HELSINKI UNIVERSITY OF TECHNOLOGY
Adaptive Informatics Research Centre

T-61.6030: Multimedia Retrieval

Ch.2: Languages for Metadata
Ch.3: Pattern Recognition for Multimedia

Mats Sjöberg

What is metadata?

- literally, “data about data”
- descriptive information about data sources
- aids in organisation, identification, representation, localisation, interoperability, management and use of data

Why do we need metadata?

- multimedia objects are typically large in size, expensive to transport and process
- e.g. images, video, hard to summarise in textual, structured form

Why do we need metadata?

- description and identification
- querying, e.g. by author, genre, . . .
- administration
- preservation, to facilitate archival and refreshing
- technical, e.g. data formats

Classification of metadata

- *content-independent*, e.g. date of creation and location

  vs

- *content-dependent*, e.g. manual annotation, extracted features

Classification of metadata

- *domain-independent*, e.g. colour histogram of image

  vs

- *domain-dependent*, e.g. land cover in GIS (geographic information system)

Semantics of metadata and metadata languages

- shared understanding of the meaning of metadata
- solution: *metadata language* with standardised semantics
- *computer technical layer*, e.g. Unicode text
- *conventional layer*, e.g. "author" is the original author of a book, not the publisher

Dublin Core (DC)

- workshop in 1995 in Dublin, Ohio (USA)
- continued development by Dublin Core Metadata Initiative (DCMI)
- specifies a framework for descriptive metadata
- widely used in e.g. libraries, universities, museums

DC: 15 core elements

- Contributor
- Coverage
- Creator
- Description
- Date
- Format
- Identifier
- Language
- Publisher
- Relation
- Right
- Source
- Subject
- Title
- Type

DC: web page example

```
Identifier = "http://dublincore.org/"

Title = "Dublin Core Metadata Initiative -- Home Page"

Description = "The Dublin Core Metadata Initiative Web site"

Date = "2006-12-18"

Format = "text/html"

Language = "en"

Creator = "The Dublin Core Metadata Initiative (DCMI)"

Contributor = "The Dublin Core Usage Board"

Type = "InteractiveResource"
```

DC: some problems

- Not very precise, values fields are just text strings
- At best a recommended practice may exist
- Good for human consumption and full text search
- Bad for interoperability

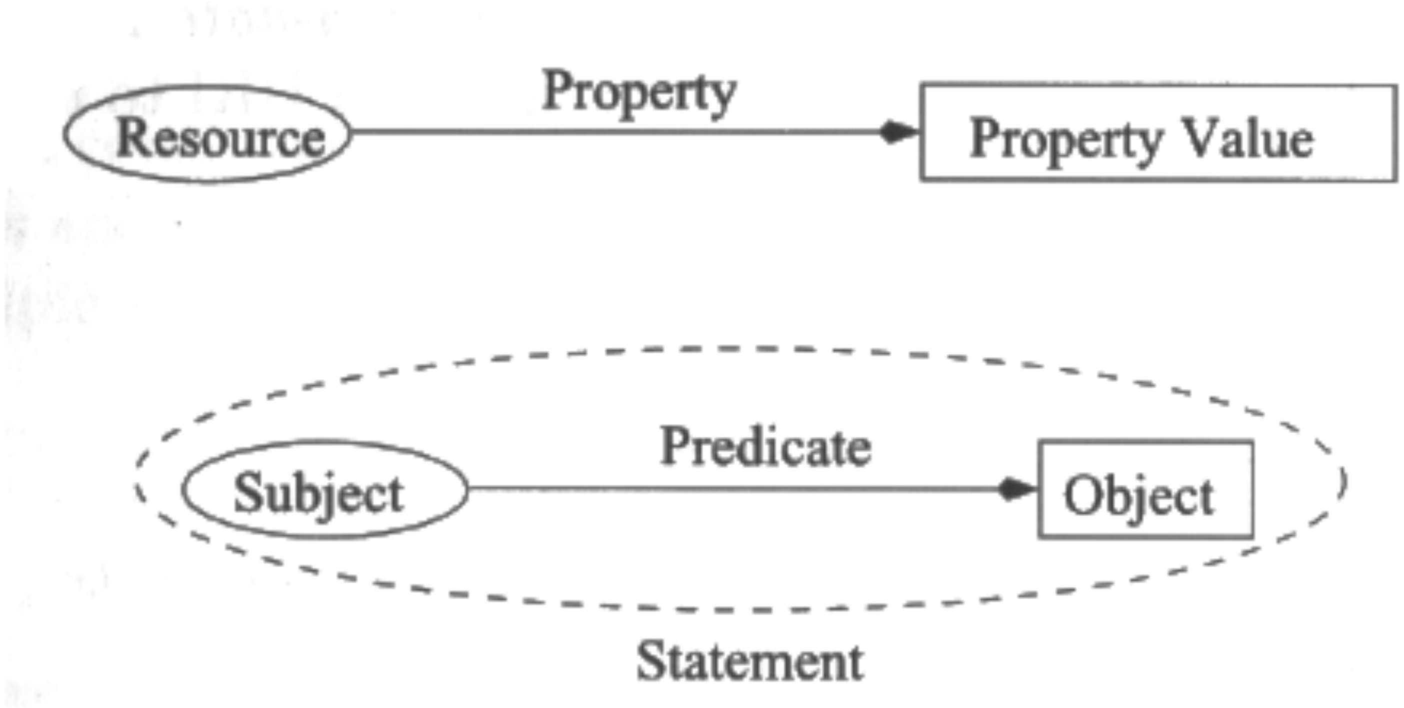
DC: extensions

- extending using Dublin Core as the baseline: e.g. MPEG-7 and IEEE-LOM
- Dublin Core qualifiers are more explicit about attributes, e.g. “date.created”
- more precise value fields: e.g. “Person” data structure for “author”

Resource Description Framework (RDF)

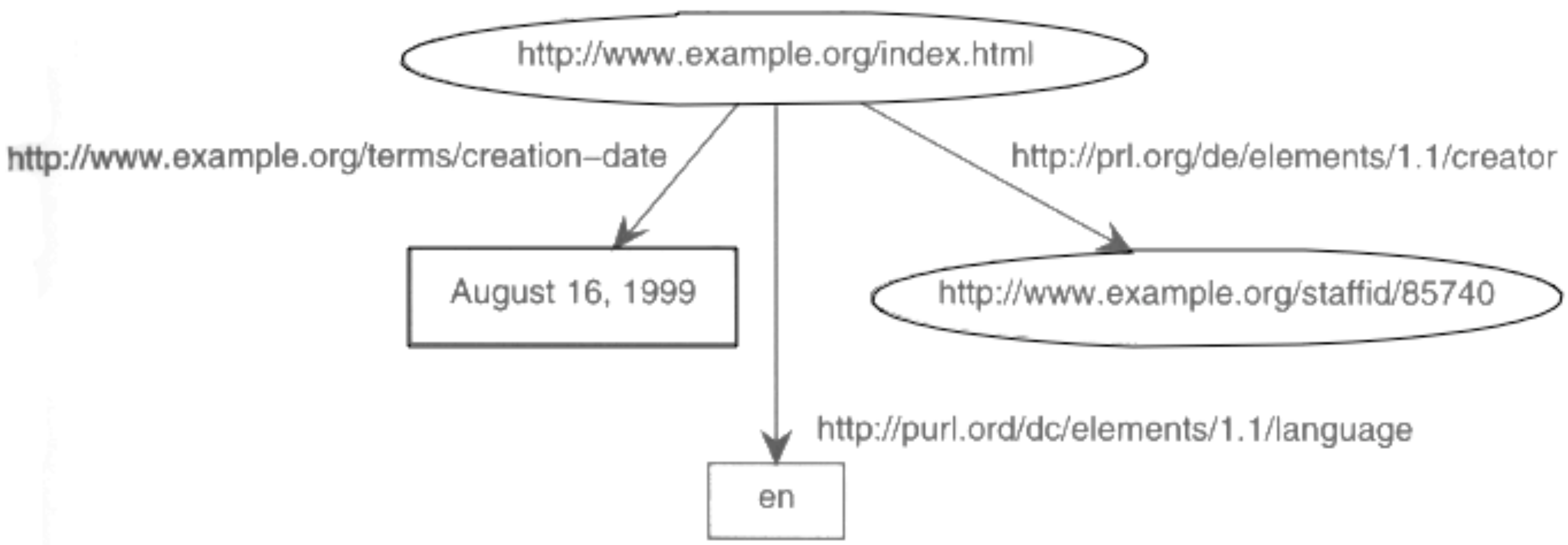
- family of W3C specifications
- initially metadata for web resources in XML
- now more general: metadata about "resources" having "properties"
- RDF language, concrete RDFS schema
- e.g. Dublin Core as RDFS schema

RDF statement



- directed labelled graph

RDF example


http://www.example.org/index.html
http://www.example.org/terms/creation–date
http://prl.org/de/elements/1.1/creator
August 16, 1999
http://www.example.org/staffid/85740
http://purl.ord/dc/elements/1.1/language
en

RDF example

```
<?xml version=”1.0”>
<rdf:RDF
    xmlns:rdf=”http://www.w3c.org/1999/02/22-rdf-syntax-ns#”
    xmlns:dc=”http://purl.org/dc/elements/1.1/”
    xmlns:exterms=”http://www.example.org/terms/”>
    <rdf:Description
        rdf:about=”http://www.example.org/index.html”>
        <exterms:creation-date
         rdf:datatype=”http://www.w3.org/2001/XMLSchema#date”
        >1999-08-16</exterms:creation-date>
        <dc:language>en</dc:language>
        <dc:creator rdf:resource=”http://www.example.org/staffid/85740”/>
    </rdf:Description>
</rdf:RDF>
```

RDF Schema

- an extension of RDF
- application specific classes and properties
- e.g. for Dublin Core:
  - “editor” is a property, domain:“Journal”, range:“Person”
  - “editor” is a sub-property of “contributor”

MPEG-7

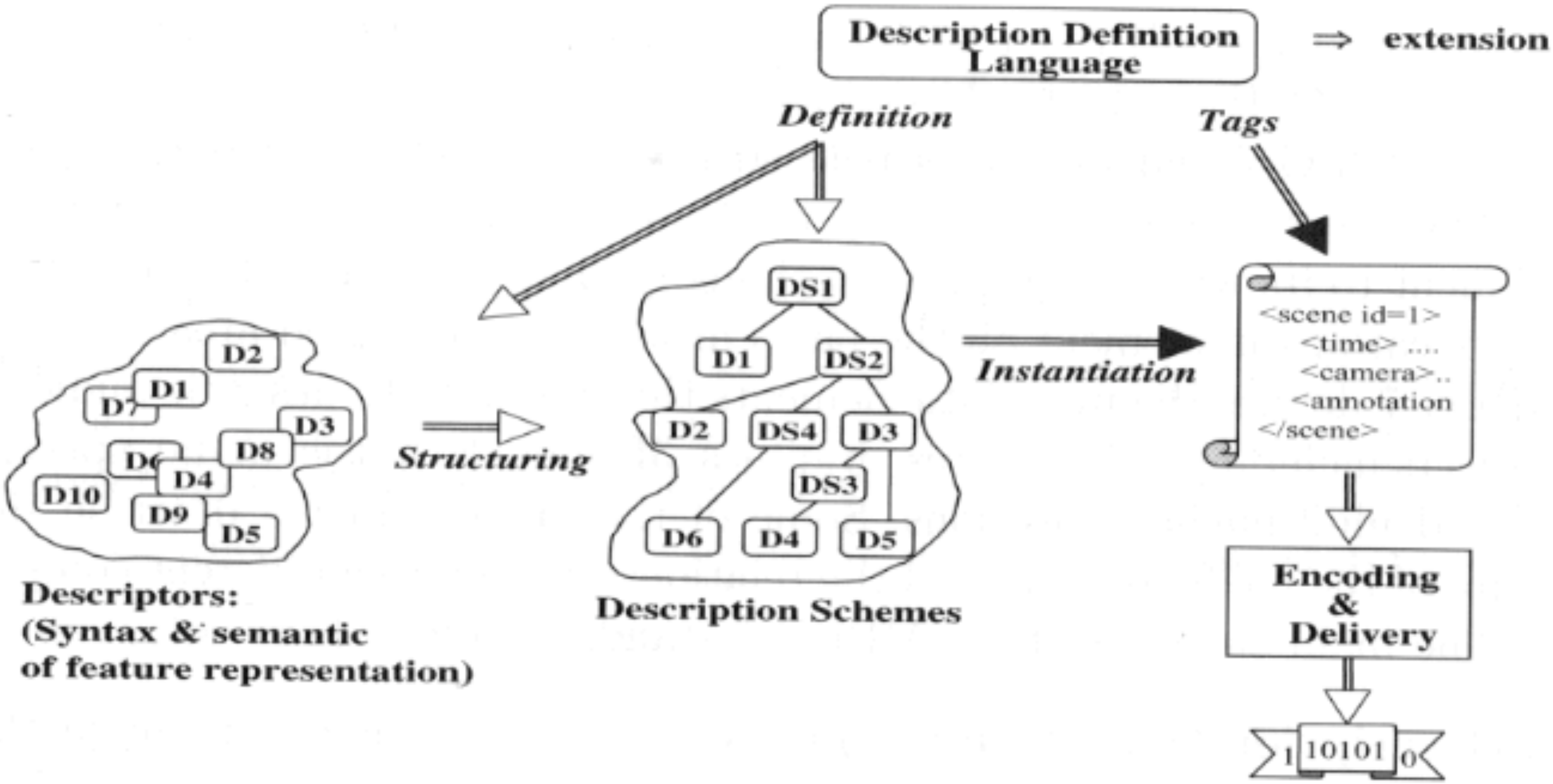
- ISO/IEC Moving Pictures Experts Groups MPEG-7 is a large and complex standard
- structure of media objects and relationships between components
- image, music, audio, video, 3D models, speech analysis and segmentation
- usually only specialised parts implemented

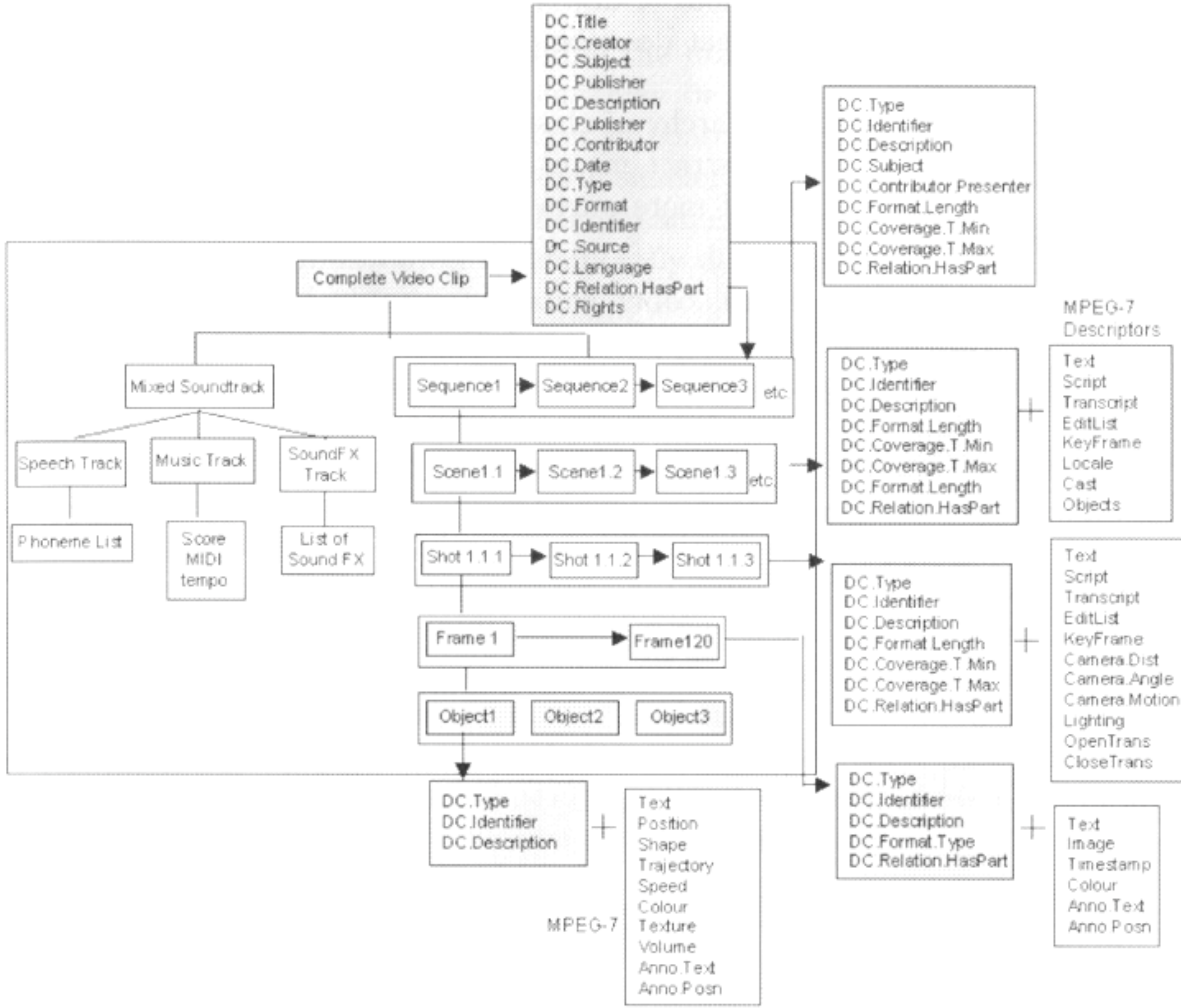
MPEG-7 elements

Main elements are:

- Description Definition Language (DDL)
- Descriptors (Ds)
- Description Schemes (DSs)
- Binary format (BiM)
- System Tools

MPEG-7 elements




DC.Title
DC.Creator
DC.Subject
DC.Publisher
DC.Description
DC.Publisher
DC.Contributor
DC.Date
DC.Type
DC.Format
DC.Identifier
DC.Source
DC.Language
DC.Relation.HasPart
DC.Rights
Complete Video Clip
DC.Type
DC.Identifier
DC.Description
DC.Subject
DC.Contributor.Presenter
DC.Format.Length
DC.Coverage.T.Min
DC.Coverage.T.Max
DC.Relation.HasPart
MPEG-7
Descriptors
Mixed Soundtrack
Sequence1
Sequence2
Sequence3
etc
DC.Type
DC.Identifier
DC.Description
DC.Format.Length
DC.Coverage.T.Min
DC.Coverage.T.Max
DC.Format.Length
DC.Relation.HasPart
Text
Script
Transcript
EditList
KeyFrame
Locale
Cast
Objects
Speech Track
Music Track
SoundFX
Track
Scene1.1
Scene1.2
Scene1.3
etc
Phoneme List
Score
MIDI
tempo
List of
Sound FX
Shot 1.1.1
Shot 1.1.2
Shot 1.1.3
DC.Type
DC.Identifier
DC.Description
DC.Format.Length
DC.Coverage.T.Min
DC.Coverage.T.Max
DC.Relation.HasPart
Text
Script
Transcript
EditList
KeyFrame
Camera.Dist
Camera.Angle
Camera.Motion
Lighting
OpenTrans
CloseTrans
Frame 1
Frame120
Object1
Object2
Object3
DC.Type
DC.Identifier
DC.Description
Text
Position
Shape
Trajectory
Speed
Colour
Texture
Volume
Anno.Text
Anno.Posn
MPEG-7
DC.Type
DC.Identifier
DC.Description
DC.Format.Type
DC.Relation.HasPart
Text
Image
Timestamp
Colour
Anno.Text
Anno.Posn

Chapter 3: Pattern Recognition for Multimedia Content Analysis

Recognising patterns in multimedia content

Example 1: semi-automatic annotation

- high-quality metadata without manual work
- pattern classification and concept hierarchies
- e.g. LSCOM: Activities (e.g. *walking*), Scene (e.g. *indoor, outdoor*), People (e.g. *soldier, pope*)...
- need to design a *classifier* for each concept

Recognising patterns in multimedia content

Example 2: automatic interpretation of multimedia streams

- e.g. monitoring customers in shops, smart home applications, airport security
- typically *modelling* with finite state descriptions
- also *unsupervised learning*

Recognising patterns in multimedia content

We will look at four specific tasks:

- pattern classification
- modelling
- unsupervised learning, clustering
- dimensionality reduction

Pattern classification

- we have labelled example patterns
- task: generalise class structure, i.e. decide class of new input patterns
- feature representation: each pattern a point in a feature space

Pattern classification: some issues

- residual uncertainty
- limited availability of data, optimal prediction function: *Bayes classifier*:

$$f(x) = \underset{k \in \mathcal{K}}{\operatorname{argmax}}\, p(k|X = x)$$

- need for prior assumptions
- noise and error
- under- and overfitting
- irrelevant features

Pattern classification

- Bayes classifier: chose class k with highest probability given feature vector x
- natural approach: compare with *n*-nearest neighbours
- other approach: discriminant methods:
  - estimate feature value densities given a certain class, from this estimate $p(k|X = x)$
  - e.g. multivariate Gaussian density

Pattern classification: support vector machines

- training examples are mapped into a high-dimensional space
- seek support vector classifier, optimal separating hyper-plane
- maximise distance of samples to decision boundary, i.e. *margin-optimisation*

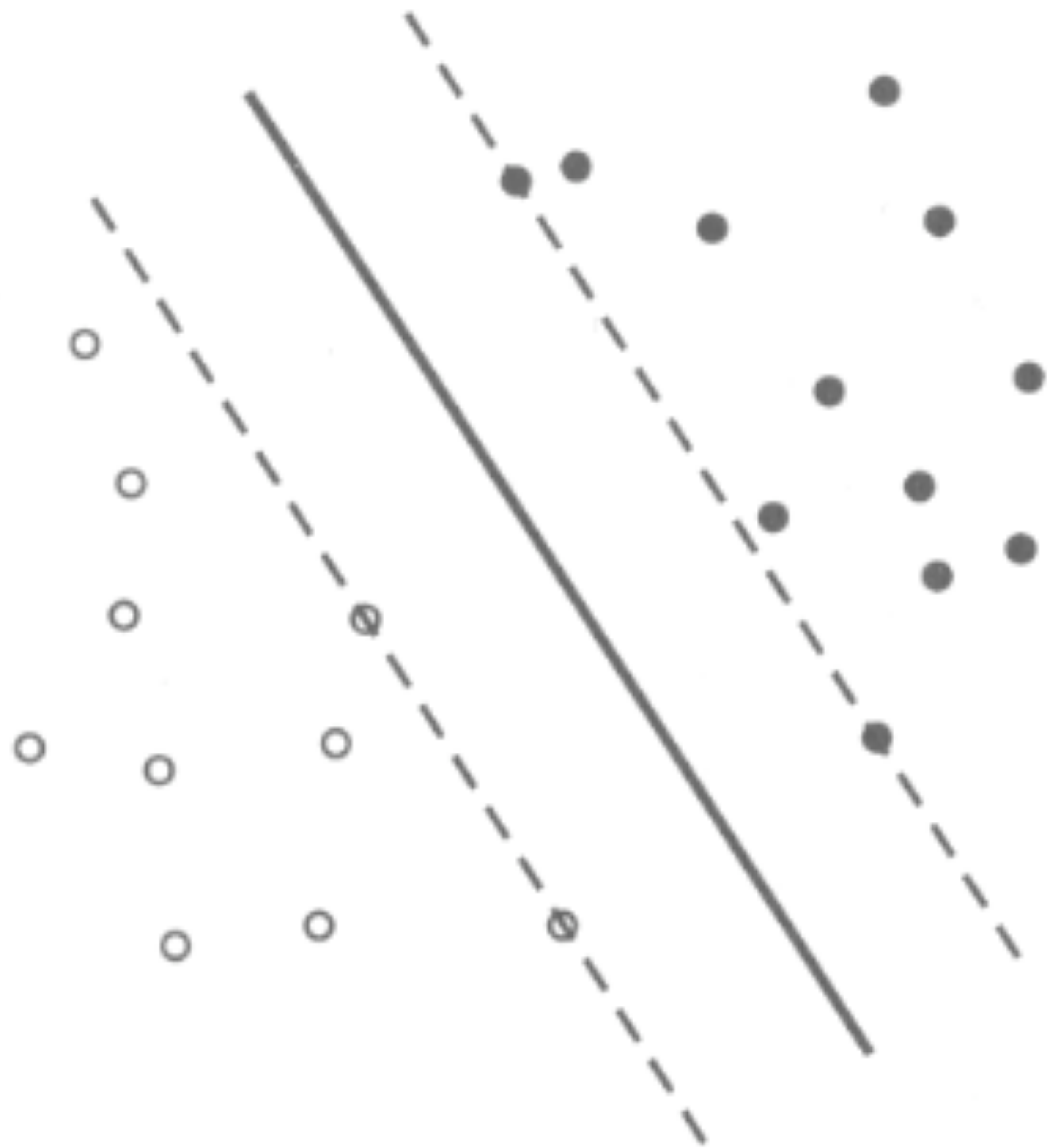


Fig. 3.2. Separating hyperplane.

Pattern classification: support vector machines

- hyper-plane defined as: $\langle w, x \rangle + b = 0$
- choose w such that smallest margin: $1/\|w\|$

  margin hyper-planes: $\langle w, x \rangle + b = \pm 1$
- constrained minimisation problem:

$$\min_{w \in \mathcal{H}, b \in \mathbb{R}} \frac{1}{2} \|w\|^2$$

subject to: $y_i(\langle w, x_i \rangle + b) \geq 1, i = 1, \ldots .n$

Pattern classification: support vector machines

- constrained optimisation solved via Lagrangian function, and *dual* problem
- "slack" variables introduced for robustness
- classifier:

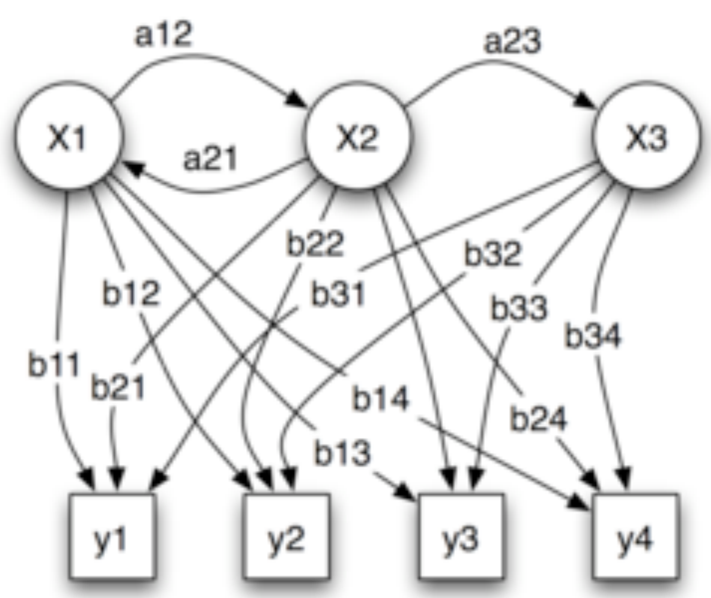
$$f(x) = \operatorname{sign}\left(\sum_{i=1}^{n} \alpha_i y_i \langle x, x_i \rangle + b\right)$$

- replace inner product with kernel,

kernel trick: $k(x, x') = \langle \Phi(x), \Phi(x') \rangle$

Modelling

- Hidden Markov Models very popular, especially in speech recognition
- states *hidden*, satisfy the Markov property



source: wikipedia

Modelling

- Example: we do not know the weather state q_i
- but can observe if people use umbrellas o_i
- Bayes' rule: $$P(q_i|o_i) = \frac{P(o_i|q_i)P(q_i)}{P(o_i)}$$
- Generalised: $$P(Q|O) \propto \prod_{i=1}^{n} P(o_i|q_i) \prod_{i=1}^{n} (q_i|q_{i-1})$$

Unsupervised learning and clustering

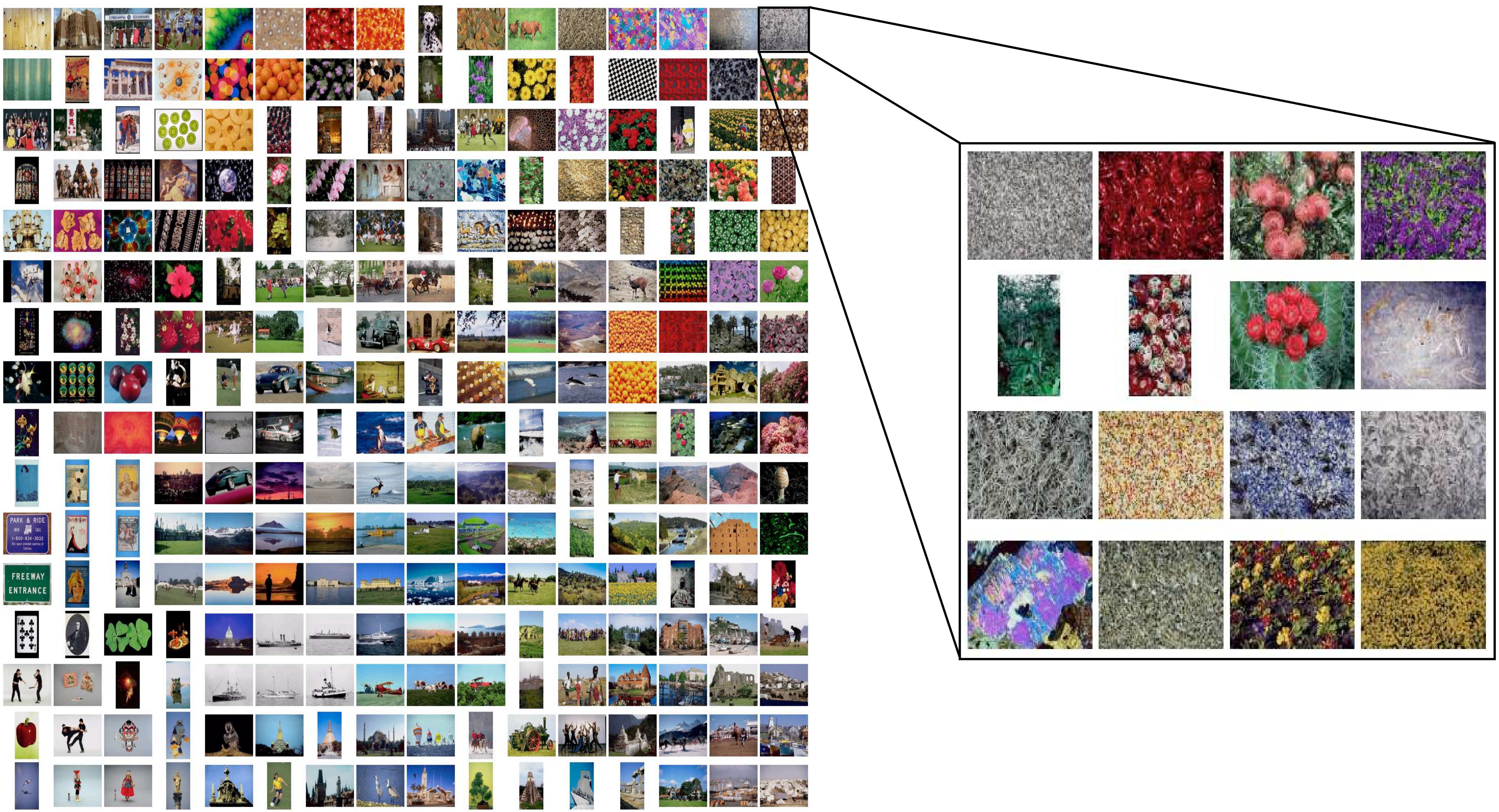
- “unsupervised classification of patterns into groups” (Jain et al. 1999)
- uses similarity or proximity measures
- seek sparse and dense regions in a data set
- hierarchical methods or iterative optimisation

Hierarchical clustering

- keeps merging closest pair of clusters/patterns until a threshold
- cluster distance: *single link* or *complete link*
- also e.g. centroid, subset of points (CURE)

Iterative optimisation

- optimises a quality criterion
- usually a single partitioning
- simple example: *k*-means minimises summed squared errors
- not feasible for large multimedia databases
- solutions: divide and conquer, incremental approach, parallel processing


PARK & RIDE
FREEWAY
ENTRANCE

Dimension reduction

- reduce the number of features for pattern representation
- irrelevant features bad for classification
- reduces computational and memory costs
- *ugly duckling theorem* (Watanabe 1969)
- *feature extraction* and *feature selection*

Feature extraction

- create new features by combination and transformation of original features
- e.g. Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA)
- PCA: retains dimensions that contribute most to variance of data
- LDA: seeks directions that best separate known classes in the data

Feature selection

- select a more *relevant* subset of features
- *filter methods*: rank variables according to some scoring function, e.g. *mutual information* between each variable and class
- *wrapper methods*: try different combinations, evaluate e.g. cross-validation
- *embedded methods*: selection embedded within learning process

Summary

- many more methods in machine learning and pattern recognition
- some main issues:
  - limited and noisy data
  - over- and underfitting
  - measuring classifier performance
- quality of pattern recognition
  $\Rightarrow$ quality of automated multimedia analysis