

# INTRODUCTION

# CLASSIFICATION

## Problem setting

Classification methods subdivide data into several, distinct classes. More formally:

- ▶ Data  $x_1, x_2, \dots$
- ▶ Each observations falls into one of  $K$  categories (the *classes*).
- ▶ Learning task: Find a classification function

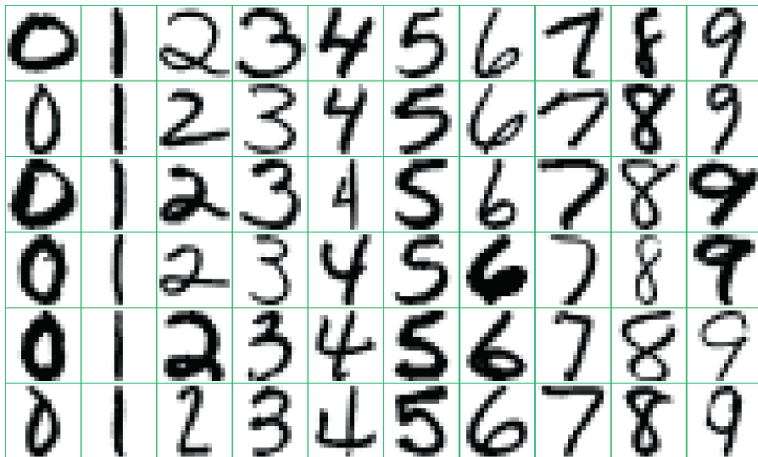
$$f : \mathbf{X} \rightarrow \{1, \dots, K\} .$$

- ▶ Input of the learning problem: Correctly categorized examples  $\tilde{\mathbf{x}}_1, \dots, \tilde{\mathbf{x}}_n$ .

## Approach

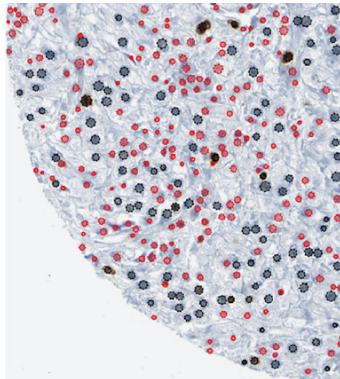
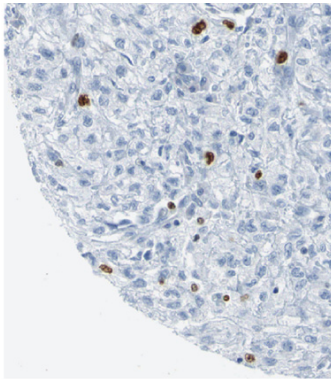
- ▶ Define:
  1. A set of possible classification functions  $f$  (the *hypothesis set*).
  2. A *cost function* which assumes a large value when mistakes are made.
- ▶ To find a good classifier, search the hypothesis class for the  $f$  which keeps costs as small as possible.
- ▶ Different types of errors can be more or less expensive.

# USPS DATA



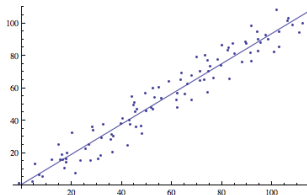
Each digit:  $16 \times 16$  pixels, i.e.  $x \in \mathbb{R}^{256}$

# CANCER DIAGNOSIS

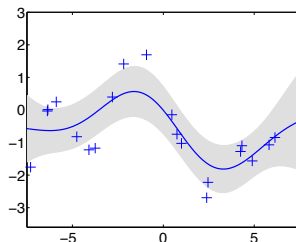


# REGRESSION

Linear regression



Nonlinear regression



## Shrinkage

Shrinkage methods make regression less susceptible to idiosyncracies of a specific data set.

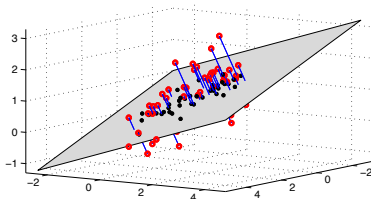
- ▶  $\ell_2$  shrinkage: Reduce variability of solutions between data sets.
- ▶  $\ell_1$  shrinkage: Weed out unimportant dimensions in high-dimensional data.

# DIMENSION REDUCTION

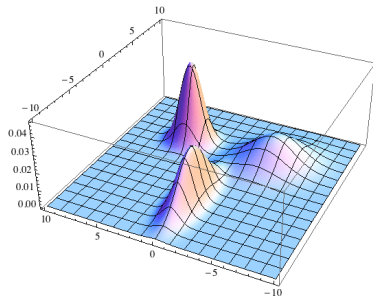
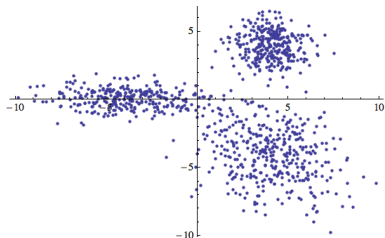
## Task

- ▶ Input: A high-dimensional data set.
- ▶ Output: A low-dimensional representation of the data *which preserves important structure*.

## Illustration: From 3D to 2D



# CLUSTERING



## Example: Image Segmentation

