

# DM825 (5 ECTS - 4th Quarter)

## Introduction to Machine Learning

Introduktion til maskinl ering

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# Machine Learning

A **computer program** is said to **learn** from experience  $E$  with respect to some class of tasks  $T$  and performance measure  $P$ , if its performance at tasks in  $T$ , as measured by  $P$ , improves with experience  $E$ .

Tom M. Mitchell (1997) Machine Learning p.2

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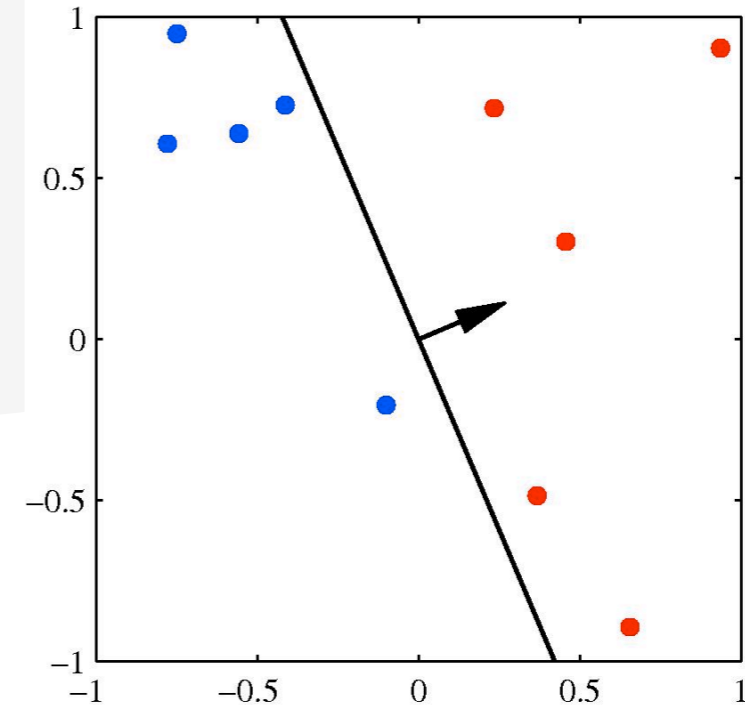
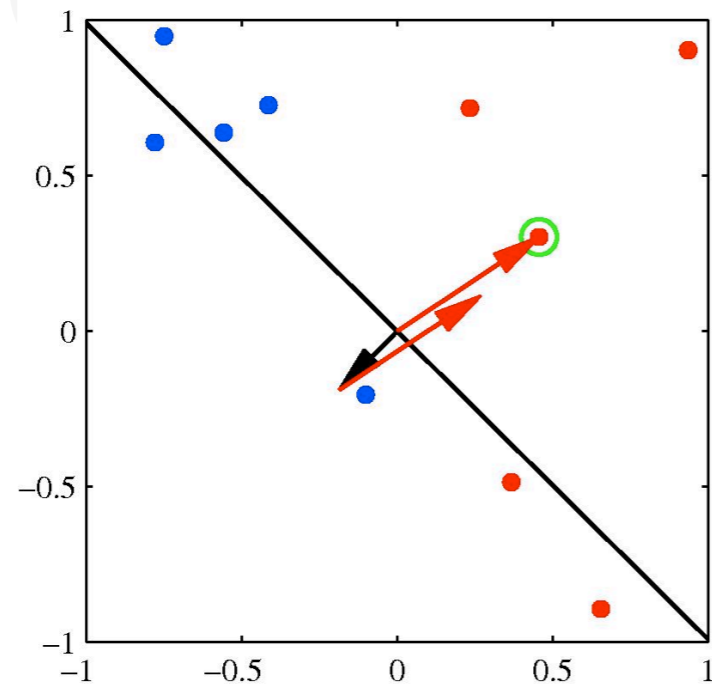
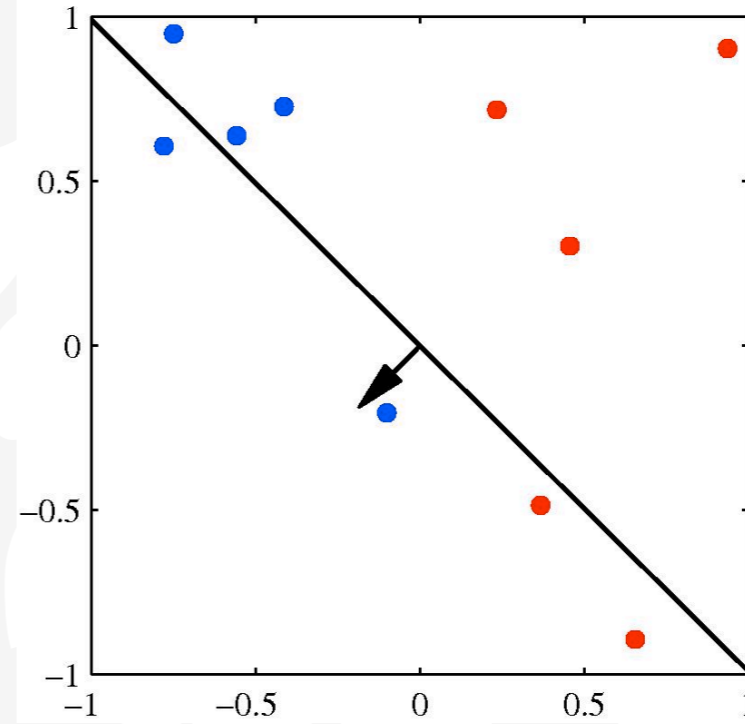
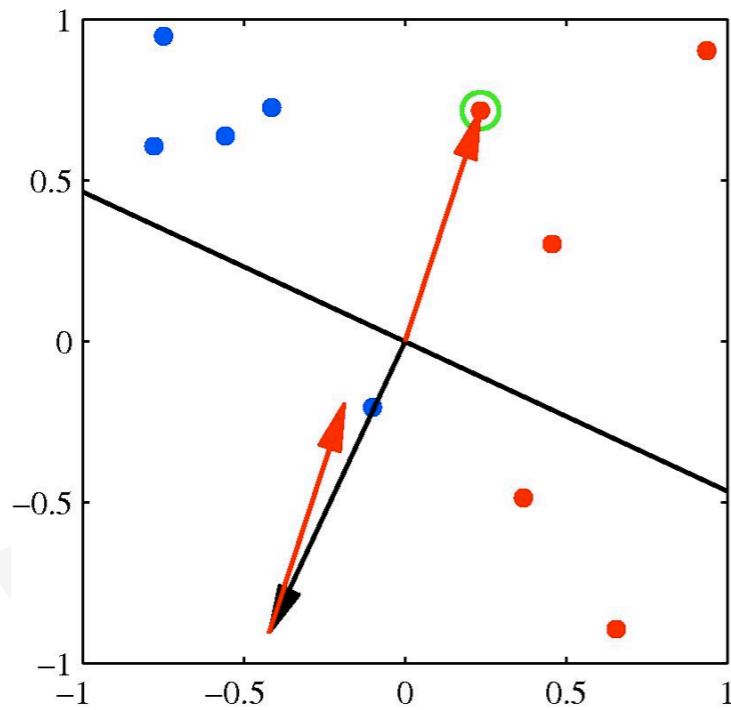
Core objective of a learner: generalize from its experience.

Training examples from experience come from unknown probability distribution. The learner has to extract something to produce a useful answer in new cases.

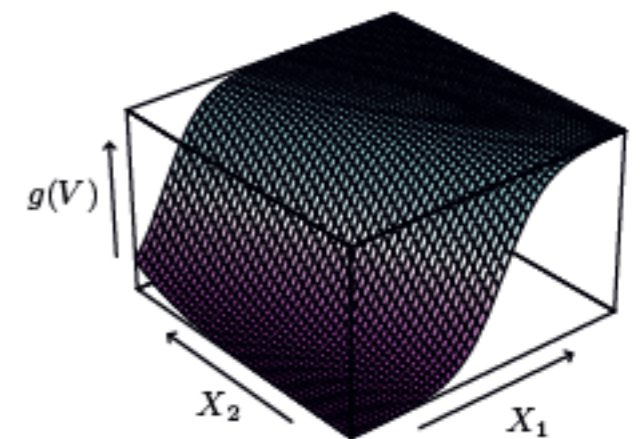
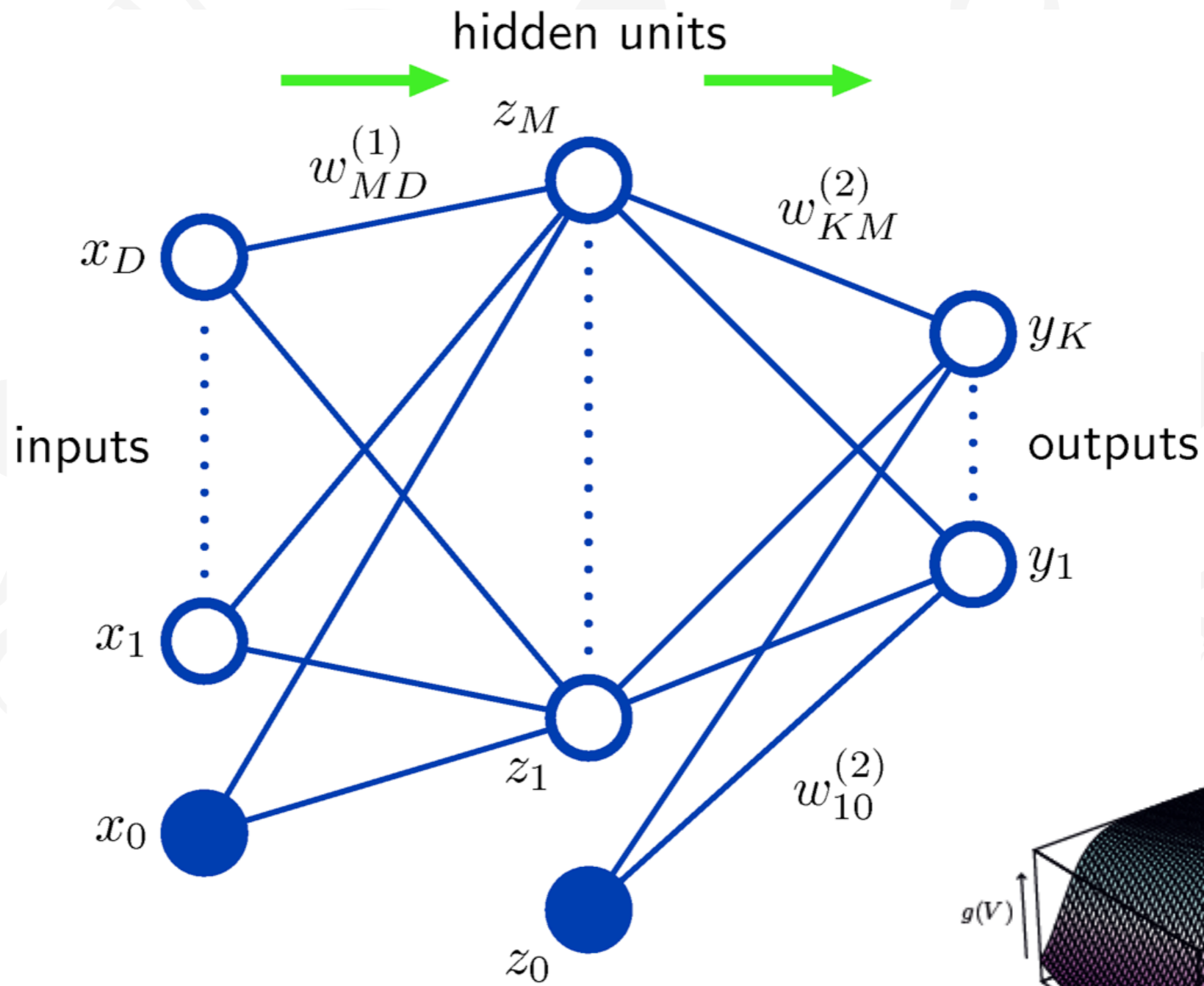
# Contents

- ▶ Classification and Regression via Linear Models
- ▶ Neural Networks
- ▶ Graphical Models
  - Bayesian Networks
  - Hidden Markov Models
- ▶ Mixture Models and Expectation Maximization
- ▶ Support Vector Machines
- ▶ Assessment and Selection
- ▶ Unsupervised Learning
  - (Association rules, cluster analysis, principal components)

# Perceptron algorithm

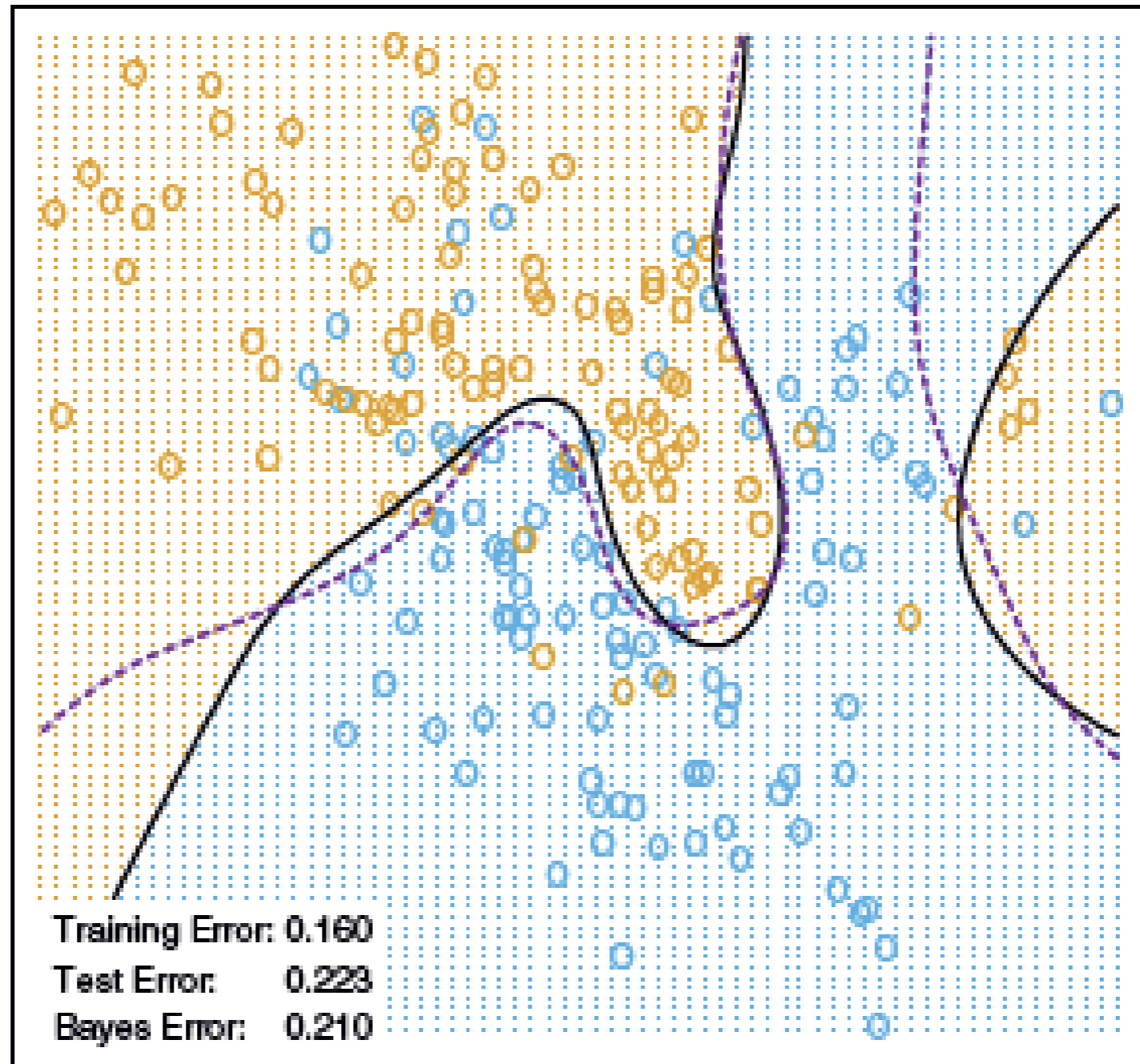


# Multilayered Neural Networks



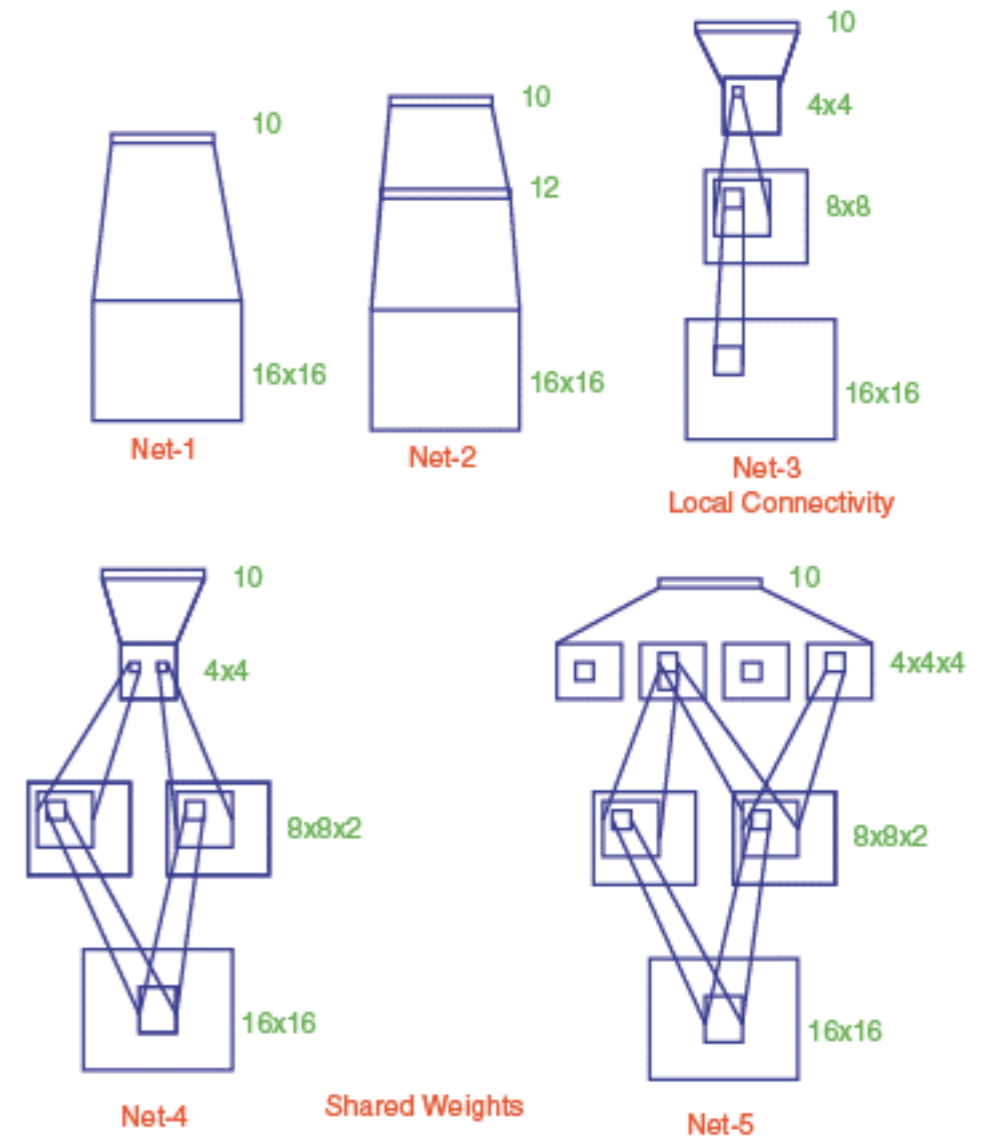
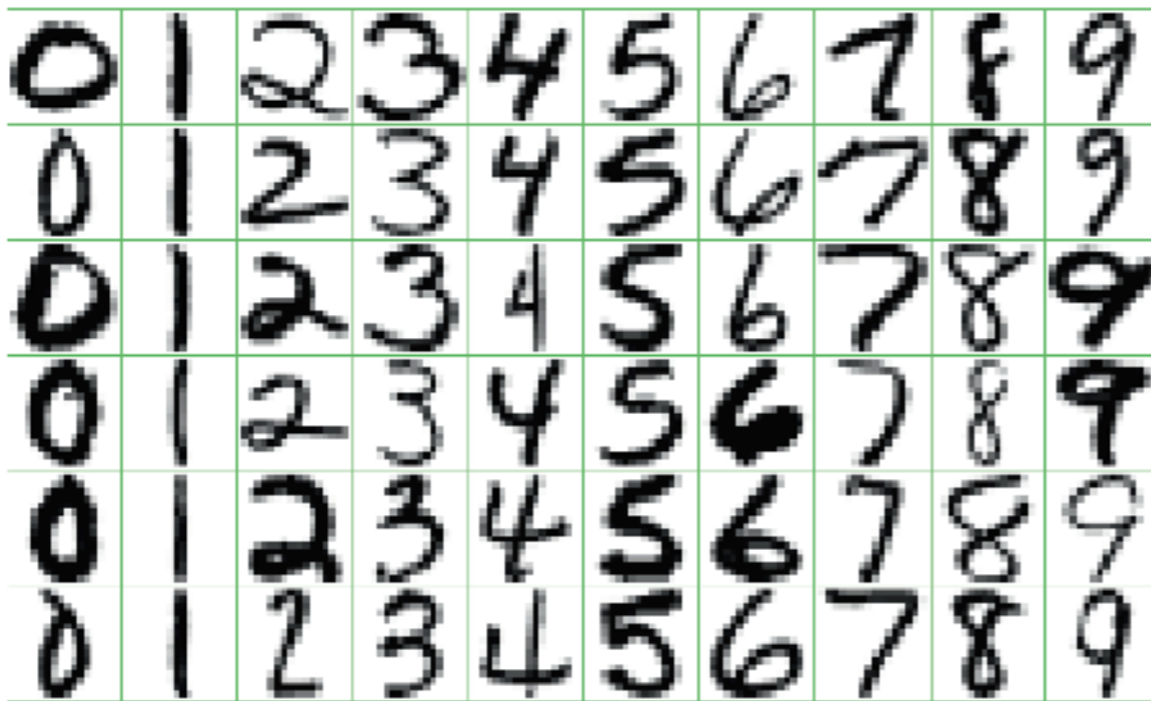
# Applications

Neural Network - 10 Units, Weight Decay=0.02



# Applications

## Handwritten digit recognition



Humans are at 0.2% – 2.5 % error

400–300–10 unit MLP = 1.6% error

LeNet: 768–192–30–10 unit MLP = 0.9% error



# Graphical Models

Allow to **represent** our prior knoweldge and to use a general suite of algorithms to make **inference** and to **improve** our models for a specific application domain

Complex systems involve **uncertainty** => Probability framework

interralated aspects of the system are modelled as **random variables**

# Example: Medical diagnosis

- two deases: Fly and Hayfever
- they are not mutually exclusive
- Season might be correlated with them
- symptoms such as Congestion and Muscle Pain

4 random variables:

Flu = {true, false}; Hayfever = {true, false}

Season = {fall, winter, spring, summer}  $2 \times 2 \times 4 \times 2 \times 2 = 64$

Congestion = {true, false}

MusclePain = {true, false}

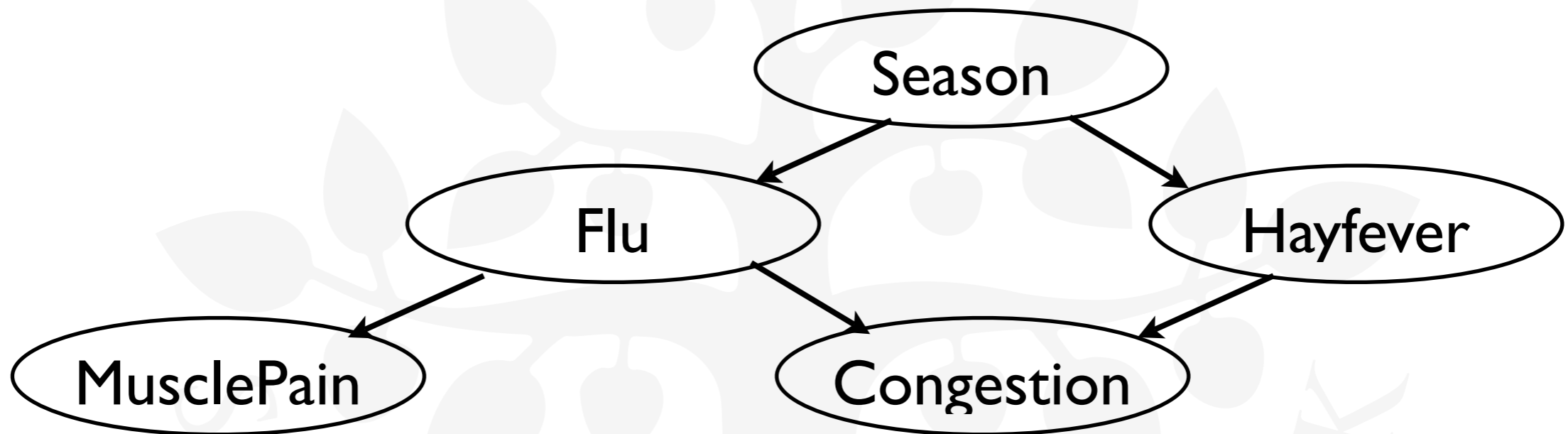
possible prob. values  
for joint distribution

$P(\text{Flu}=\text{true} \mid \text{Season}=\text{fall}, \text{Congestion}=\text{true}, \text{MusclePain}=\text{false})$

If the number of variables grows the problem becomes intractable

# Example: continued

Graphical models use graph-based representation to encode independencies



F and H independent given Season

C and S independent given F and H

M and H,C independent given F

M and C independent given F

We thus only need to define  
 $3 + 4 + 4 + 4 + 2 = 17$  parameters

$$P(S, F, H, C, M) = P(S)P(F|S)P(H|S)P(C|F, H)P(M|F)$$

# Bayesian Learning

What can we do from here?

- Inference: Complexity issues  $O(2^n)$
- Learning (parameters and structure)

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Flip the thumbtack in the air and observe the number of times it lands with head and tail

We wish to learn how much the probability deviates from 0.5

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Suppose we observe 3 heads in 10 tosses.

- With no prior knowledge we would set  $p=3/10=0.33$
- With a prior of 10 heads over 20 tosses we would set  $p=(3+10)/(10+20)=13/30=0.43$
- However if we obtain more data the effect diminishes:  
 $(300+1)/1000+2=0.3$  and  $(300+10)/(1000+20)=0.3$



# Course Organization

## Prerequisites

- ✓ MM501 Calculus I
- ✓ MM505 Linear Algebra
- ✓ Basics of Probability Calculus

## Final Assessment (5 ECTS)

- ▶ Mandatory assignments, pass/fail, internal evaluation by the teacher. Include programming work in R
- ▶ 3 hours written exam, Danish 7 mark scale
- ▶ External examiner

# Course Material

- ▶ Text book
  - C.M. Bishop. Pattern recognition and Machine Learning Springer, 2006
  - Slides
- ▶ Source code and data sets
- ▶ [www.imada.sdu.dk/~marco/DM825](http://www.imada.sdu.dk/~marco/DM825)

