Chapter 11: Data Analytics

Database System Concepts, 7th Ed.

Chapter 11: Data Analytics

- Overview
- Data Warehousing
- Online Analytical Processing
- Data Mining

Overview

- **Data analytics**: the processing of data to infer patterns, correlations, or models for prediction
- Primarily used to make business decisions
  - Per individual customer
    - E.g., what product to suggest for purchase
  - Across all customers
    - E.g., what products to manufacture/stock, in what quantity
- Critical for businesses today

Overview (Cont.)

- Common steps in data analytics
  - Gather data from multiple sources into one location
    - Data warehouses also integrated data into common schema
    - Data often needs to be **extracted** from source formats, **transformed** to common schema, and **loaded** into the data warehouse
      - Can be done as **ETL (extract-transform-load)**, or **ELT (extract-load-transform)**
  - Generate aggregates and reports summarizing data
    - Dashboards showing graphical charts/reports
    - **Online analytical processing (OLAP) systems** allow interactive querying
    - Statistical analysis using tools such as R/SAS/SPSS
      - Including extensions for parallel processing of big data
  - Build **predictive models** and use the models for decision making

Overview (Cont.)

- Predictive models are widely used today
  - E.g., use customer profile features (e.g. income, age, gender, education, employment) and past history of a customer to predict likelihood of default on loan
    - and use prediction to make loan decision
  - E.g., use past history of sales (by season) to predict future sales
    - And use it to decide what/how much to produce/stock
    - And to target customers
- Other examples of business decisions:
  - What items to stock?
  - What insurance premium to change?
  - To whom to send advertisements?

Overview (Cont.)

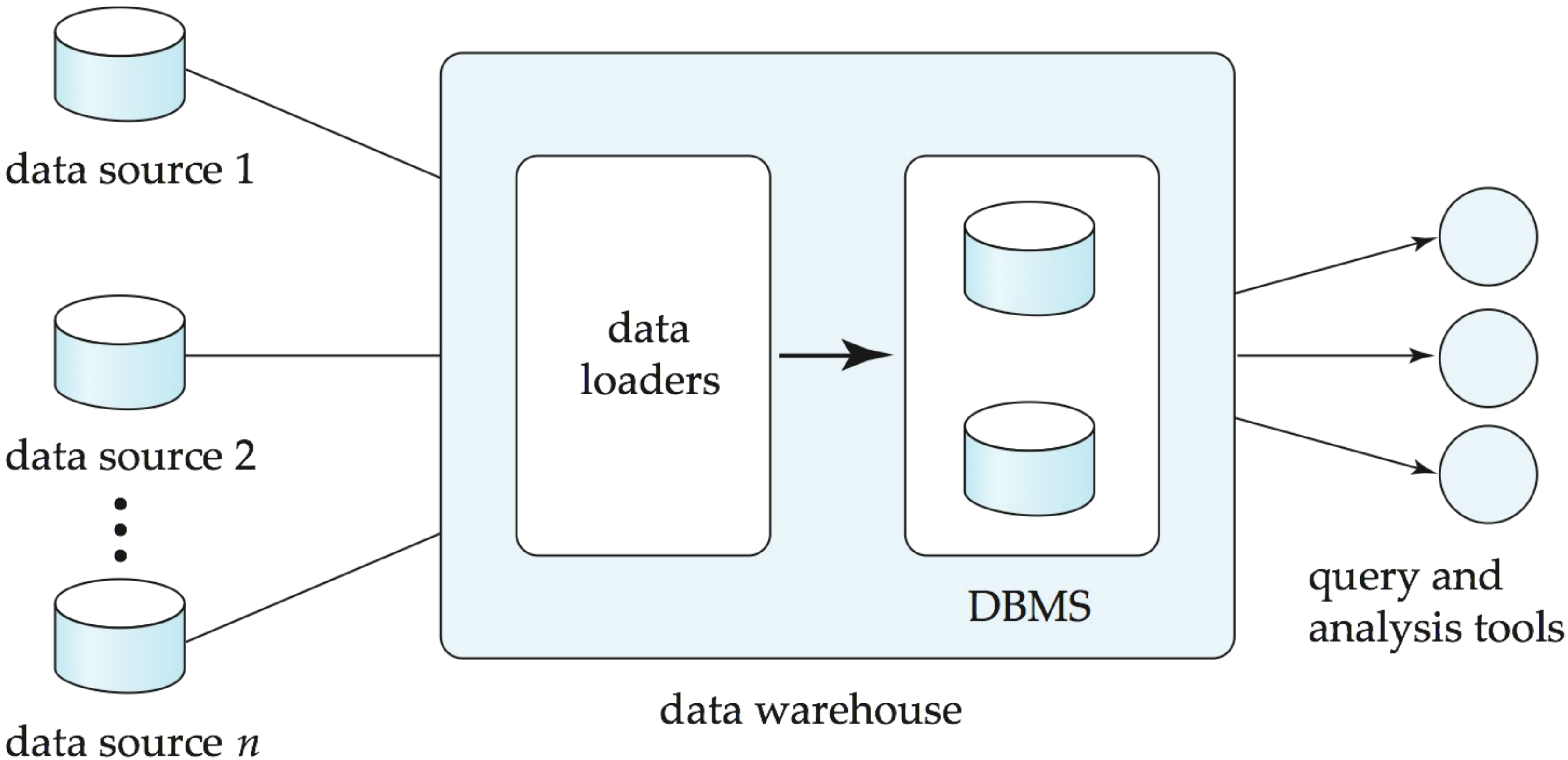
- **Machine learning** techniques are key to finding patterns in data and making predictions
- **Data mining** extends techniques developed by machine-learning communities to run them on very large datasets
- The term **business intelligence (BI)** is synonym for data analytics
- The term **decision support** focuses on reporting and aggregation

DATA WAREHOUSING

Data Warehousing

- Data sources often store only current data, not historical data
- Corporate decision making requires a unified view of all organizational data, including historical data
- A **data warehouse** is a repository (archive) of information gathered from multiple sources, stored under a unified schema, at a single site
  - Greatly simplifies querying, permits study of historical trends
  - Shifts decision support query load away from transaction processing systems

Data Warehousing



Design Issues

- *When and how to gather data*
  - **Source driven architecture**: data sources transmit new information to warehouse
    - either continuously or periodically (e.g., at night)
  - **Destination driven architecture:** warehouse periodically requests new information from data sources
  - **Synchronous** vs **asynchronous replication**
    - Keeping warehouse exactly synchronized with data sources (e.g., using two-phase commit) is often too expensive
    - Usually OK to have slightly out-of-date data at warehouse
    - Data/updates are periodically downloaded form online transaction processing (OLTP) systems.
- *What schema to use*
  - Schema integration

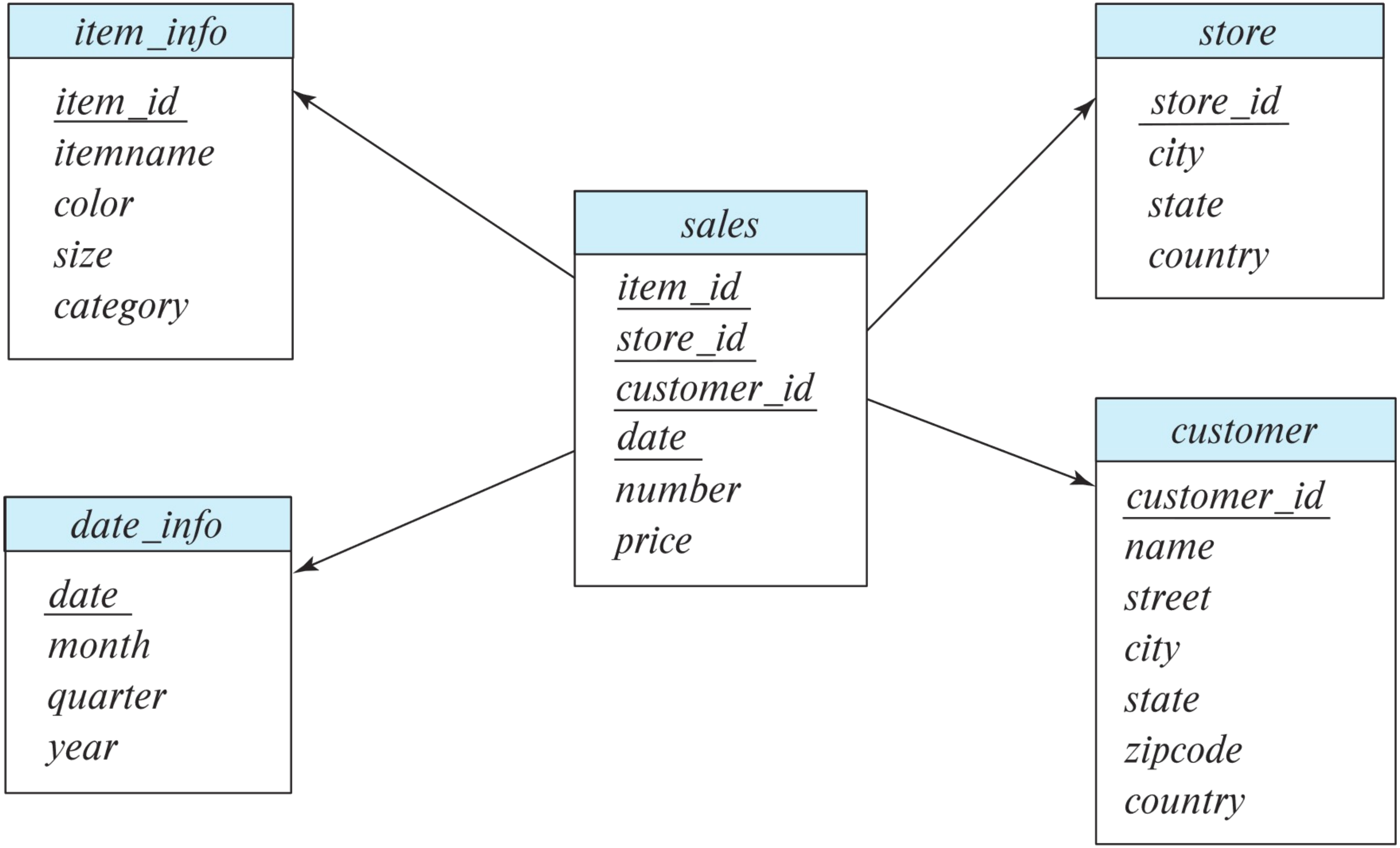
More Warehouse Design Issues

- **Data transformation** and **data cleansing**
  - E.g., correct mistakes in addresses (misspellings, zip code errors)
  - Merge address lists from different sources and purge duplicates
- *How to propagate updates*
  - Warehouse schema may be a (materialized) view of schema from data sources
    - View maintenance
- *What data to summarize*
  - Raw data may be too large to store on-line
  - Aggregate values (totals/subtotals) often suffice
  - Queries on raw data can often be transformed by query optimizer to use aggregate values

Multidimensional Data and Warehouse Schemas

- Data in warehouses can usually be divided into
  - **Fact tables**, which are large
    - E.g, *sales*(*item_id, store_id, customer_id, date, number, price*)
  - **Dimension tables**, which are relatively small
    - Store extra information about stores, items, etc.
- Attributes of fact tables can be usually viewed as
  - **Measure attributes**
    - measure some value, and can be aggregated upon
    - e.g., the attributes *number* or *price* of the *sales* relation
  - **Dimension attributes**
    - dimensions on which measure attributes are viewed
    - e.g., attributes *item_id, color,* and *size* of the *sales* relation
    - Usually small ids that are foreign keys to dimension tables

Data Warehouse Schema



Multidimensional Data and Warehouse Schemas

- Resultant schema is called a **star schema**
  - More complicated schema structures
    - **Snowflake schema**: multiple levels of dimension tables
    - May have multiple fact tables
- Typically
  - fact table joined with dimension tables and then
  - group-by on dimension table attributes, and then
  - aggregation on measure attributes of fact table
- Some applications do not find it worthwhile to bring data to a common schema
  - **Data lakes** are repositories which allow data to be stored in multiple formats, without schema integration
  - Less upfront effort, but more effort during querying

Database Support for Data Warehouses

- Data in warehouses usually append only, not updated
  - Can avoid concurrency control overheads
- Data warehouses often use **column-oriented storage**
  - E.g., a sequence of *sales* tuples is stored as follows
    - Values of item_id attribute are stored as an array
    - Values of store_id attribute are stored as an array,
    - And so on
  - Arrays are compressed, reducing storage, IO and memory costs significantly
  - Queries can fetch only attributes that they care about, reducing IO and memory cost
  - More details in Section 13.6
- Data warehouses often use parallel storage and query processing infrastructure
  - Distributed file systems, Map-Reduce, Hive, …

OLAP

Data Analysis and OLAP

- **Online Analytical Processing (OLAP)**
  - Interactive analysis of data, allowing data to be summarized and viewed in different ways in an online fashion (with negligible delay)
- We use the following relation to illustrate OLAP concepts
  - *sales* (*item_name*, *color*, *clothes_size*, *quantity*)

  This is a simplified version of the *sales* fact table joined with the dimension tables, and many attributes removed (and some renamed)

Example sales relation

item_name	*color*	*clothes_size*	*quantity*
dress	dark	small	2
dress	dark	medium	6
dress	dark	large	12
dress	pastel	small	4
dress	pastel	medium	3
dress	pastel	large	3
dress	white	small	2
dress	white	medium	3
dress	white	large	0
pants	dark	small	14
pants	dark	medium	6
pants	dark	large	0
pants	pastel	small	1
pants	pastel	medium	0
pants	pastel	large	1
pants	white	small	3
pants	white	medium	0
pants	white	large	2
shirt	dark	small	2
shirt	dark	medium	6
shirt	dark	large	6
shirt	pastel	small	4
shirt	pastel	medium	1
shirt	pastel	large	2
shirt	white	small	17
shirt	white	medium	1
shirt	white	large	10
skirt	dark	small	2
skirt	dark	medium	5

... ...

... ...

Cross Tabulation of *sales* by *item_name* and *color*

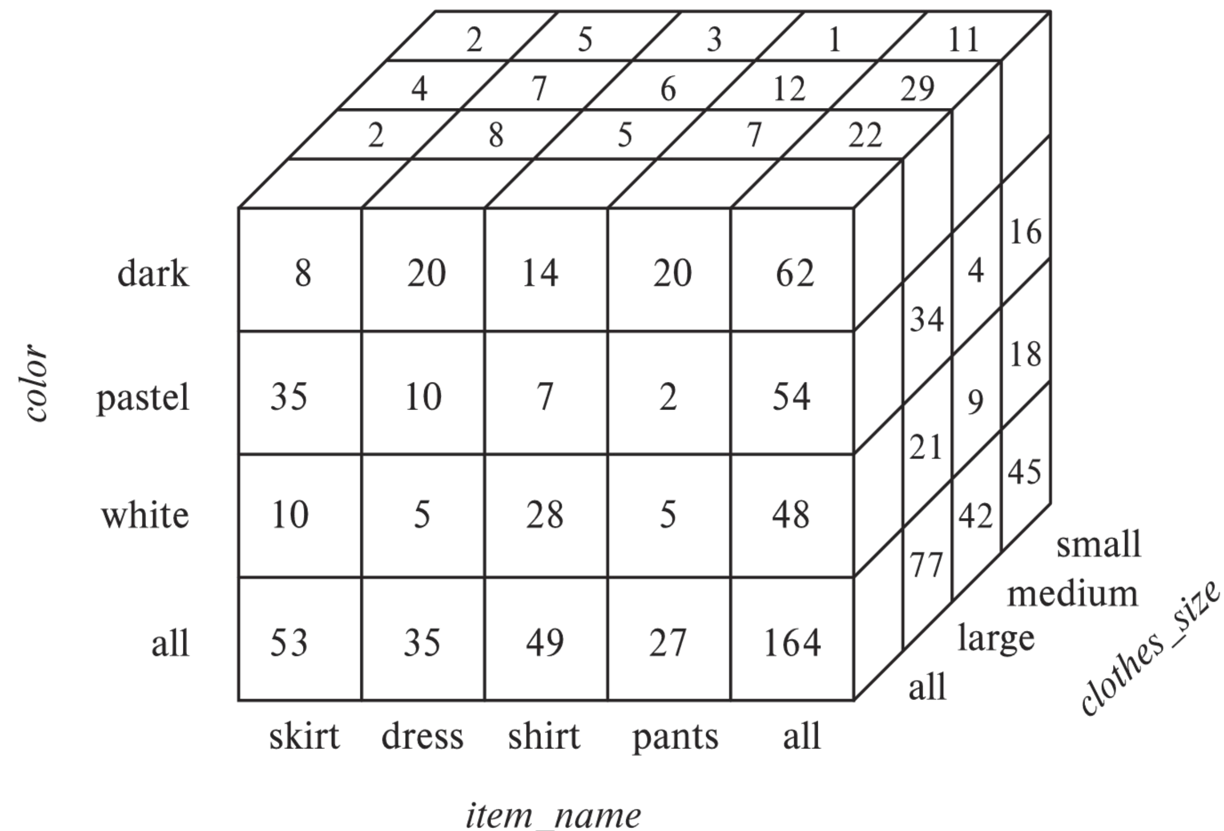
clothes_size **all**

item_name	*color*: dark	pastel	white	total
skirt	8	35	10	53
dress	20	10	5	35
shirt	14	7	28	49
pants	20	2	5	27
total	62	54	48	164

- The table above is an example of a **cross-tabulation** (**cross-tab**), also referred to as a **pivot-table**.
  - Values for one of the dimension attributes form the row headers
  - Values for another dimension attribute form the column headers
  - Other dimension attributes are listed on top
  - Values in individual cells are (aggregates of) the values of the dimension attributes that specify the cell.

Data Cube

- A **data cube** is a multidimensional generalization of a cross-tab
- Can have n dimensions; we show 3 below
- Cross-tabs can be used as views on a data cube

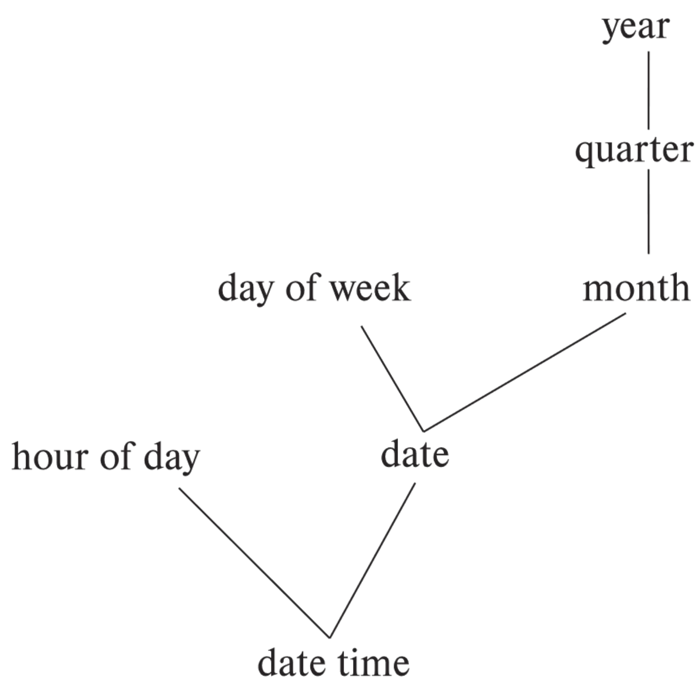


Online Analytical Processing Operations

- **Pivoting:** changing the dimensions used in a cross-tab
  - E.g., moving colors to column names
- **Slicing:** creating a cross-tab for fixed values only
  - E.g., fixing color to white and size to small
  - Sometimes called **dicing**, particularly when values for multiple dimensions are fixed.
- **Rollup:** moving from finer-granularity data to a coarser granularity
  - E.g., aggregating away an attribute
  - E.g., moving from aggregates by day to aggregates by month or year
- **Drill down:** The opposite operation - that of moving from coarser-granularity data to finer-granularity data

Hierarchies on Dimensions

- **Hierarchy** on dimension attributes: lets dimensions be viewed at different levels of detail
- E.g., the dimension *datetime* can be used to aggregate by hour of day, date, day of week, month, quarter or year



(a) time hierarchy

(b) location hierarchy

Cross Tabulation With Hierarchy

- Cross-tabs can be easily extended to deal with hierarchies
- Can drill down or roll up on a hierarchy
- E.g. hierarchy: *item_name* → *category*

clothes_size: **all**

category	*item_name*	*color*: dark	pastel	white	total	
womenswear	skirt	8	8	10	53	
	dress	20	20	5	35	
	subtotal	28	28	15		88
menswear	pants	14	14	28	49	
	shirt	20	20	5	27	
	subtotal	34	34	33		76
total		62	62	48		164

Relational Representation of Cross-tabs

- Cross-tabs can be represented as relations
- We use the value **all** to represent aggregates.
- The SQL standard actually uses *null* values in place of **all**
  - Works with any data type
  - But can cause confusion with regular null values.

item_name	*color*	*clothes_size*	*quantity*
skirt	dark	**all**	8
skirt	pastel	**all**	35
skirt	white	**all**	10
skirt	**all**	**all**	53
dress	dark	**all**	20
dress	pastel	**all**	10
dress	white	**all**	5
dress	**all**	**all**	35
shirt	dark	**all**	14
shirt	pastel	**all**	7
shirt	white	**all**	28
shirt	**all**	**all**	49
pants	dark	**all**	20
pants	pastel	**all**	2
pants	white	**all**	5
pants	**all**	**all**	27
all	dark	**all**	62
all	pastel	**all**	54
all	white	**all**	48
all	**all**	**all**	164

DATA MINING

Data Mining

- **Data mining** is the process of semi-automatically analyzing large databases to find useful patterns
  - Similar goals to machine learning, but on very large volumes of data
- Part of the larger area of **knowledge discovery in databases** (**KDD**)
- Some types of knowledge can be represented as rules
- More generally, knowledge is discovered by applying machine learning techniques on past instances of data, to form a **model**
  - Model is then used to make predictions for new instances

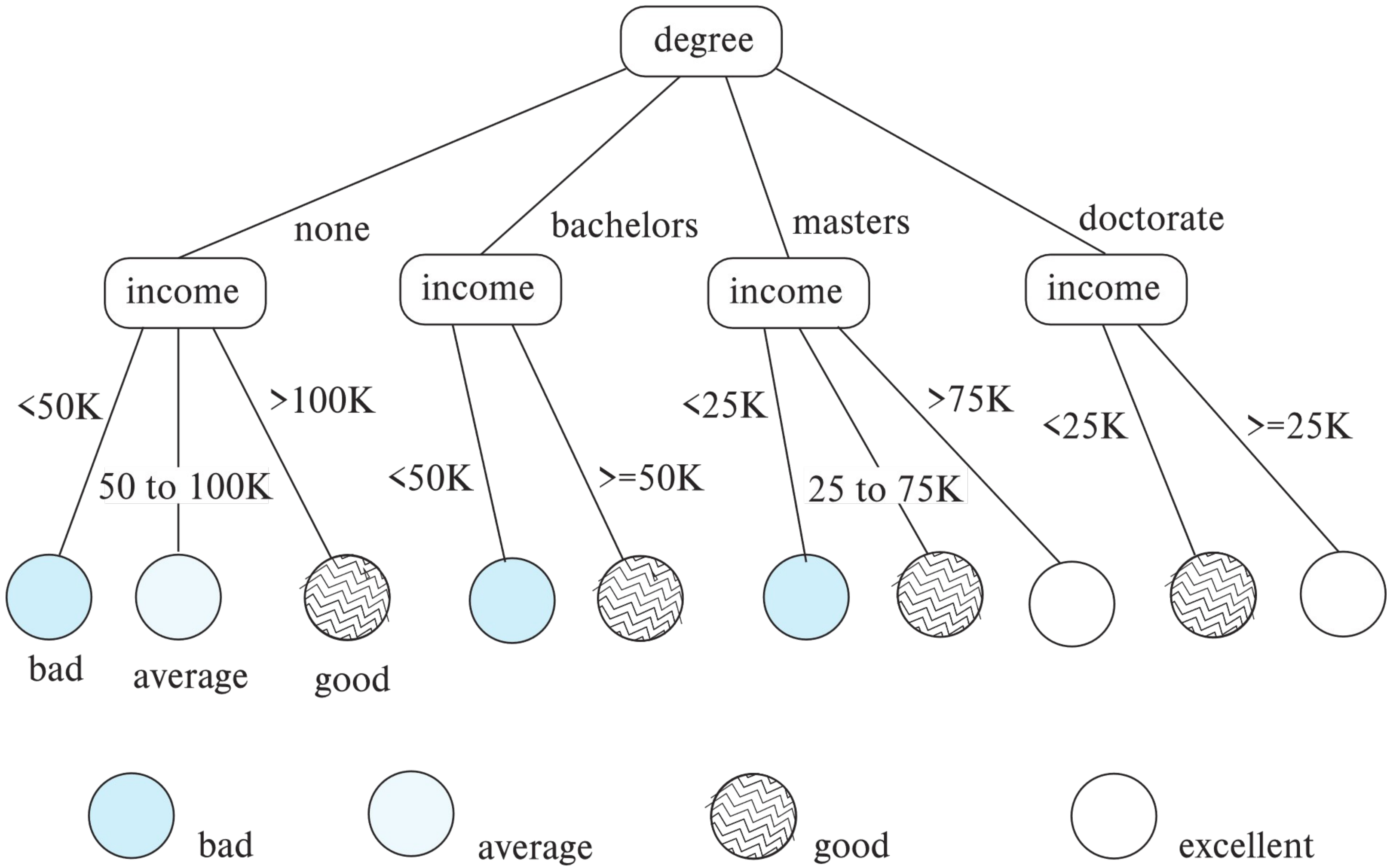
Types of Data Mining Tasks

- **Prediction** based on past history
  - Predict if a credit card applicant poses a good credit risk, based on some attributes (income, job type, age, ..) and past history
  - Predict if a pattern of phone calling card usage is likely to be fraudulent
- Some examples of prediction mechanisms:
  - **Classification**
    - Items (with associated attributes) belong to one of several classes
    - **Training instances** have attribute values and classes provided
    - Given a new item whose class is unknown, predict to which class it belongs based on its attribute values
  - **Regression** formulae
    - Given a set of mappings for an unknown function, predict the function result for a new parameter value

Data Mining (Cont.)

- **Descriptive Patterns**
  - **Associations**
    - Find books that are often bought by “similar” customers. If a new such customer buys one such book, suggest the others too.
    - Associations may be used as a first step in detecting **causation**
      - E.g., association between exposure to chemical X and cancer,
  - **Clusters**
    - E.g., typhoid cases were clustered in an area surrounding a contaminated well
    - Detection of clusters remains important in detecting epidemics

Decision Tree Classifiers



Decision Trees

- Each internal node of the tree partitions the data into groups based on a **partitioning attribute**, and a **partitioning condition** for the node
- Leaf node:
  - all (or most) of the items at the node belong to the same class, or
  - all attributes have been considered, and no further partitioning is possible.
- Traverse tree from top to make a prediction
- Number of techniques for constructing decision tree classifiers
  - We omit details

Bayesian Classifiers

- Bayesian classifiers use **Bayes theorem**, which says

$$p\,(c_j \mid d\,) = \frac{p\,(d \mid c_j)\; p(c_j\,)}{p\,(d)}$$

where

$p\,(c_j \mid d)$ = probability of instance d being in class c_j,

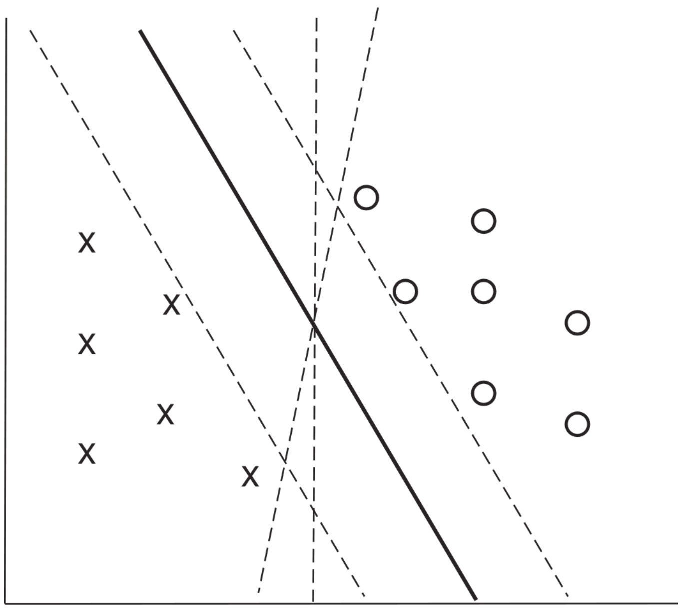
$p\,(d \mid c_j)$ = probability of generating instance d given class c_j,

$p\,(c_j\,)$ = probability of occurrence of class c_j, and

$p\,(d)$ = probability of instance d occuring

Support Vector Machine Classifiers

- Simple 2-dimensional example:
  - Points are in two classes
  - Find a line (**maximum margin line**) s.t. line divides two classes, and distance from nearest point in either class is maximum

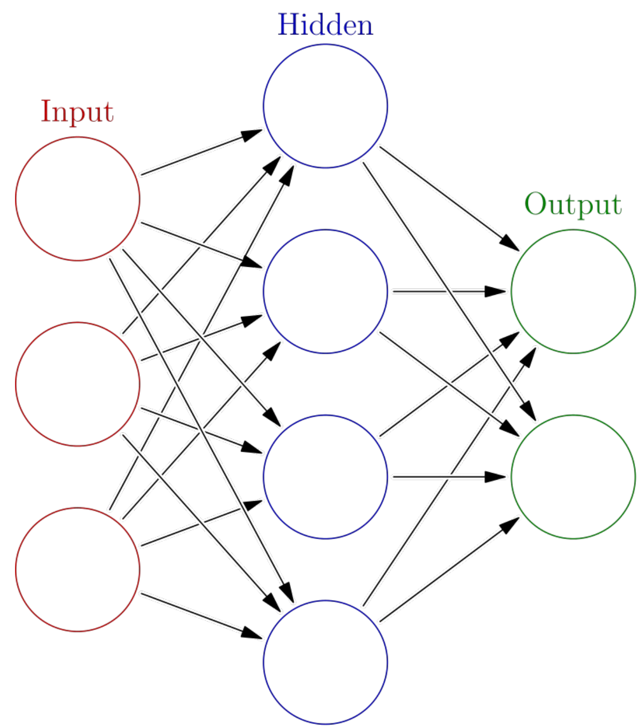


Support Vector Machine

- In n-dimensions points are divided by a plane, instead of a line
- SVMs can be used separators that are curve, not necessarily linear, by transforming points before classification
  - Transformation functions may be non-linear and are called kernel functions
  - Separator is a plane in the transformed space, but maps to curve in original space
- There may not be an exact planar separator for a given set of points
  - Choose plane that best separates points
- N-ary classification can be done by N binary classifications
  - In class *i* vs. not in class *i.*

Neural Network Classifiers

- Neural network has multiple layers
  - Each layer acts as input to next later
- First layer has input nodes, which are assigned values from input attributes
- Each node combines values of its inputs using some weight function to compute its value
  - Weights are associated with edges
- For classification, each output value indicates likelihood of the input instance belonging to that class
  - Pick class with maximum likelihood
- Weights of edges are key to classification
- Edge weights are learnt during training phase



Neural Networks (Cont.)

- **Deep neural networks** have a large number of layers with large number of nodes in each layer
- **Deep learning** refers to training of deep neural network on very large numbers of training instances
- Each layer may be connected to previous layers in different ways
  - Convolutional networks used for image processing
  - More complex architectures used for text processing, and machine translation, speech recognition, etc.
- Neural networks are a large area in themselves
  - Further details beyond scope of this chapter

Regression

- Regression deals with the prediction of a value, rather than a class.
  - Given values for a set of variables, $X_1, X_2, \ldots, X_n$, we wish to predict the value of a variable Y.
- One way is to infer coefficients $a_0, a_1, a_1, \ldots, a_n$ such that

  $$Y = a_0 + a_1 * X_1 + a_2 * X_2 + \ldots + a_n * X_n$$

- Finding such a linear polynomial is called **linear regression**.
  - In general, the process of finding a curve that fits the data is also called **curve fitting**.
- The fit may only be approximate
  - because of noise in the data, or
  - because the relationship is not exactly a polynomial
- Regression aims to find coefficients that give the best possible fit.

Clustering

- **Clustering**: Intuitively, finding clusters of points in the given data such that similar points lie in the same cluster
- Can be formalized using distance metrics in several ways
  - Group points into *k* sets (for a given *k*) such that the average distance of points from the centroid of their assigned group is minimized
    - Centroid: point defined by taking average of coordinates in each dimension.
  - Another metric: minimize average distance between every pair of points in a cluster
- **Hierarchical clustering**: example from biological classification
  - (the word classification here does not mean a prediction mechanism)

chordata

mammalia reptilia

leopards humans snakes crocodiles

Other Types of Mining

- **Text mining**: application of data mining to textual documents
- **Sentiment analysis**
  - E.g., learn to predict if a user review is positive or negative about a product
- **Information extraction**
  - Create structured information from unstructured textual description or semi-structured data such as tabular displays
- **Entity recognition** and **disambiguation**
  - E.g., given text with name “Michael Jordan” does the name refer to the famous basketball player or the famous ML expert
- **Knowledge graph** (see Section 8.4)
  - Can be constructed by information extraction from different sources, such as Wikipedia