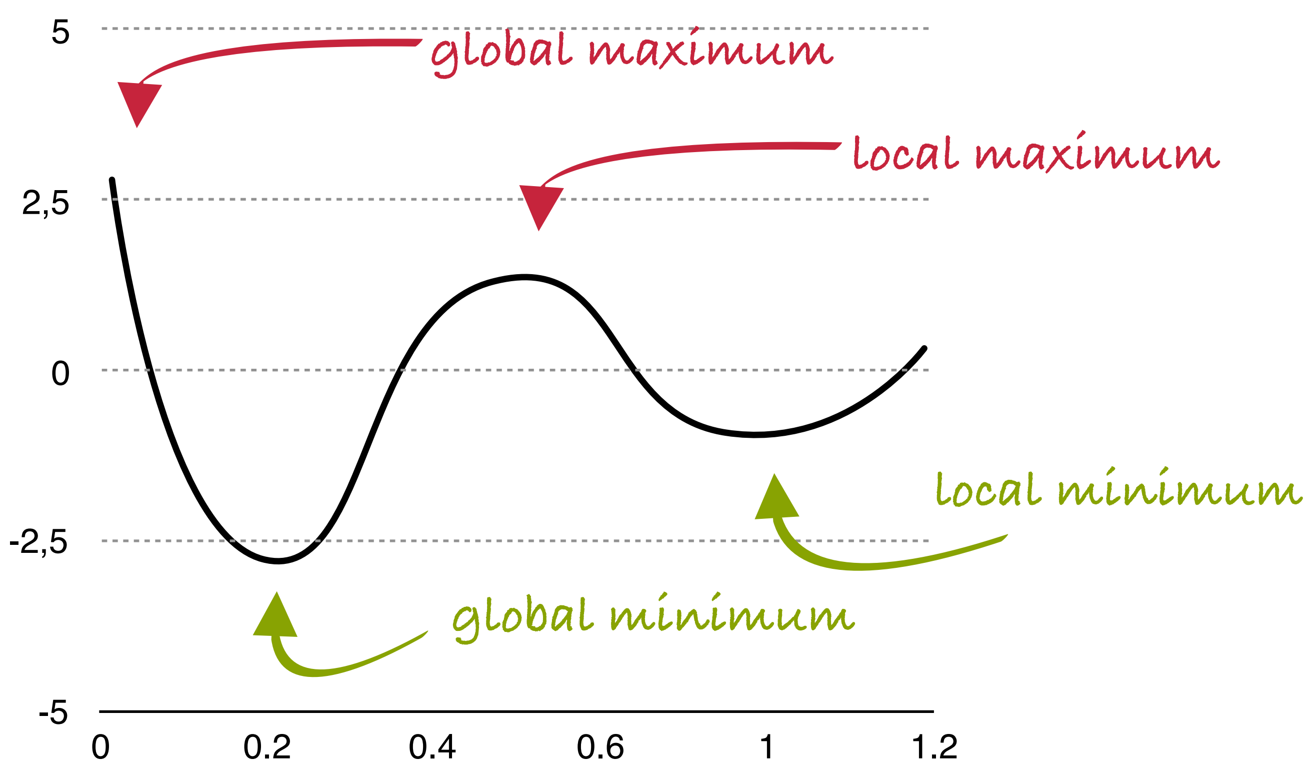
$$E(w) = \sum_{i=1}^{n} E_i(w) = \sum_{i=1}^{n} (w_1 + w_2 x_i - y_i)^2$$

- **Adjusted Weights**

$$\begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} - \eta \begin{bmatrix} 2(w_1 + w_2 x_i - y_i) \\ 2x_i(w_1 + w_2 x_i - y_i) \end{bmatrix}$$

Backpropagation Limitations

- Slow for large networks
- Learning rate trade-off between speed and stability
- Not guaranteed to find global minimum of error function



Basic Network Architectures

Autoencoder

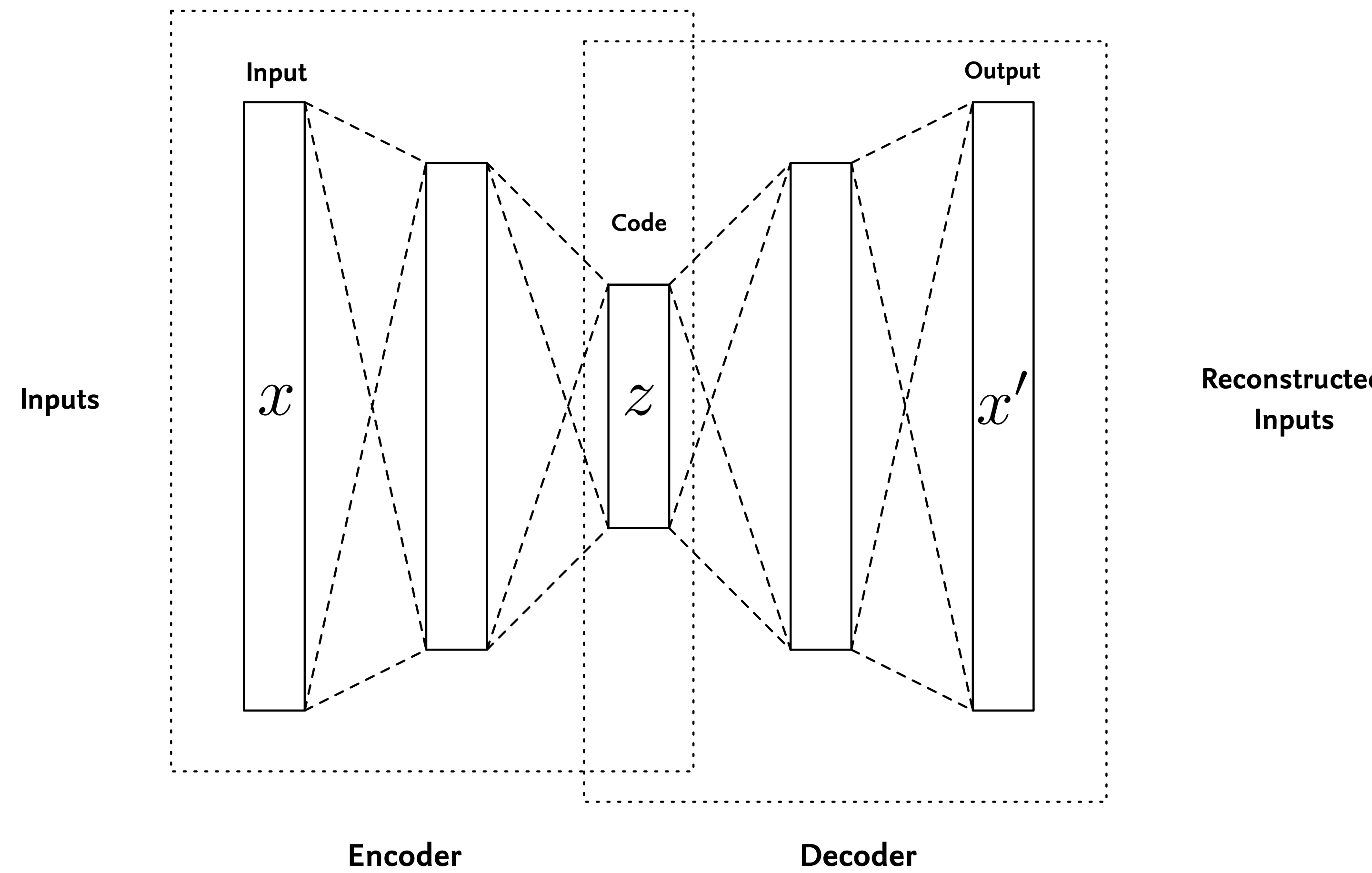
- **Feedforward non-recurrent neural network**
  - Input, output and one or more hidden layers
  - Input and output layers have **same size**
- **Learn a representation (encoding) of the data**
  - Dimensionality reduction
  - Learning generative models
- **Autoencoders build unsupervised learning models**

Autoencoder Architecture

- **2 Parts**
  - Encoder $\phi : \chi \rightarrow \mathcal{F}$
  - Decoder $\psi : \mathcal{F} \rightarrow \chi$
- **Map $x \in \mathbb{R}^d$ onto $z \in \mathbb{R}^p$ and z onto x'**

$$z = \sigma_1(Wx + b)$$

$$z' = \sigma_2(W'z + b')$$



- **Minimise reconstruction errors**

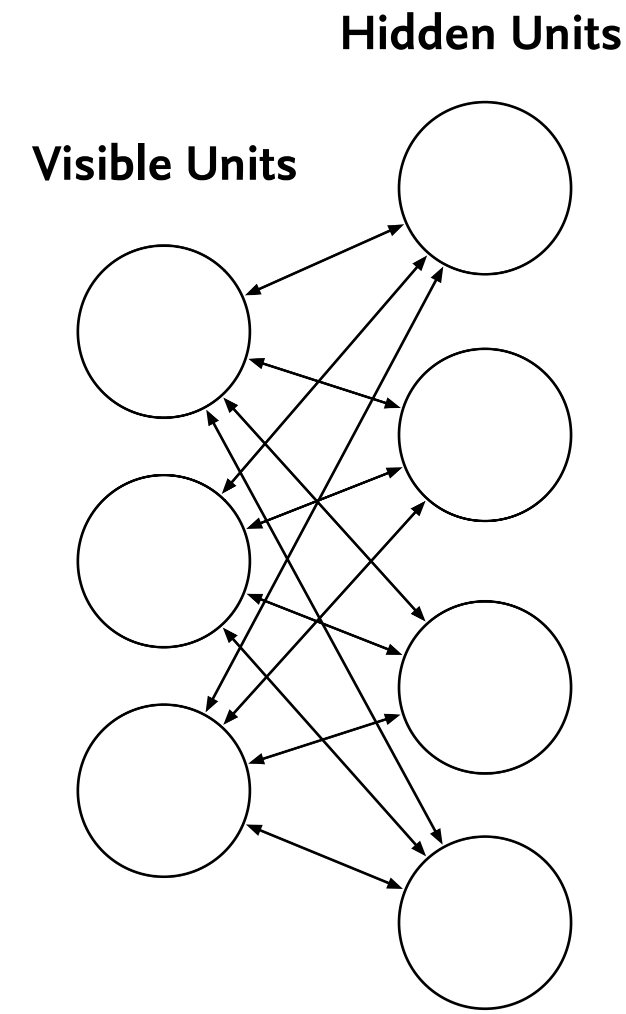
$$\mathcal{L}(x, x') = ||x - x'||^2 = ||x - \sigma_2(W'(\sigma_{1(Wx+b)}) + b')||^2$$

Autoencoder Variations

- **Denoising Autoencoders**
  - Goal is to obtain a good representation
  - Partially corrupted input ➜ train to recover the undistorted input
- **Sparse Autoencoders**
  - Learn useful structures in input data with larger hidden layers
  - Impose sparsity hidden units ➜ learn sparse input representations

Restricted Boltzmann Machine

- **Learn a probability distribution over inputs**
- **Composed of visible and hidden layers**
  - Undirected connections
  - Fully connected
- **Binary unit activation with Bernoulli distribution**
- **Trained through contrastive divergence**



Contrastive Divergence

1. **Positive phase**
   - Input sample x is clamped to the input layer
   - Propagate x to hidden layer resulting in activations h
2. **Negative phase**
   - Propagate h back to visible layer with result x'
   - Propagate $x'$to hidden layer resulting in activations h'
3. **Weight Update**

$$w_{t+1} = w_t + a(xh^T - x'h'^T)$$

Deep Network Architectures

Shallow vs. Deep Architectures

- **Shallow networks have only one hidden layer**
- **Multiple hidden layers required to learn complex functions**
- **Drawbacks**
  - Overfitting
    - Fit training data too well but perform poorly on test data
  - Vanishing gradients
    - Gradients become small in relation to weights
    - Hard for backpropagation to pass info to lower layers

Recent Advancements

- **To prevent overfitting ➜ Dropout**
  - Randomly drop units during training
  - Prevents units from co-adapting too much
- **To prevent vanishing gradients ➜ Greedy layer-wise training**
  - Trains parameters of each layer individually
  - Freeze parameters for the remainder of the model
  - Fine-tuning using backpropagation

Deep Networks

- **Autoencoders and RBMs are effective feature detectors**
- **They can be stacked to form deep networks**
  - Greedily training to avoid vanishing gradient and overfitting
- **Result in powerful learning structures**
  - e.g.: Google deep autoencoders learnt…

Deep Networks

- **Autoencoders and RBMs are effective feature detectors**
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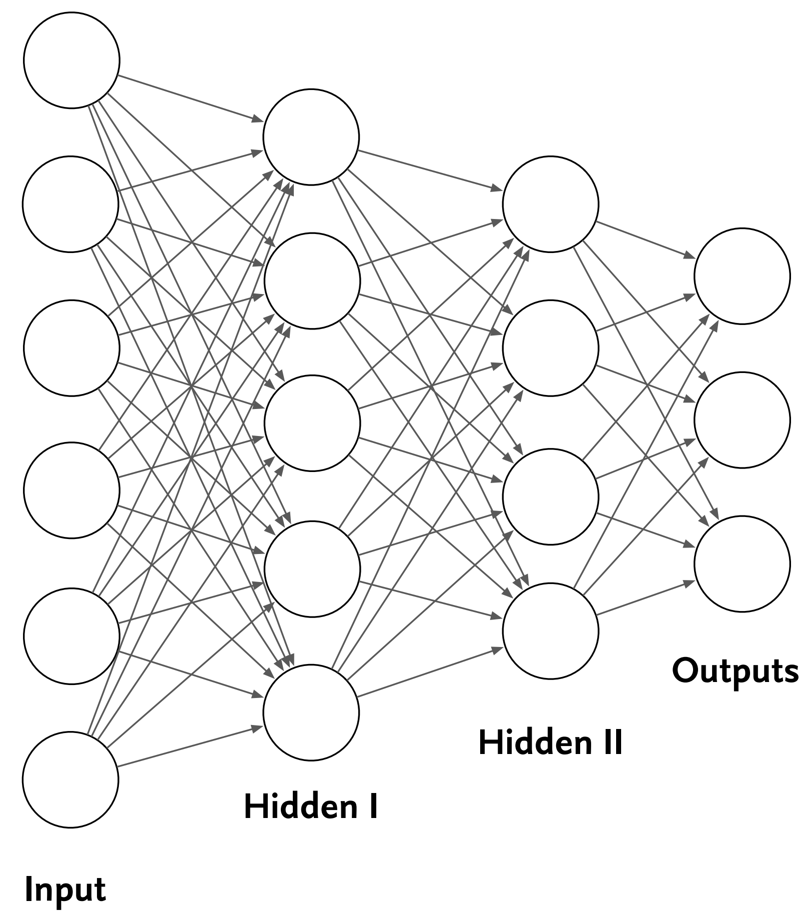
  - Greedily training to avoid vanishing gradient and overfitting
- **Result in powerful learning structures**
  - e.g.: Google deep autoencoders learnt…
    …high-level features from unlabeled data

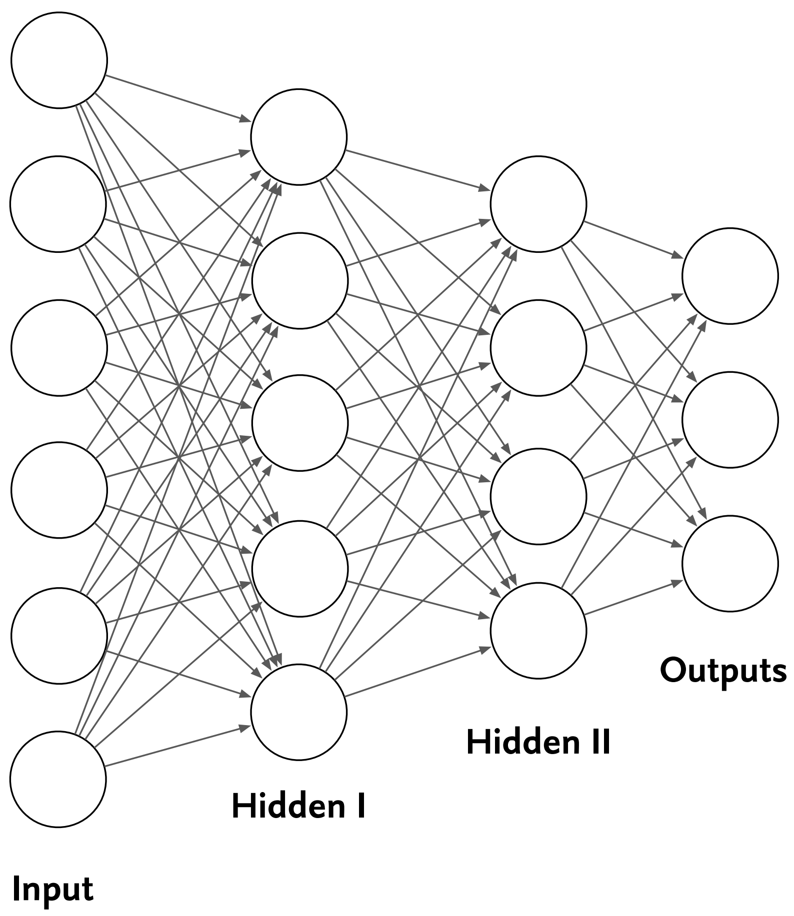
Stacked Autoencoders

- Input layer of first AE is the input layer for the network
- Hidden layer of AE t as input layer to AE t + 1



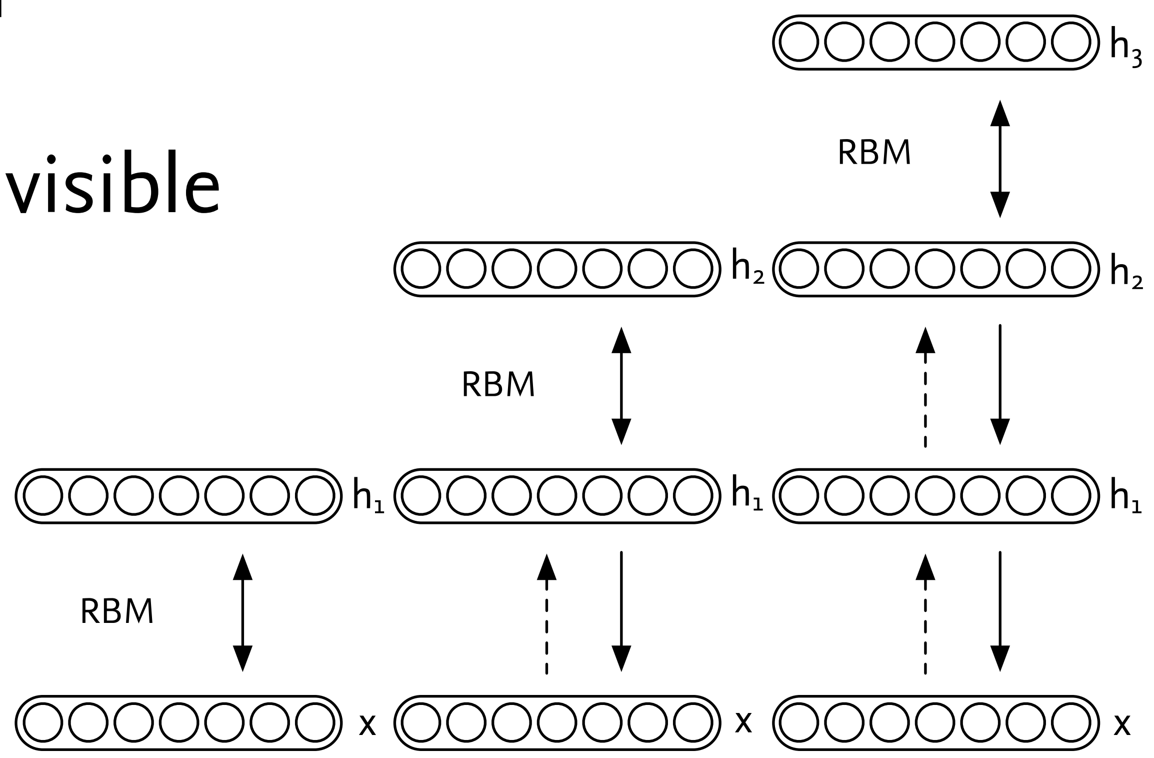
Training Stacked Autoencoders

1. **Train first AE with additional output layer**
   - All training data + backpropagtion
2. **Train second AE with hidden I as input**
   - Propagate sample from input of first AE
   - Update weights using backpropagation
3. **Repeat 1-2 for all layers ➜ pre-training**
4. **Add one fully connected layer and train with BP ➜ fine-tuning**



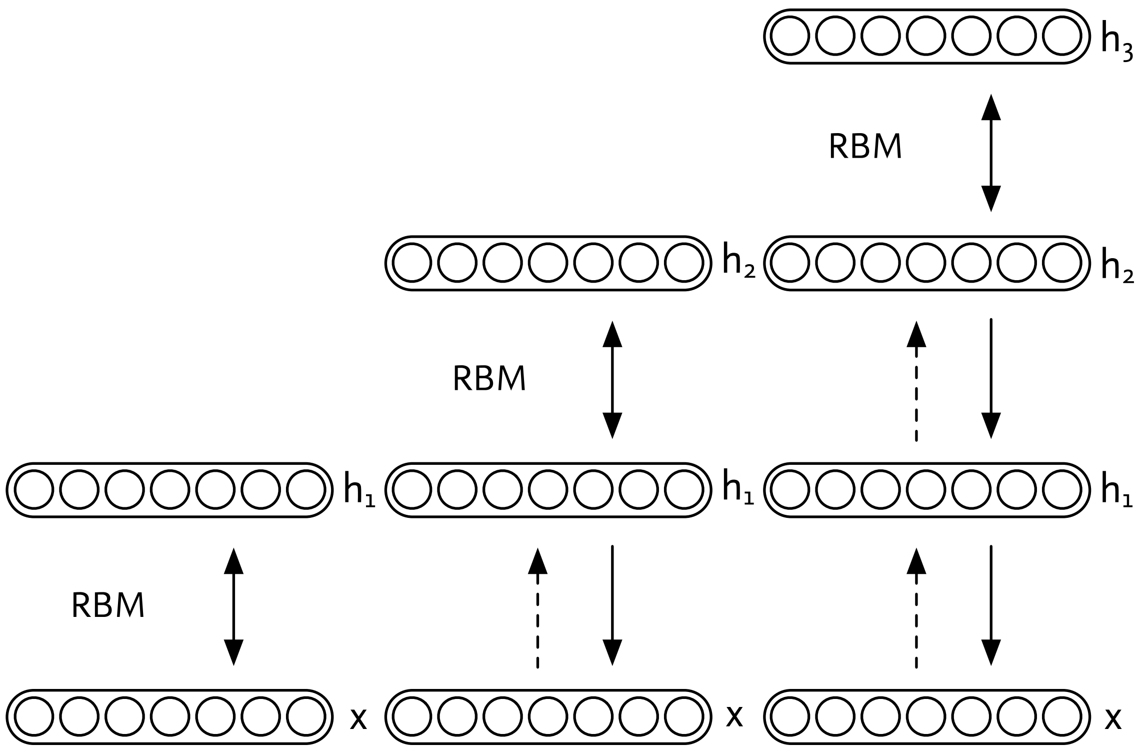
Deep Belief Networks

- **Stacked Restricted Boltzmann Machines**
  - Input layer of first RBM is the input layer for the network
  - Hidden layer of RBM t becomes visible layer of RBM t + 1



Training Deep Belief Networks

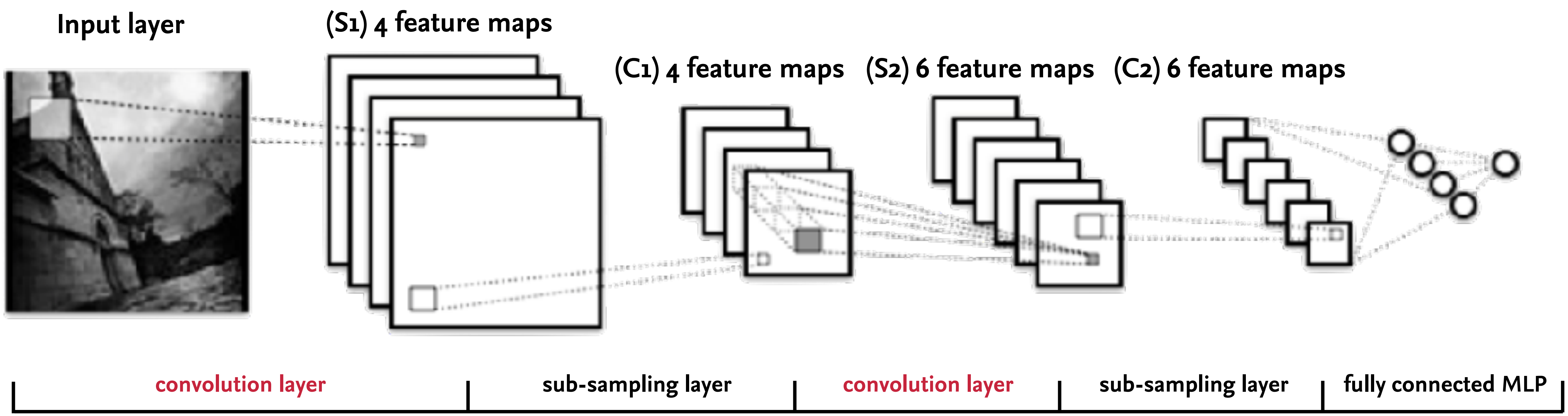
1. Train first RBM using contrastive divergence
2. Train second RBM with hidden 1 as visible layer
3. Repeat 1-2 for all layers
4. Add one fully connected layer and train with BP



Convolutional Networks

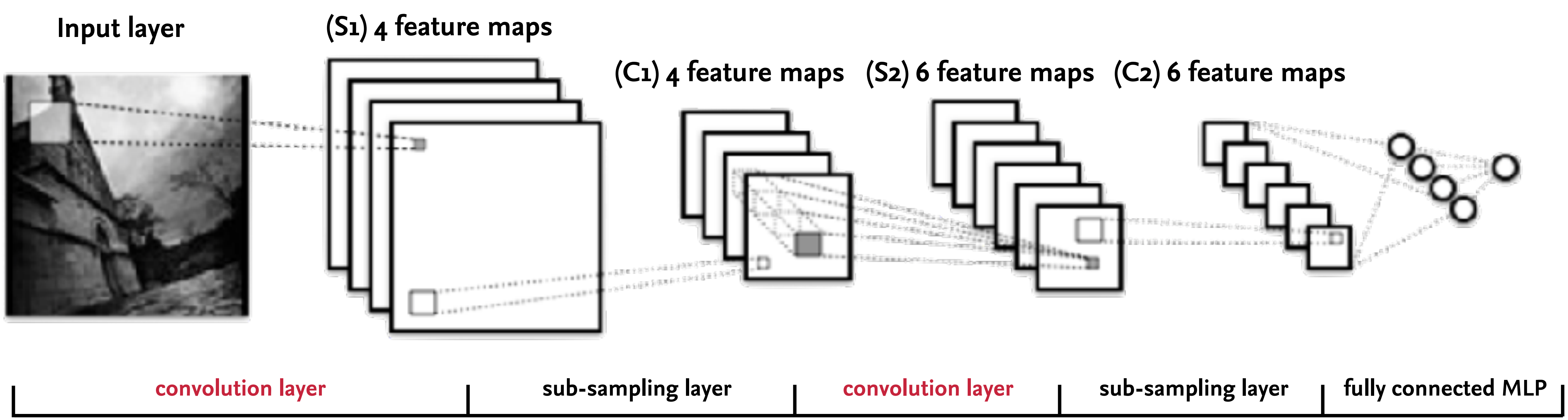
- **Feedforward non-recurrent neural network**
- **Specially suited for image recognition**
- **Based on the concept of filters**

Convolution Layers



- Apply a number of filters to input
- Results of a filter applied to the image is a feature map

Convolution Layers



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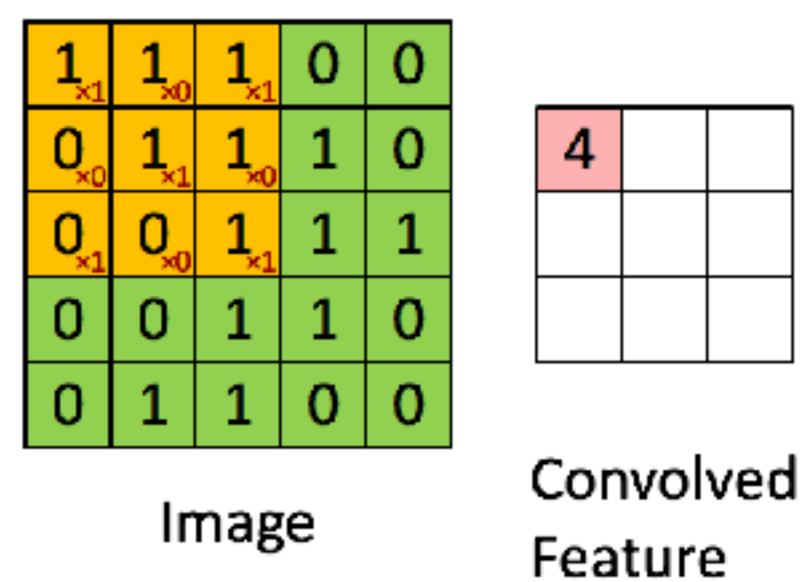
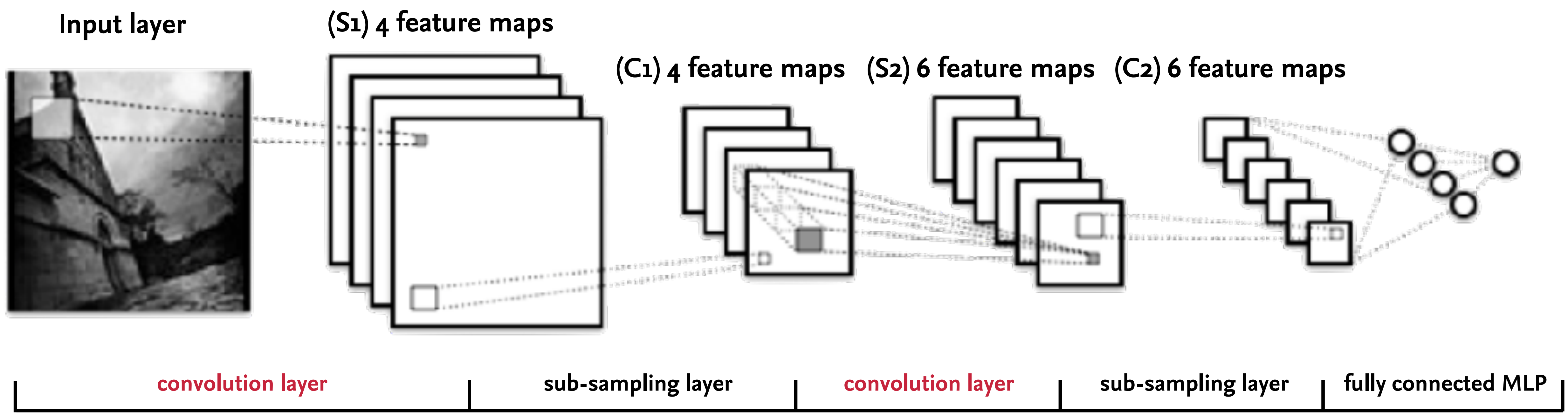


Convolution Layers



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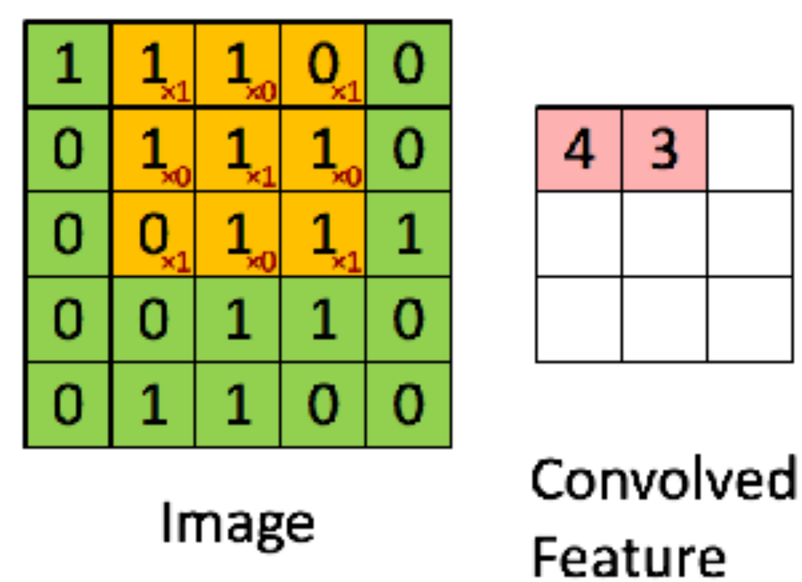

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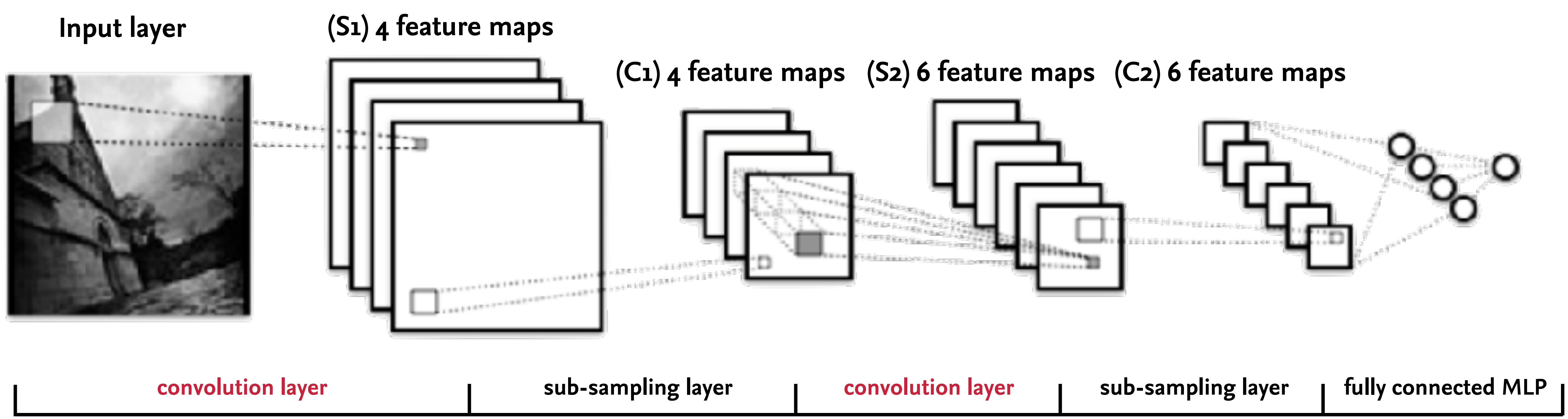

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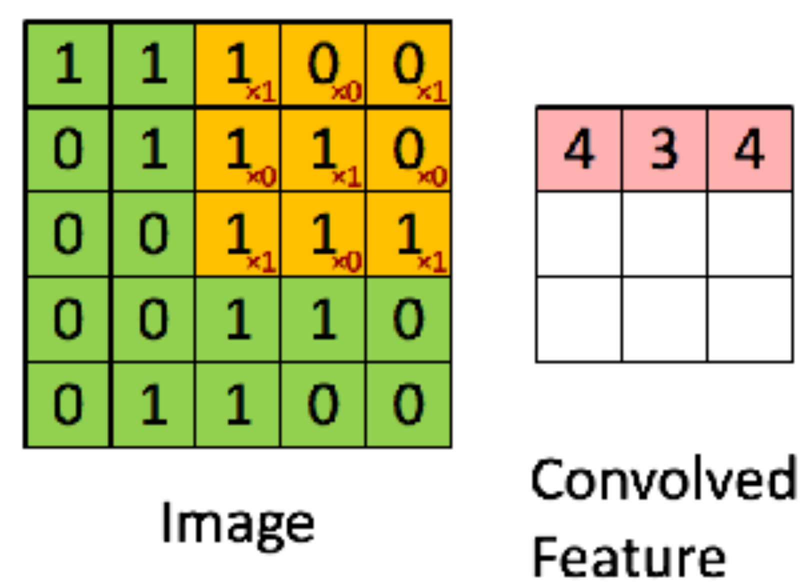

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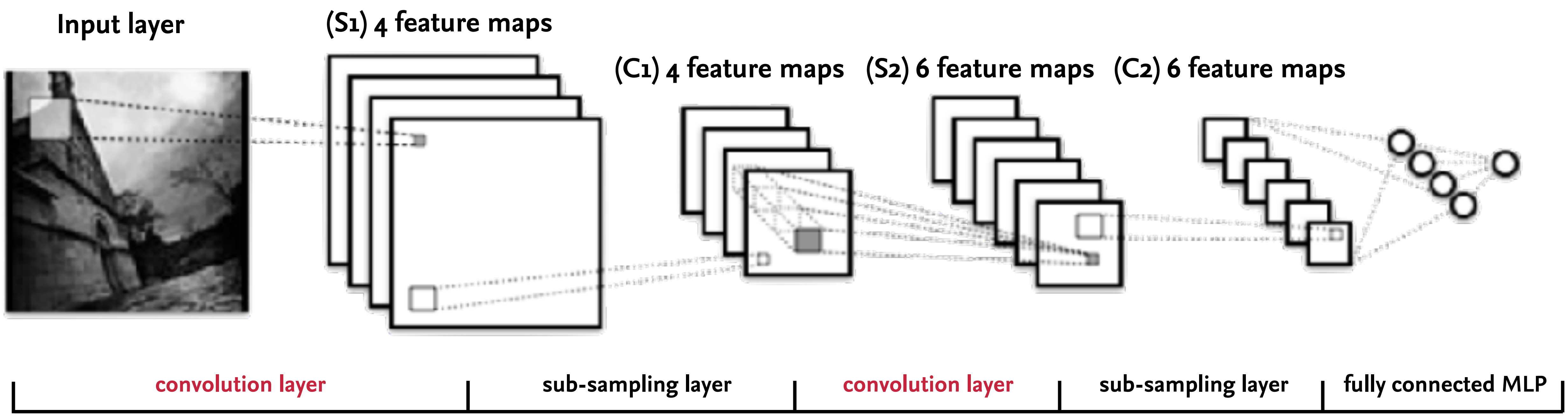

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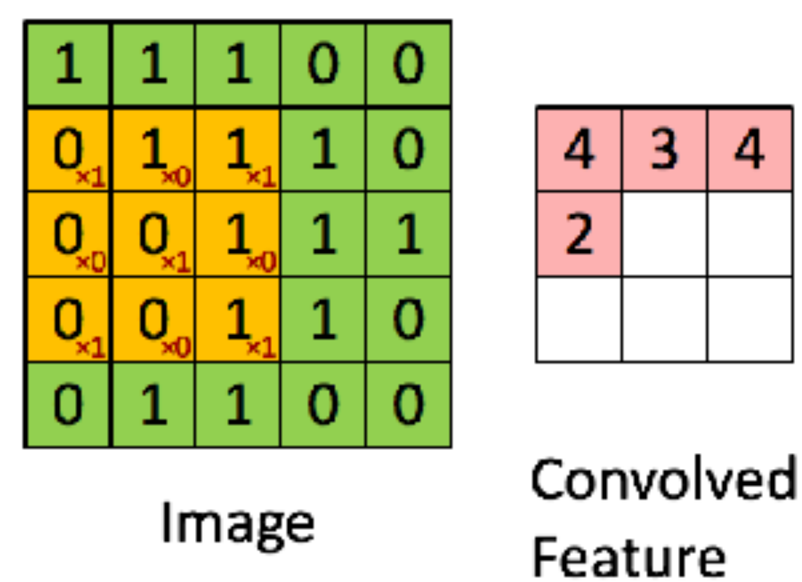

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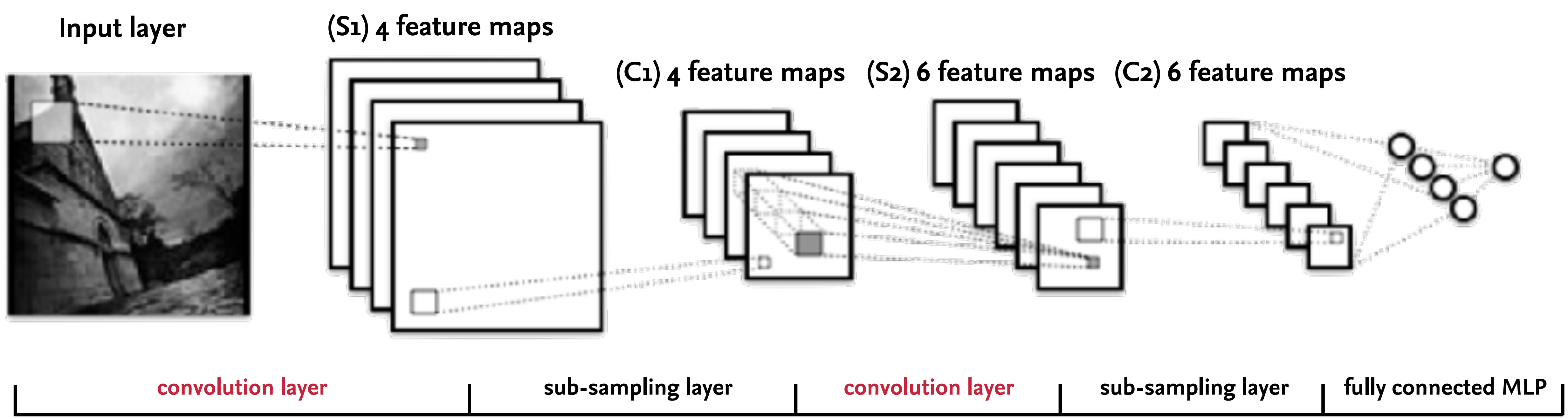

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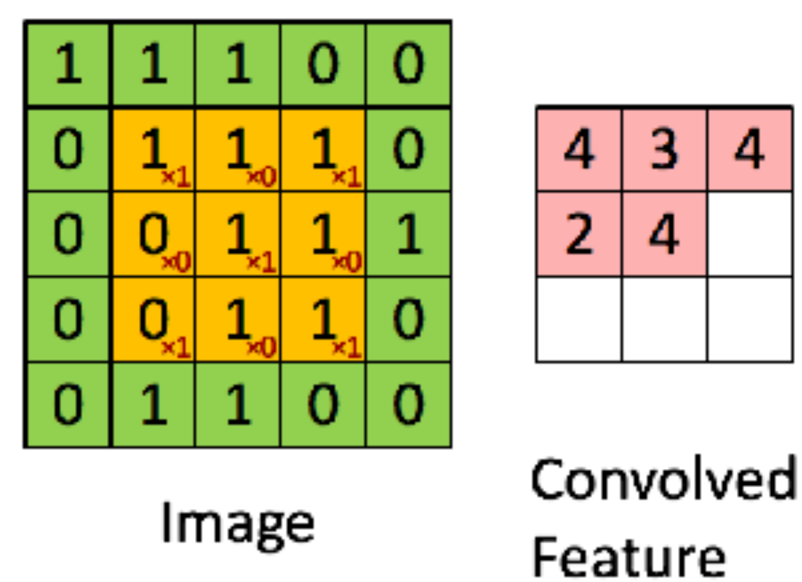

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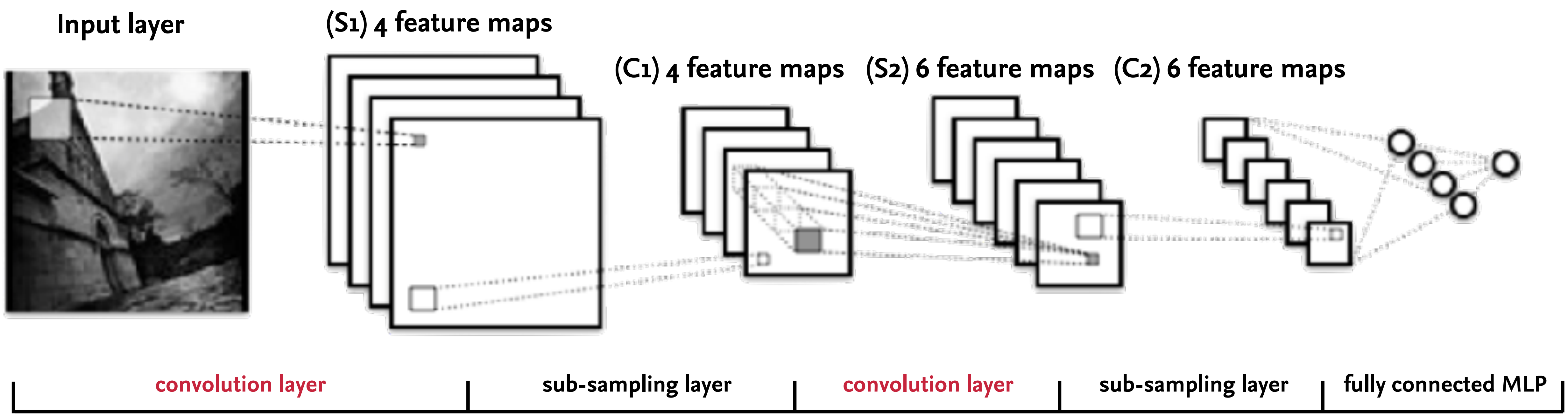

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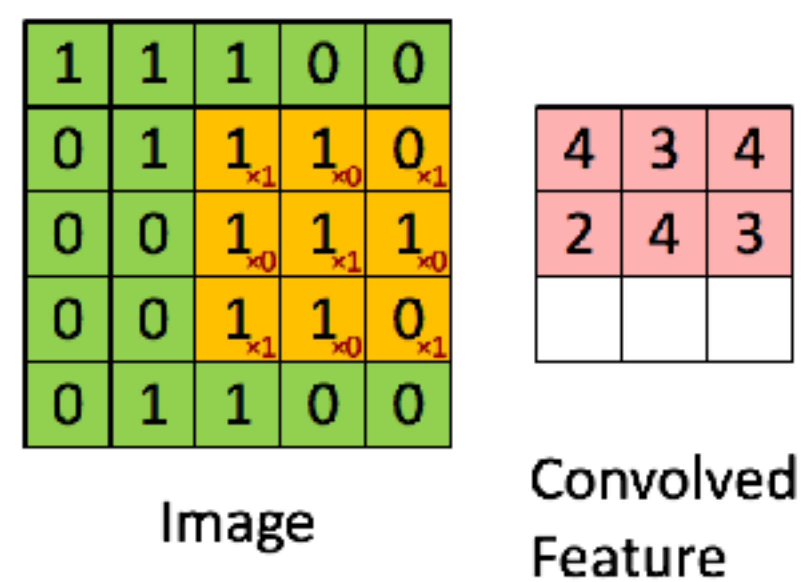
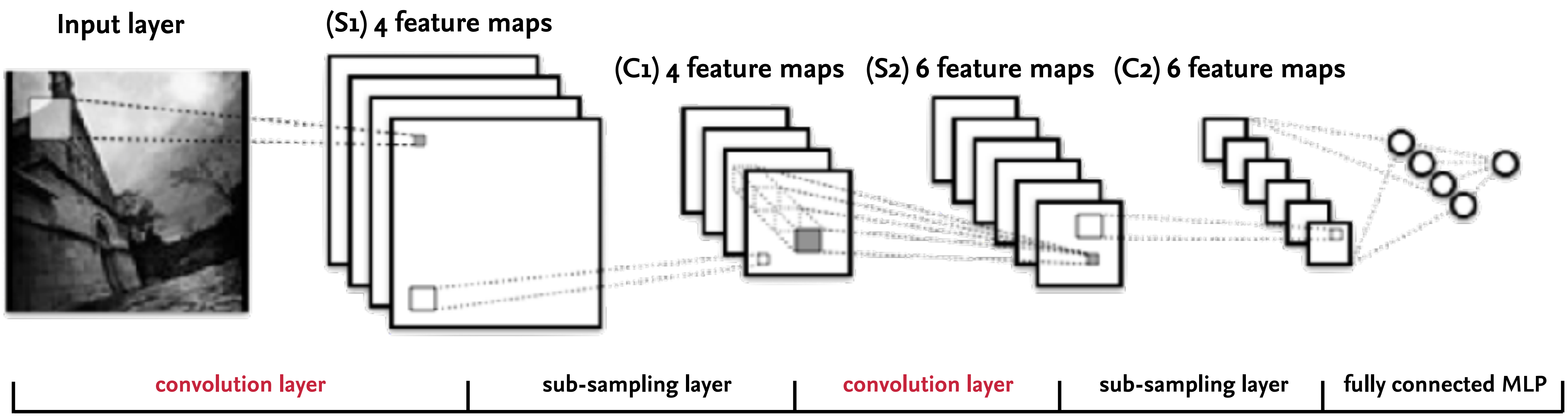


Convolution Layers



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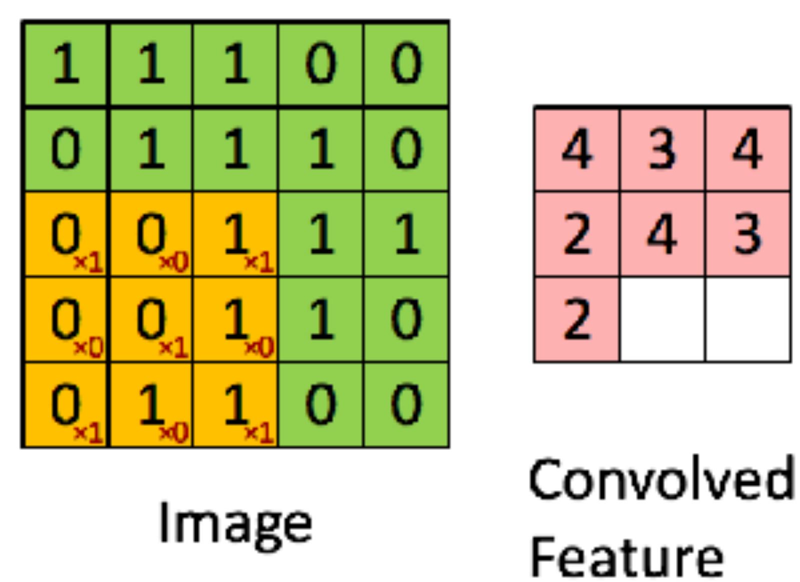
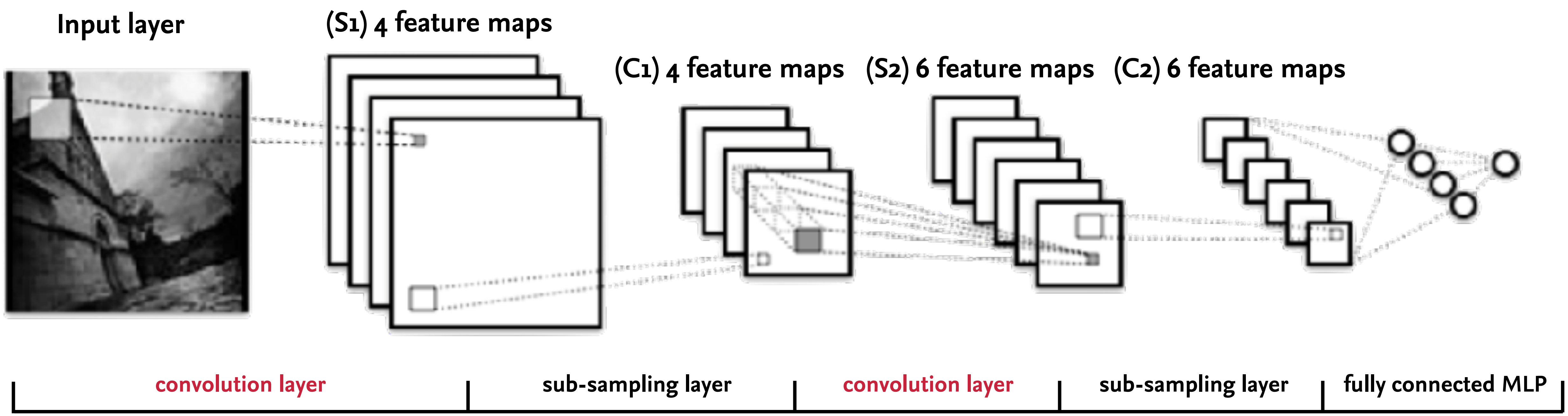


Convolution Layers



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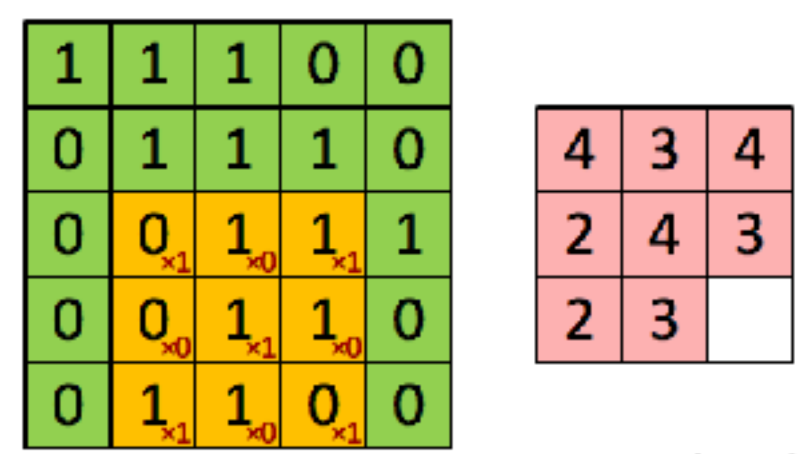
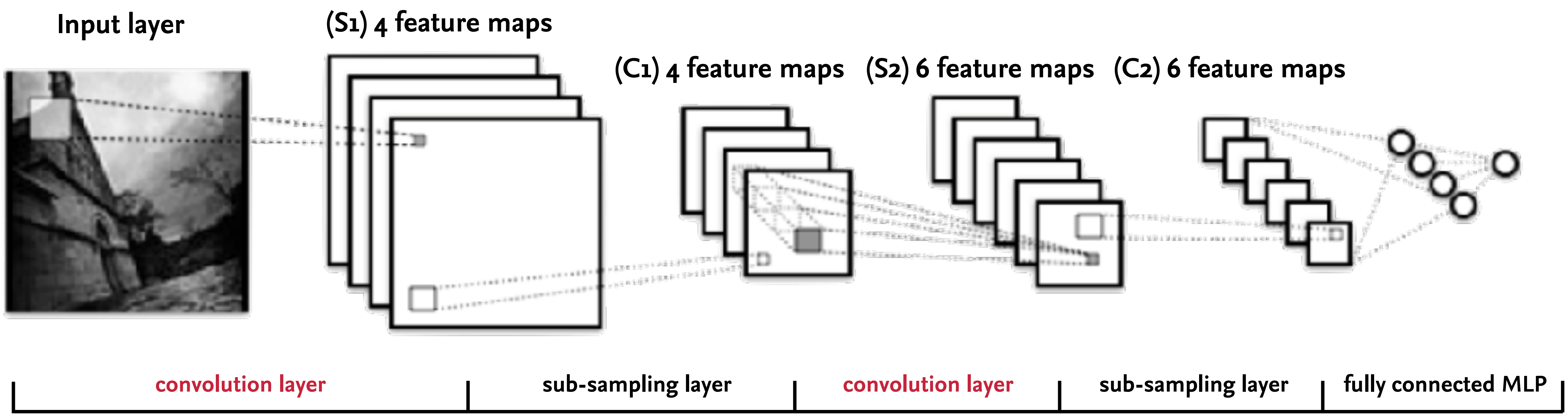


Image

Convolved Feature

Convolution Layers



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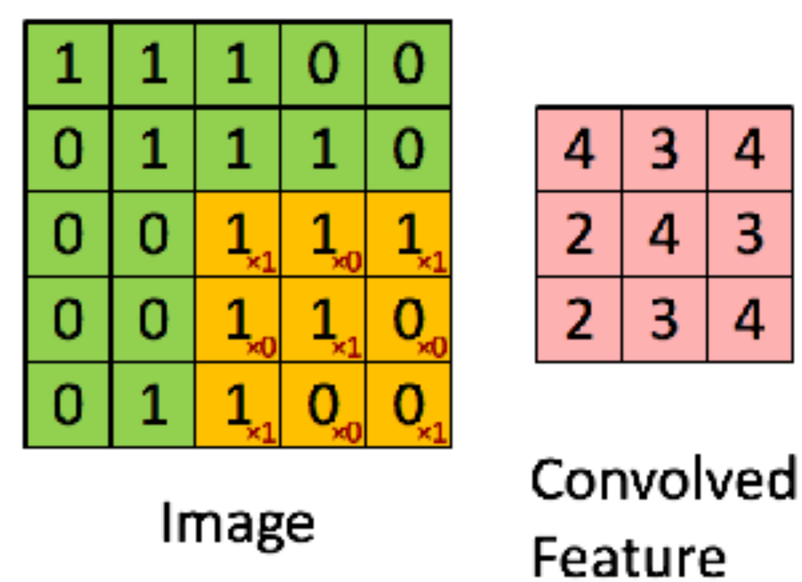
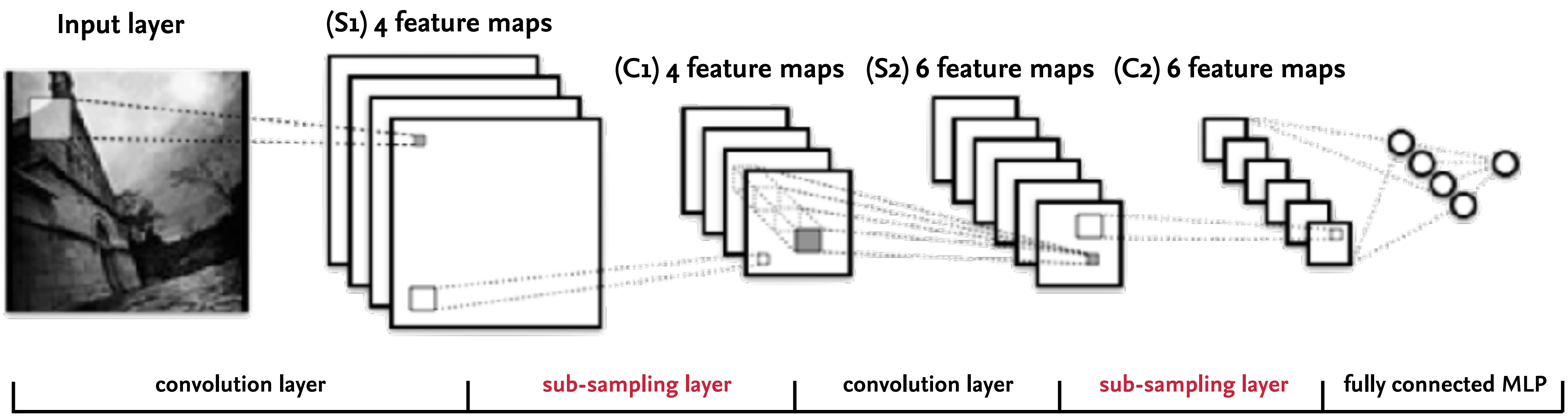
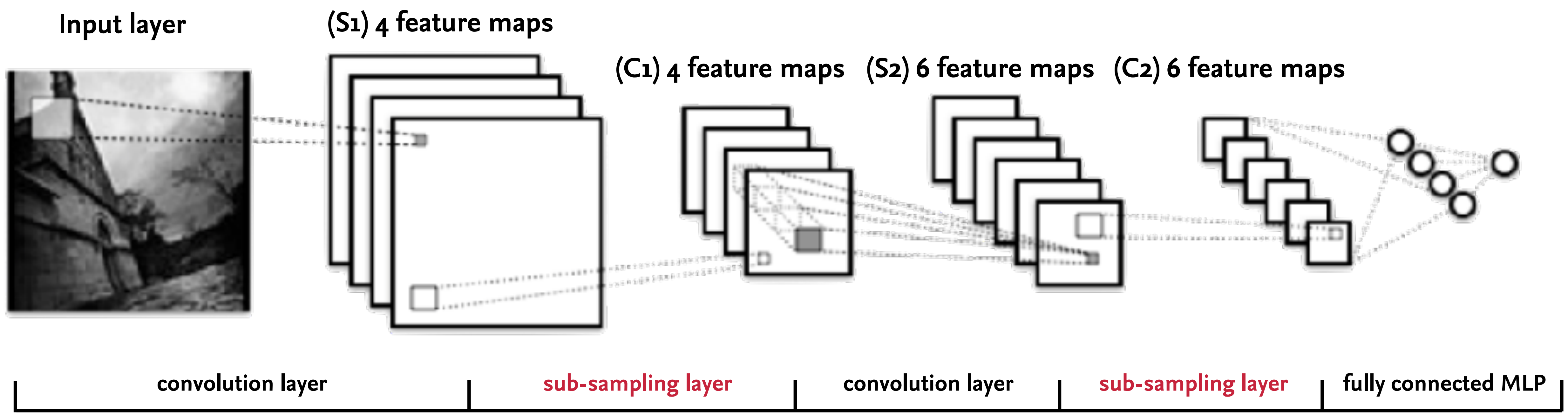


Sub-sampling Layers

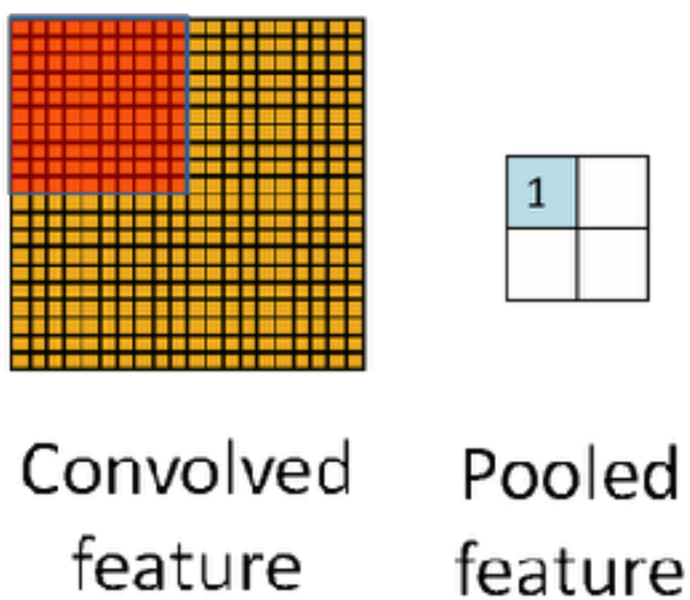


- Reduce the size of the input
- Max pooling, average pooling, stochastic pooling, etc

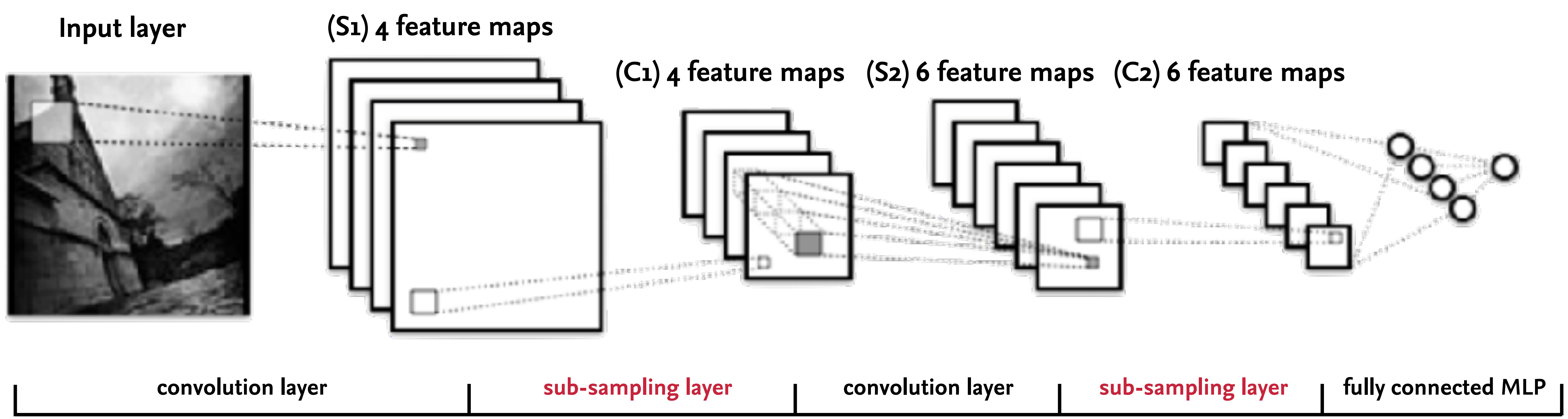
Sub-sampling Layers



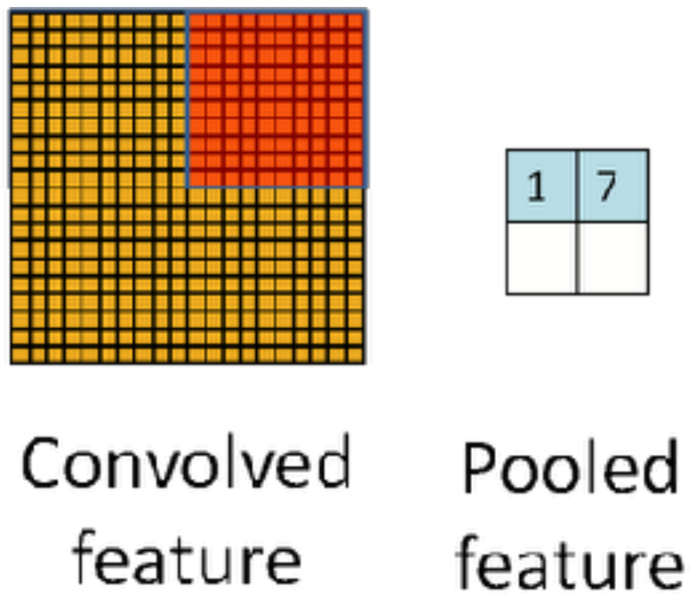
- **Reduce the size of the input**
- **Max pooling, average pooling, stochastic pooling, etc**



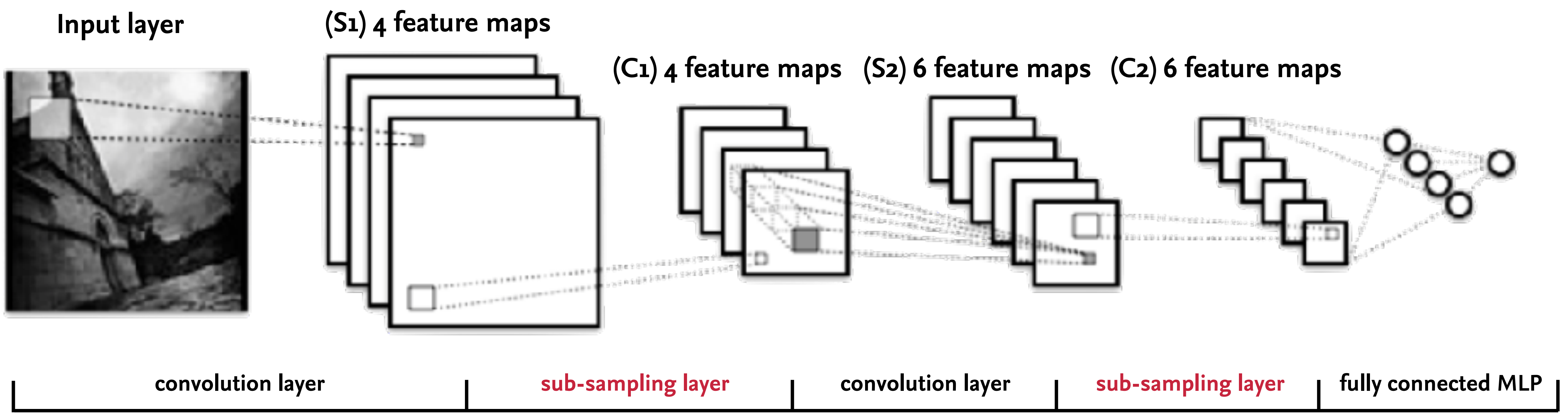
Sub-sampling Layers



- Reduce the size of the input
- Max pooling, average pooling, stochastic pooling, etc



Sub-sampling Layers



- Reduce the size of the input
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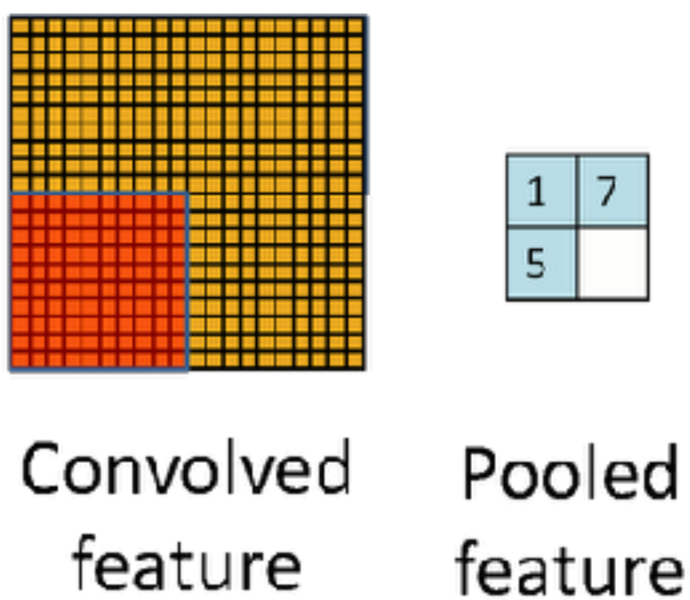
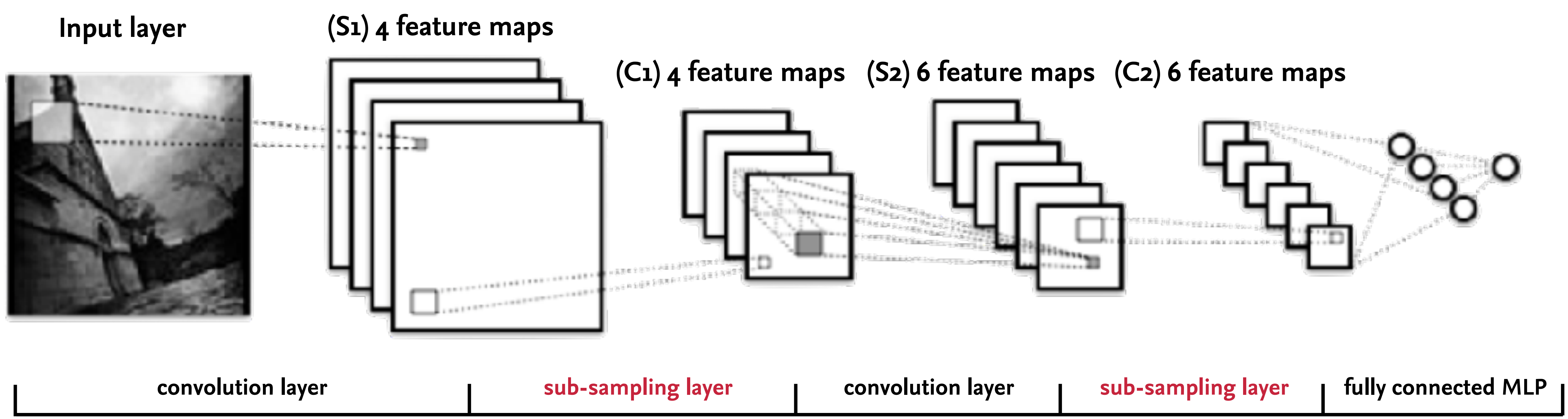
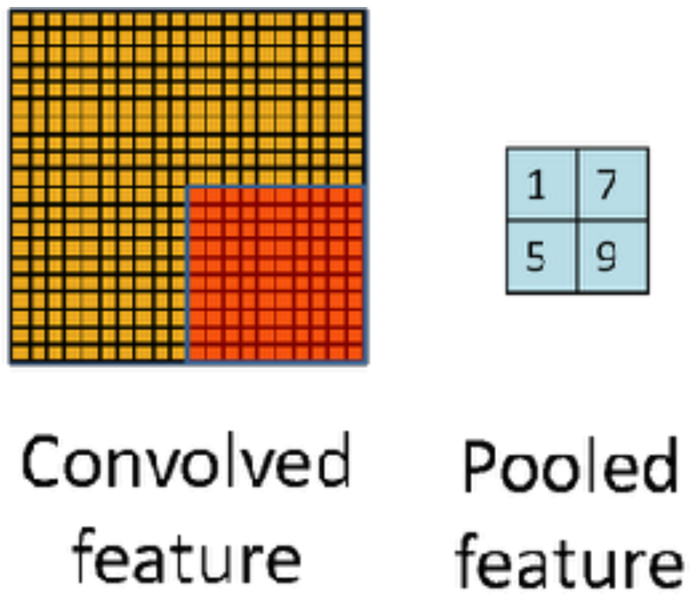


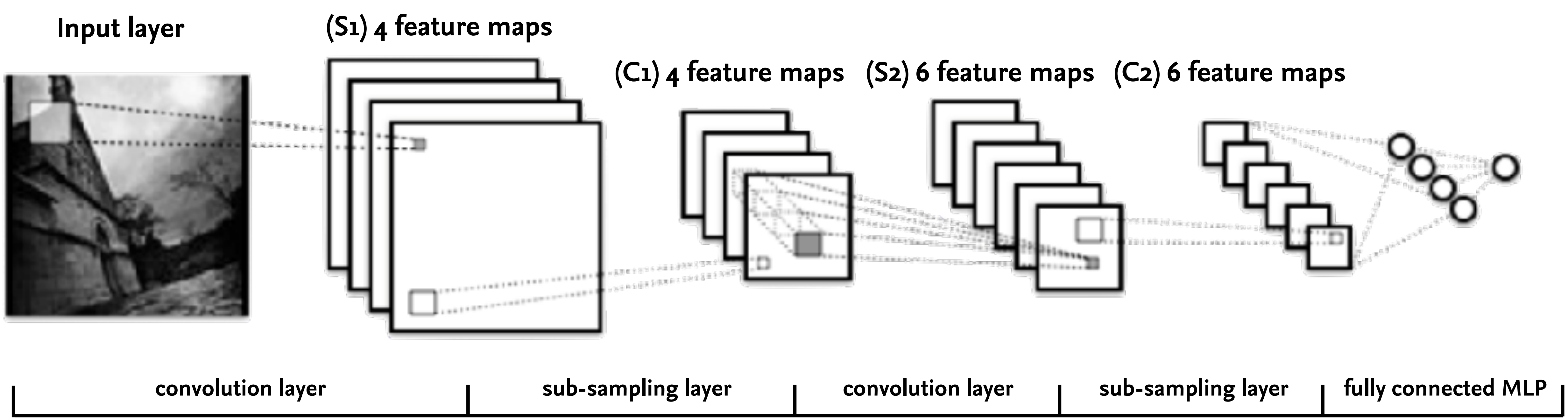
Sub-sampling Layers



- **Reduce the size of the input**
- **Max pooling, average pooling, stochastic pooling, etc**



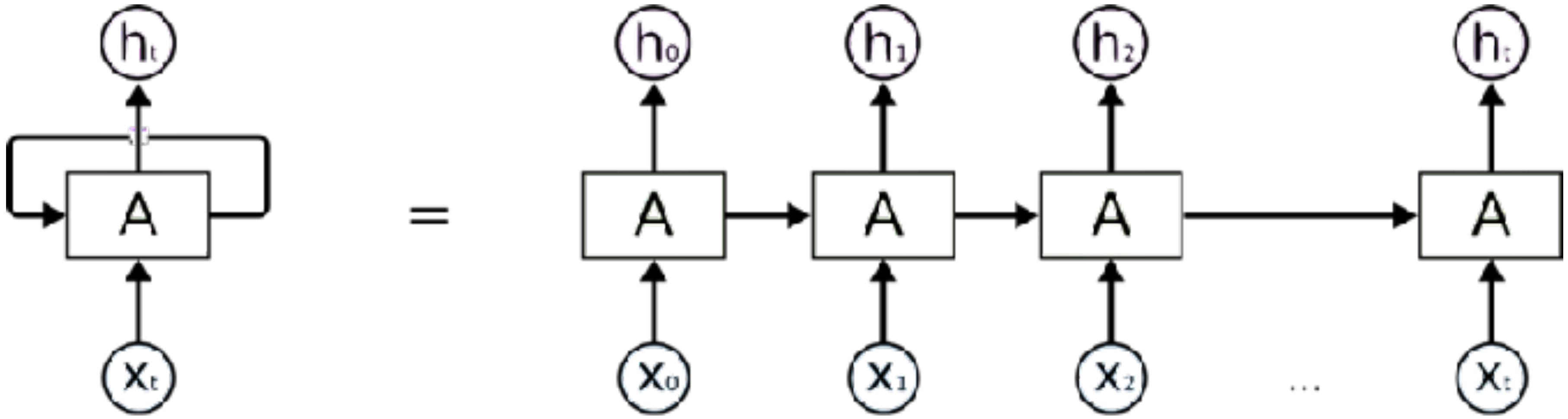
Convolutional Networks



- **Training**
  - Backpropagation
  - Consider sub-sampling values
  - Update weights of convolutional filters

Recurrent Neural Networks

- Neurons connections form a directed graph along a sequence
- Input is ordered (e.g. time)
- Specially suited for speech recognition



Deep Learning for Malware Analysis and Detection

Current Research

- **Recent new interest in neural networks and security**
- **Applications of learning algorithms to security problems**
  - Prevention of fraud and abuse
  - Malware detection and analysis
  - Vulnerability discovery
  - ...
- **Security of learning algorithms**
  - Adversarial learning (e.g. evasion of NN, GANs)

Malware Characterization

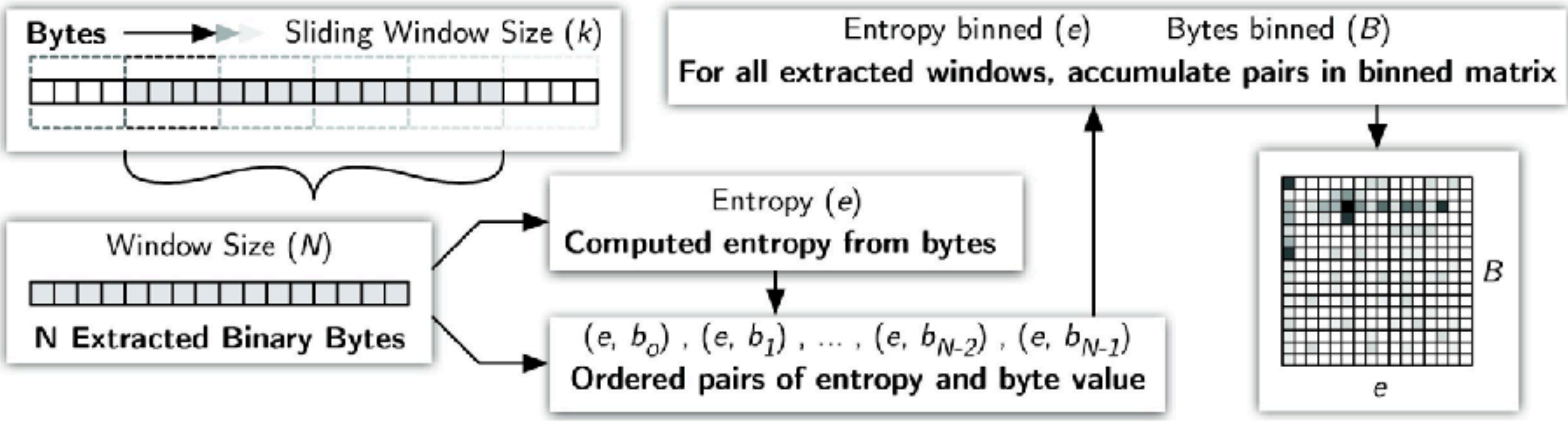
- **General approach for learning**
  - Fixed size input vector representation of malware behavior
- **Low-level raw features or high-level feature engineering?**
  - Bytes: Shannon Entropy, Bytes N-grams, Strings…
  - Code: Instruction N-grams, Function, Calls, Branches…
- **Neural networks assume spatial and temporal structure**
  - Pixels in image data
  - Audio samples in spoken language

Spatial Structure in x86 Instructions

- **Static analysis ➜ raw binary code as images**

Spatial Structure in x86 Instructions

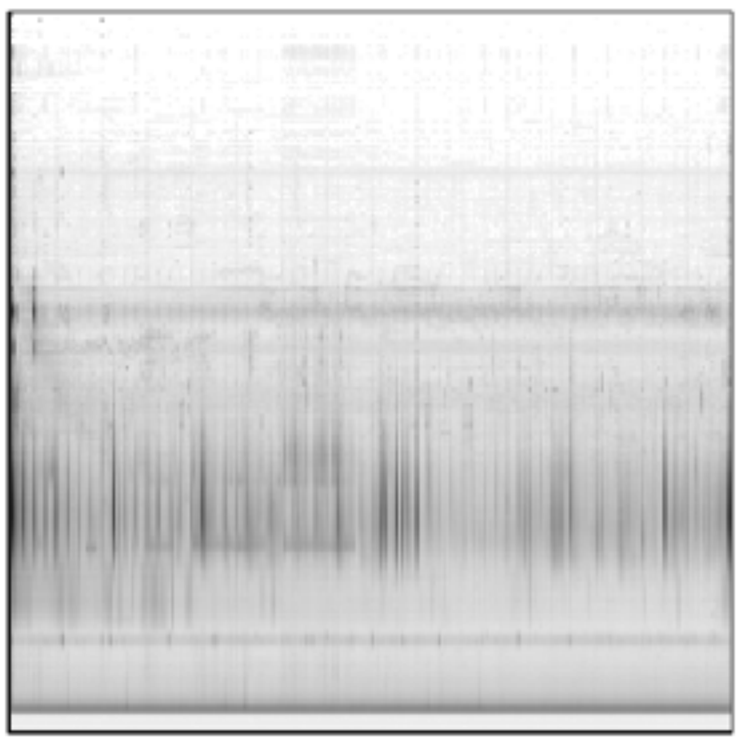
- **Static analysis ➜ raw binary code as images or matrices**



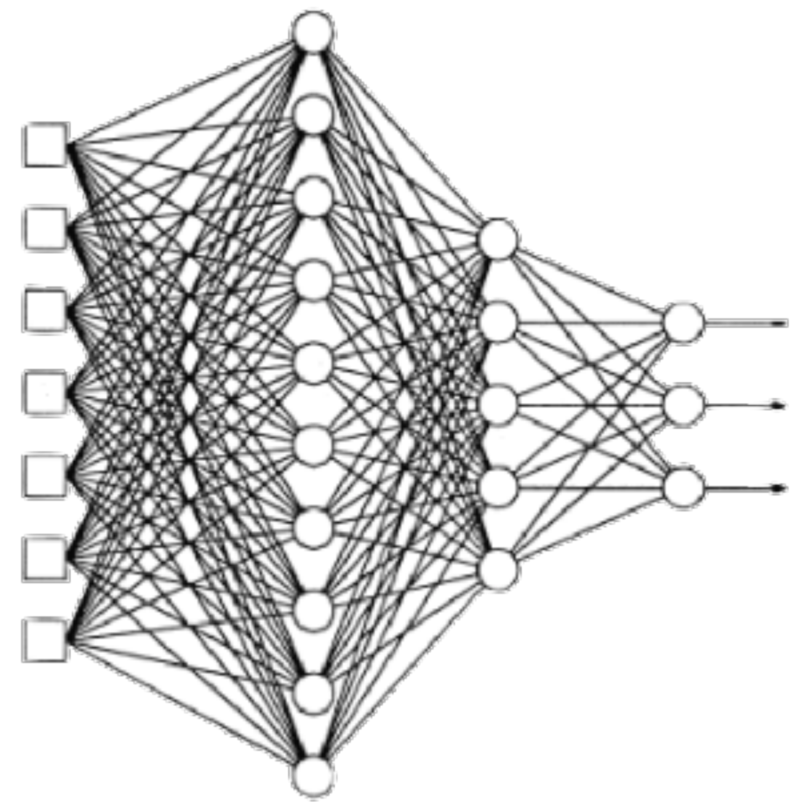
Spatial Structure in x86 Instructions

- **Static analysis ➜ raw binary code as images or matrices**

Shannon Entropy



Bytes

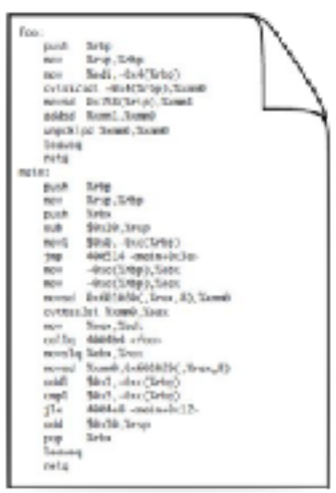


MLP

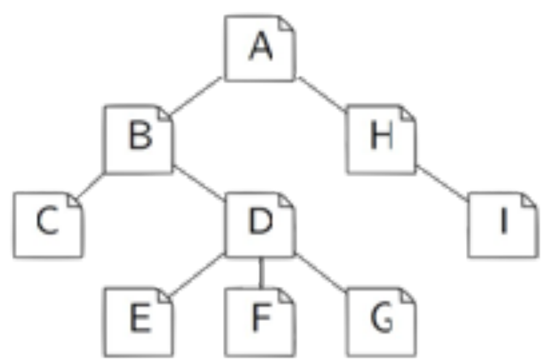
Spatial Structure in Code Graphs

- Static analysis ➜ Raw binary code as graphs

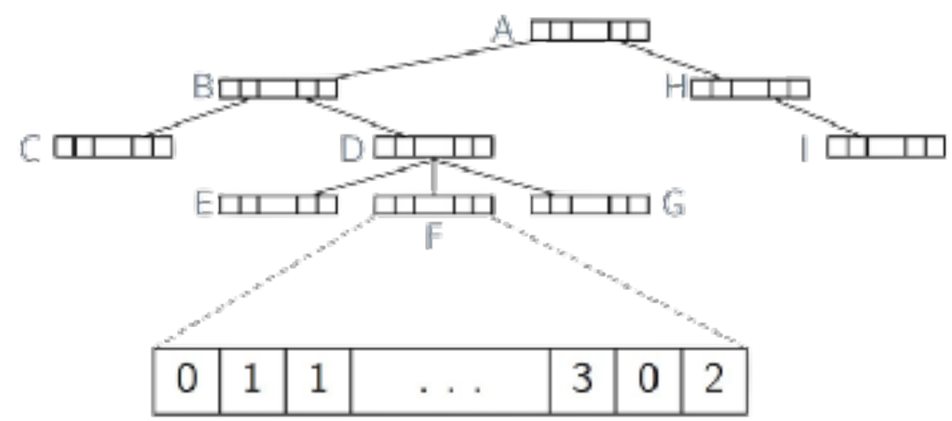
Binary Code



Call graphs
Control flow graphs
Dependency graphs

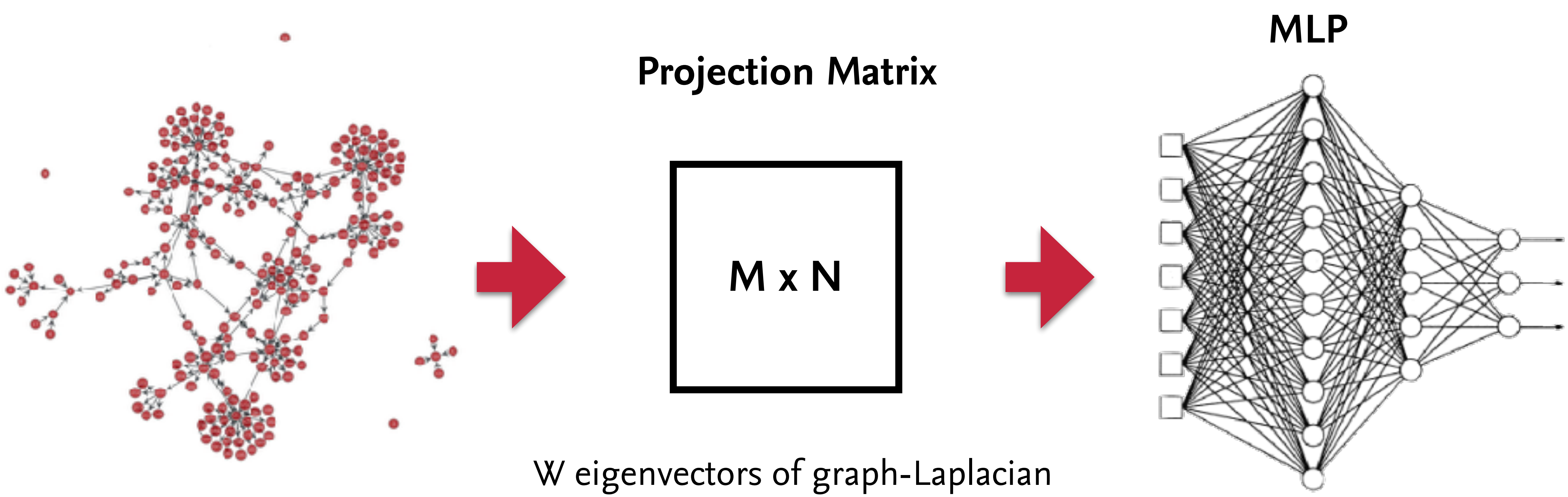


Features from Graphs



Spatial Structure in Code Graphs

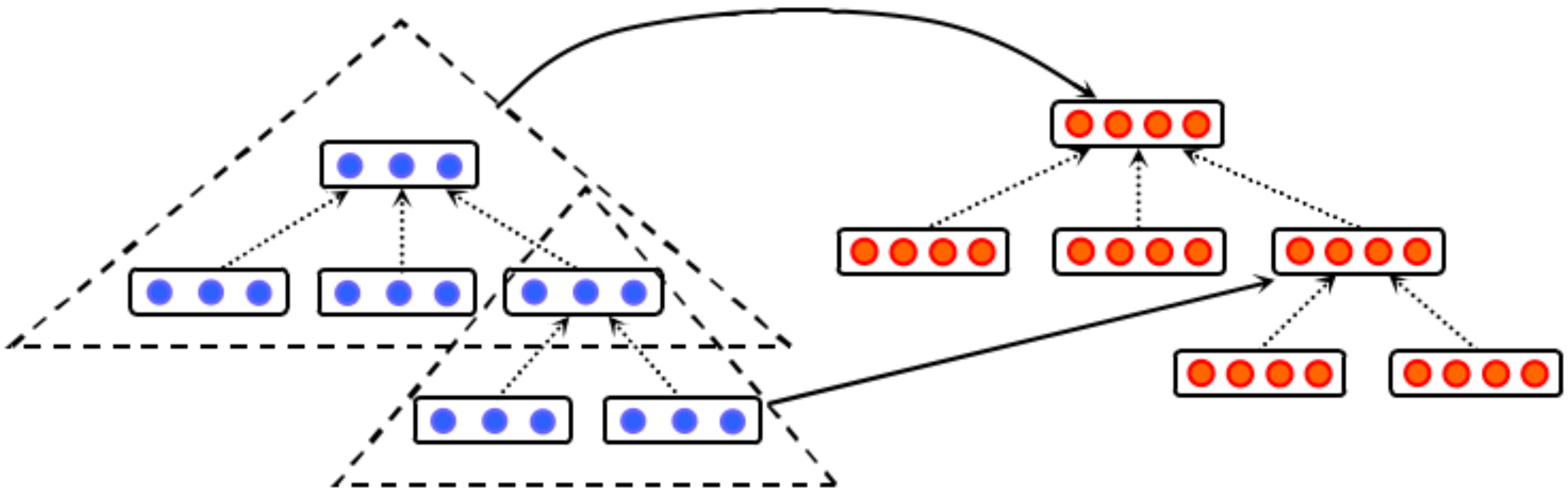
- **Static analysis ➜ Raw binary code as graphs**



W eigenvectors of graph-Laplacian
N dimensions from node feature vectors

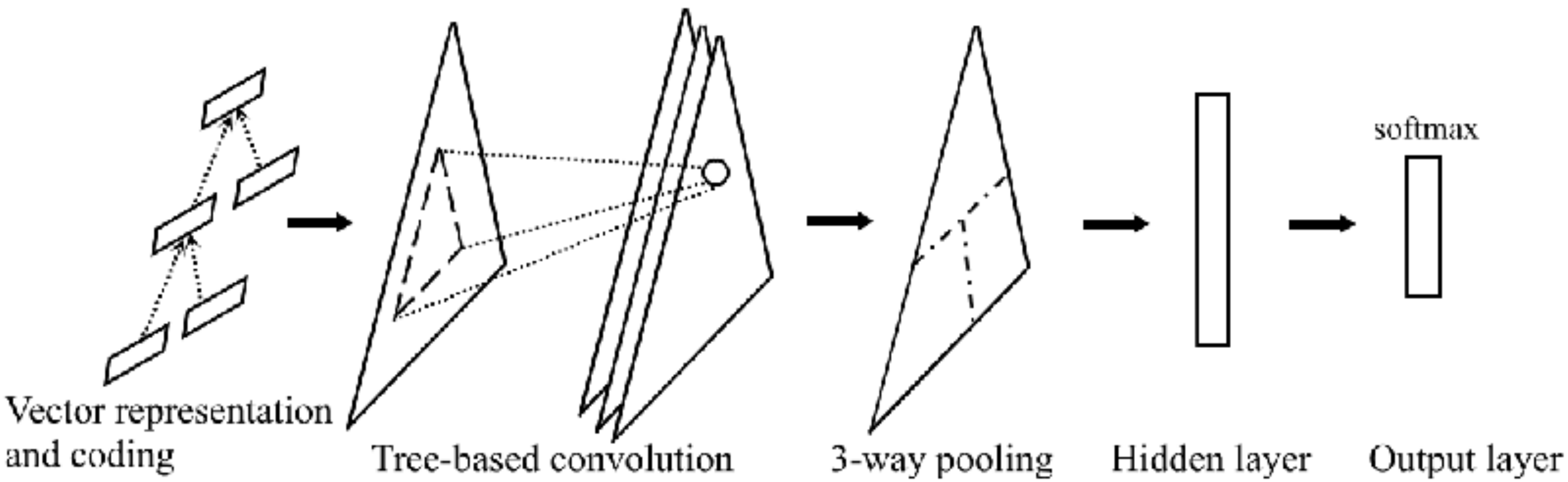
Spatial Structure in Code Graphs

- **Tree-based convolution**



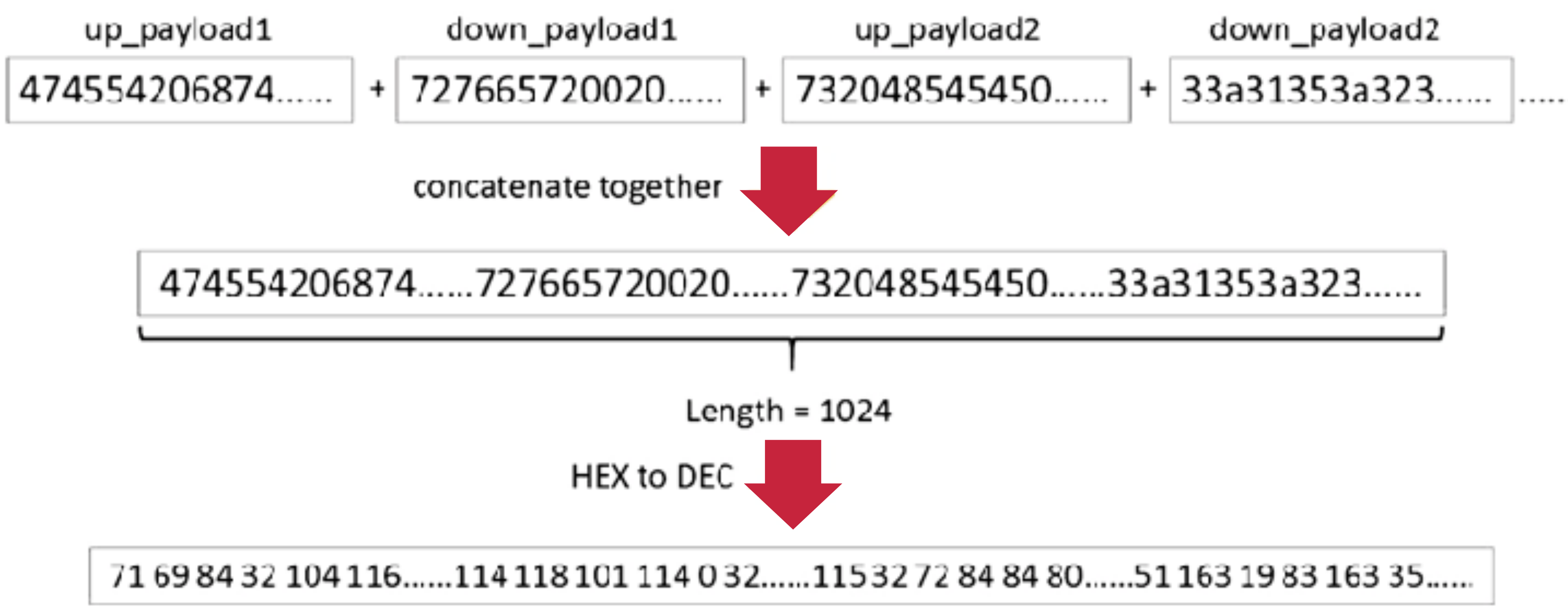
Spatial Structure in Code Graphs

- **Tree-based convolutional network**



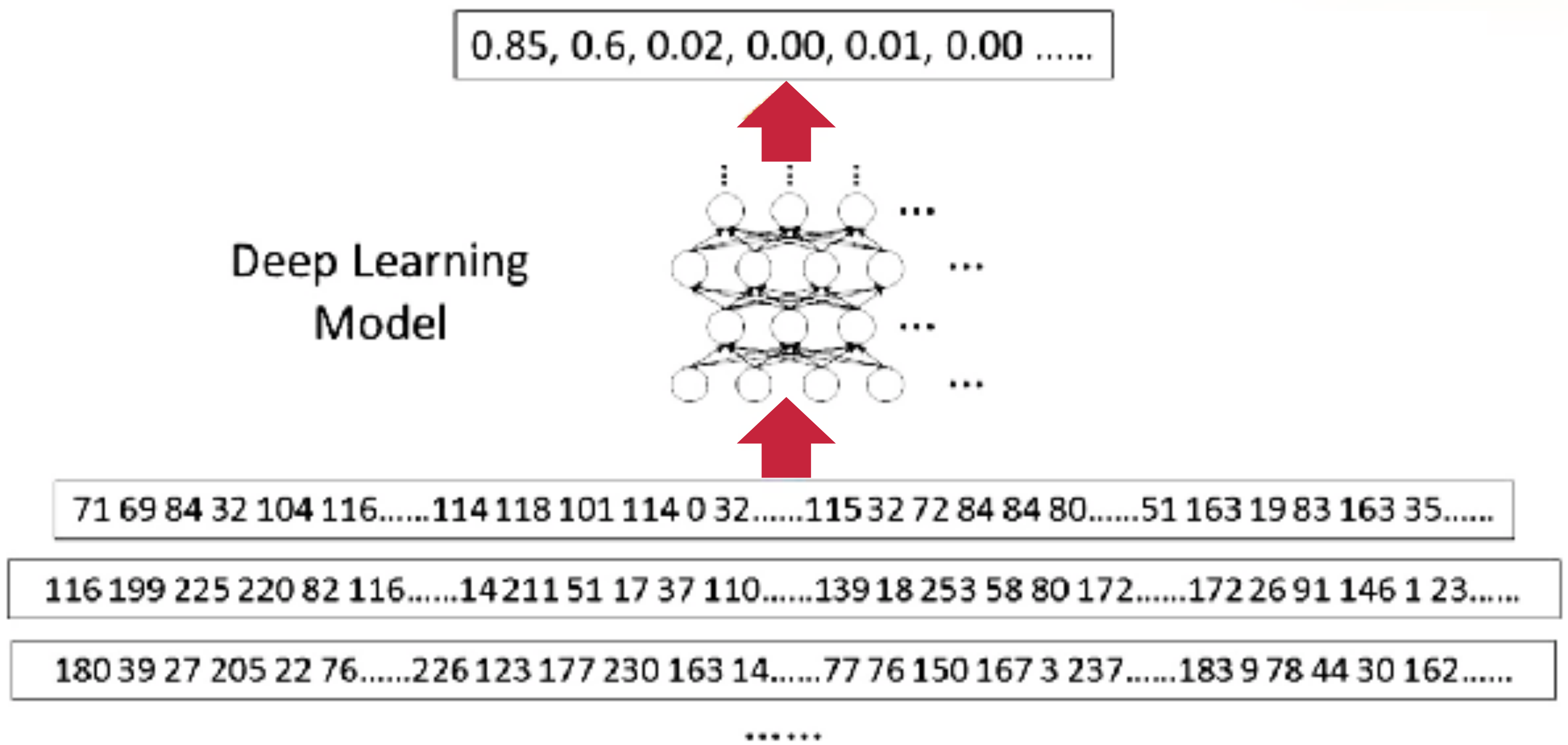
Temporal Structure in Malware Behavior

- **Dynamic analysis ➜ network payloads in 1024-dim vectors**



Temporal Structure in Malware Behavior

- **Feed deep stack autoencoders to predict protocol type**



Protocol classification ➜ 97.9% avg. precision
Application identification ➜ 96.3% avg. precision

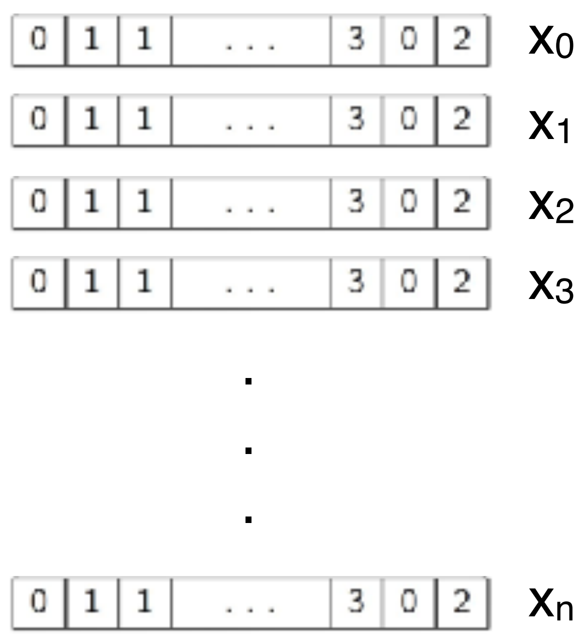
Temporal Structure in Malware Behavior

- **Dynamic analysis ➜ System behavior + RNN**

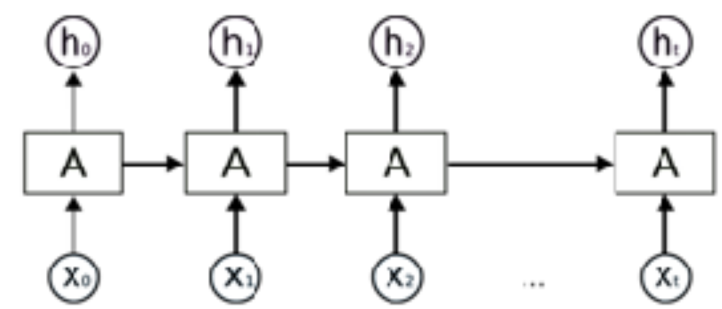
Execution in VM

Execution Time
Total processes
Max. Process ID
CPU User (%)
CPU System (%)
Memory Use (MB)
Swap Use (MB)
Packets Received
Packets Sent
Bytes Received (MB)
Bytes Sent (MB)

Feature Vectors in Time



RNN



Challenges & Limitations

Problems	Solutions
Non-stationarity	Retraining Highly generalizable models (more data, more diverse) Human Feedback
Lack of Ground Truth	Clustering Methods Honeypots GAN's
Ambiguous Data & Taxonomy	Model Context Personalized Models Human Feedback
Lack of Obvious Features	Model Context Temporal Behavior Anomaly Detection

Tutorials & Tools

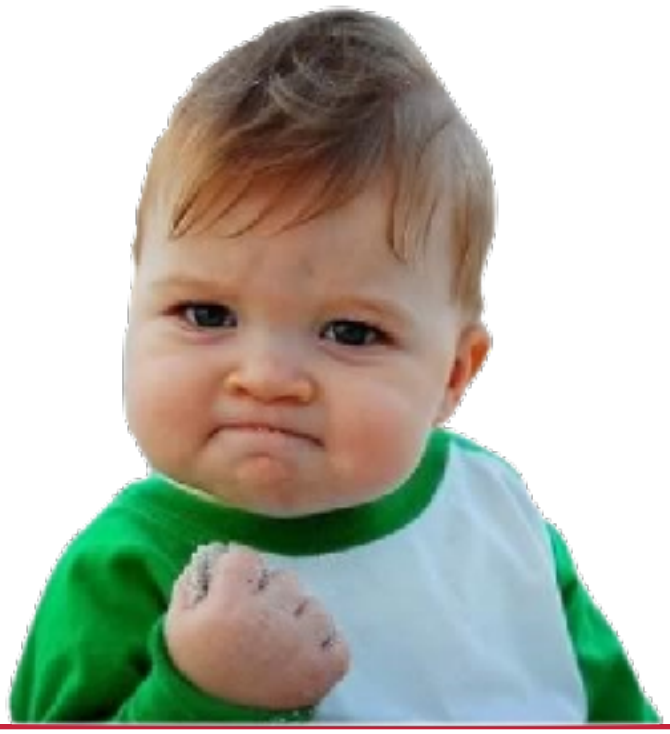
- **Many introductory tutorials and How-To's**
  - http://deeplearning.net/reading-list/
- **Well documented and open source frameworks**

Framework	Language	Type	Developed @
TensorFlow	Python interface	back-end	G
PYTORCH	Python interface	back-end	f
K Keras	Python	front-end	G

Summary

- **Neural Networks & Deep Learning**
  - Deep nets ➜ stacked autoencoders and RBMs
  - Efficient learning with **greedy layer-wise training** and **dropout**

- **Lots of hope for new security applications**
  - Opportunity for smarter **representations**
  - and **large-scale** approaches



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