Data Mining and Data Warehousing

Data Mining and Data Warehousing

- Decision Support Systems
- Data Warehousing
- Data Mining
- Classification
- Clustering

Decision Support Systems

- **Decision-support systems** are used to make business decisions, often based on data collected by on-line transaction-processing systems.
- Examples of business decisions:
  - What items to stock?
  - What insurance premium to change?
  - To whom to send advertisements?
- Examples of data used for making decisions
  - Retail sales transaction details
  - Customer profiles (income, age, gender, etc.)

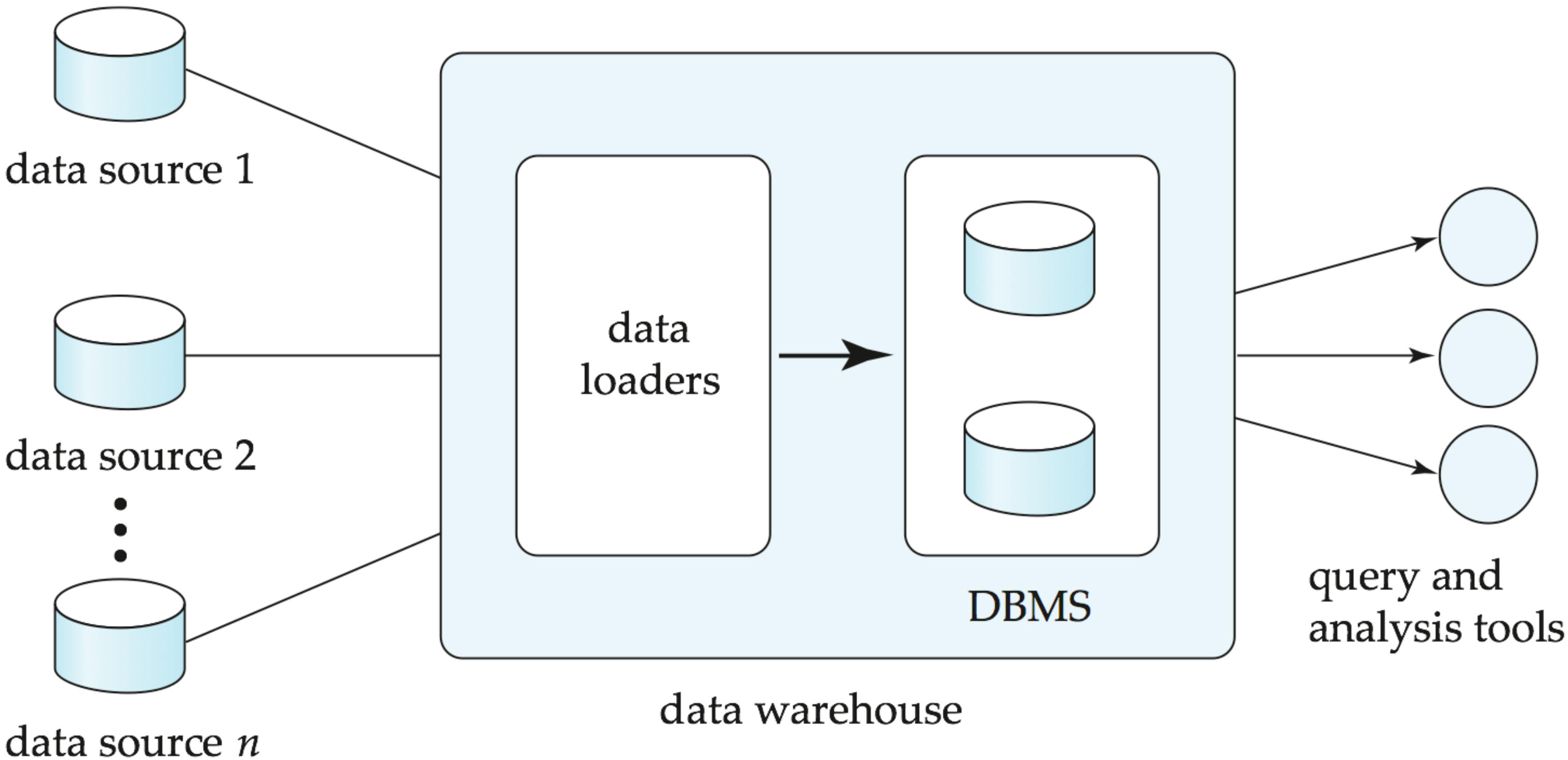
Decision-Support Systems: Overview

- **Data analysis** tasks are simplified by specialized tools and SQL extensions
  - Example tasks
    - For each product category and each region, what were the total sales in the last quarter and how do they compare with the same quarter last year
    - As above, for each product category and each customer category
- **Statistical analysis** packages (e.g., : S++) can be interfaced with databases
  - Statistical analysis is a large field, but not covered here
- **Data mining** seeks to discover knowledge automatically in the form of statistical rules and patterns from large databases.
- A **data warehouse** archives information gathered from multiple sources, and stores it under a unified schema, at a single site.
  - Important for large businesses that generate data from multiple divisions, possibly at multiple sites
  - Data may also be purchased externally

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
  - Keeping warehouse exactly synchronized with data sources (e.g., using two-phase commit) is 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

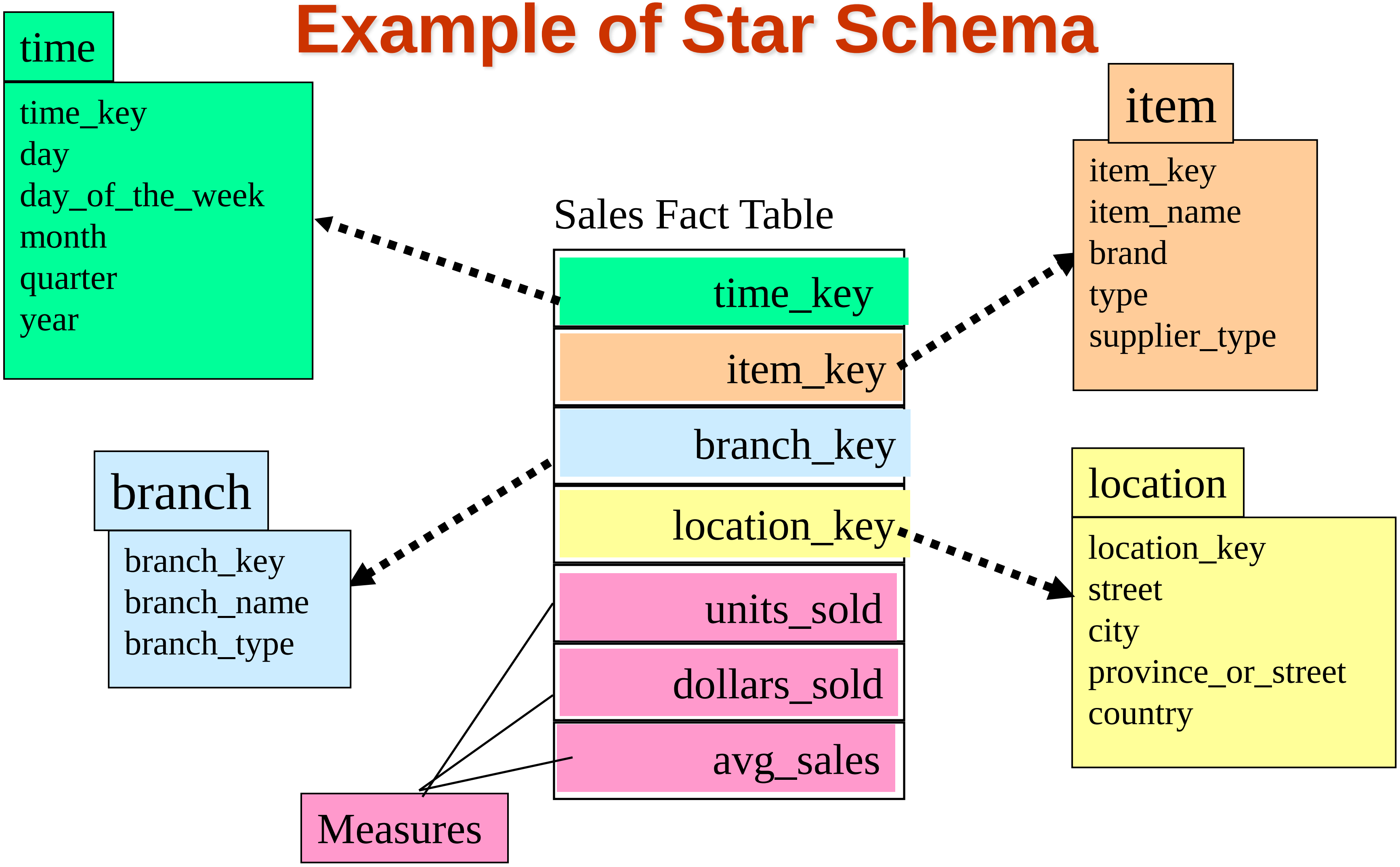
More Warehouse Design Issues

- *Data 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
- *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

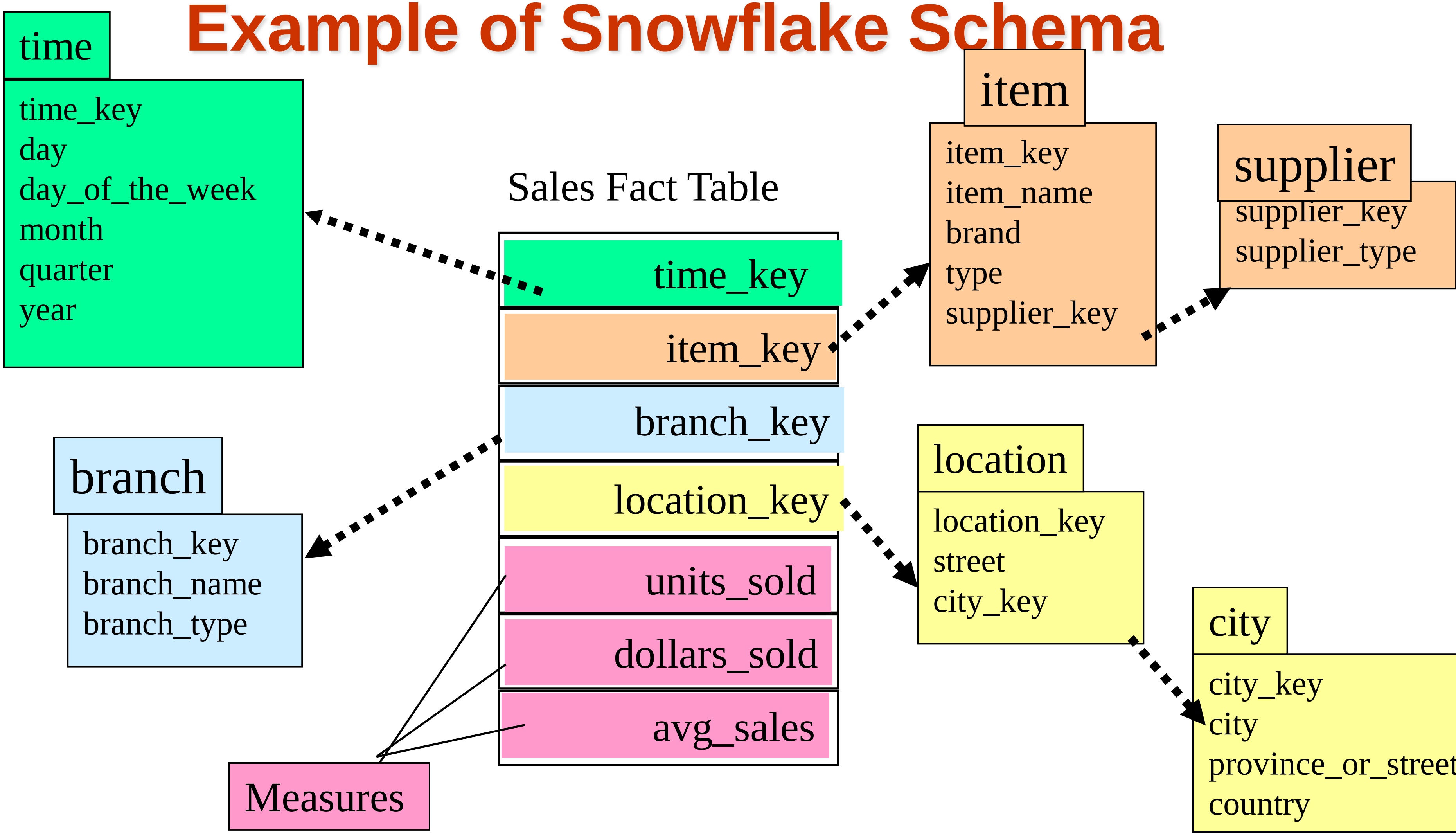
Warehouse Schemas

- Dimension values are usually encoded using small integers and mapped to full values via dimension tables
- Resultant schema is called a **star schema**
  - More complicated schema structures
    - **Snowflake schema**: multiple levels of dimension tables
    - **Constellation**: multiple fact tables

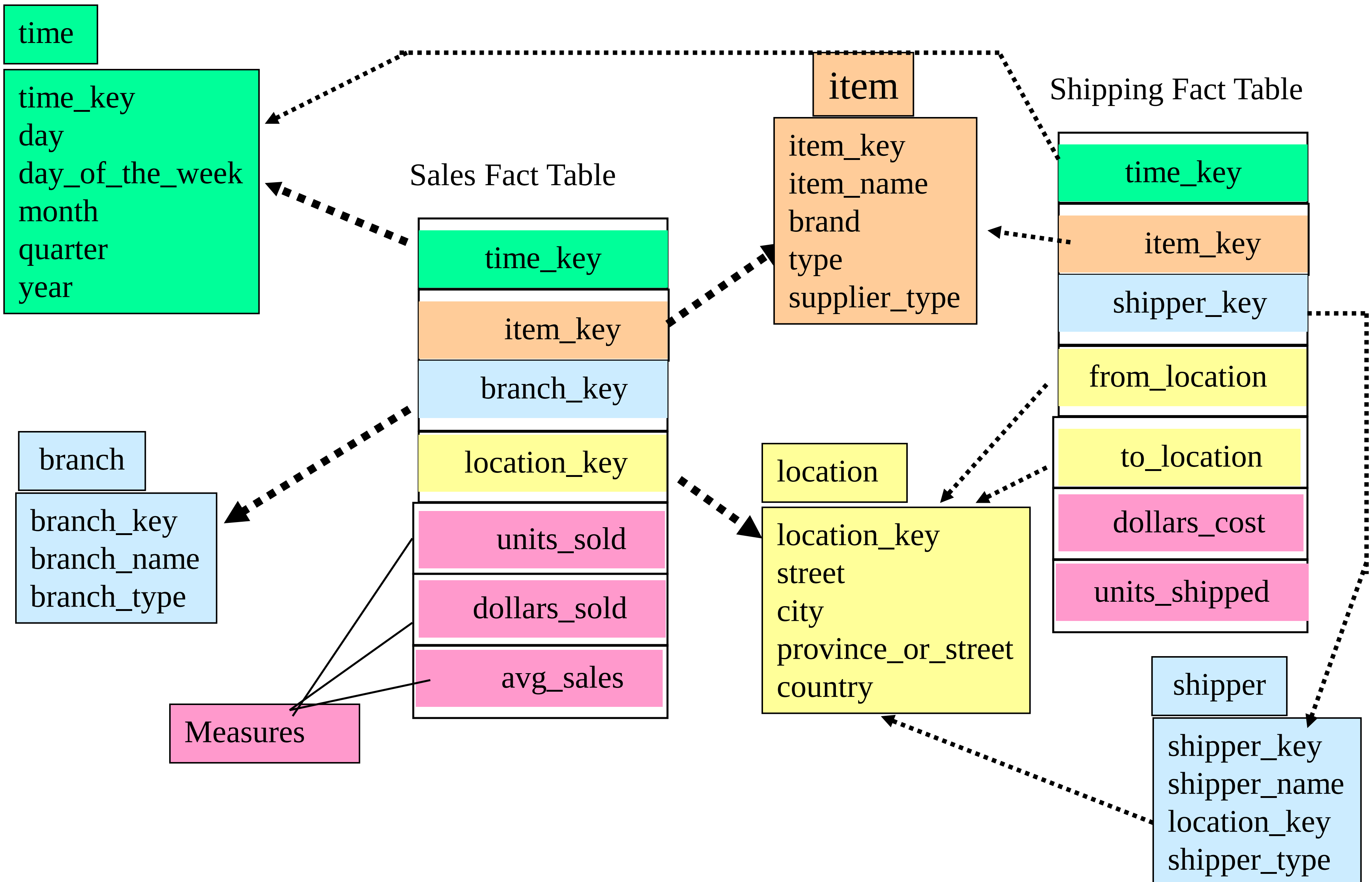
Example of Star Schema



Example of Snowflake Schema

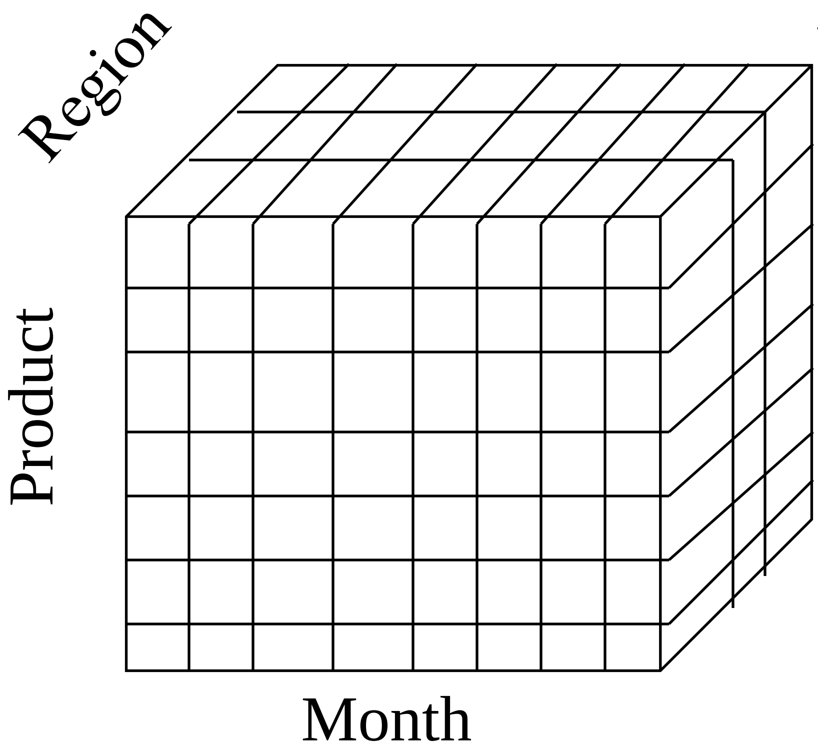


Example of Fact Constellation

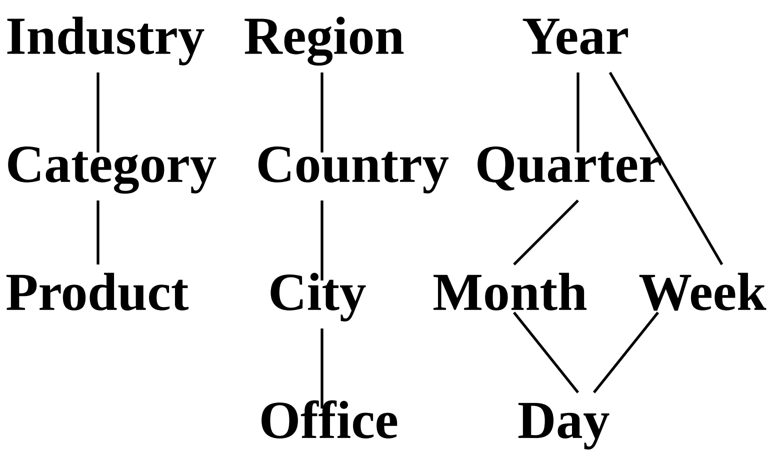


Multidimensional Data

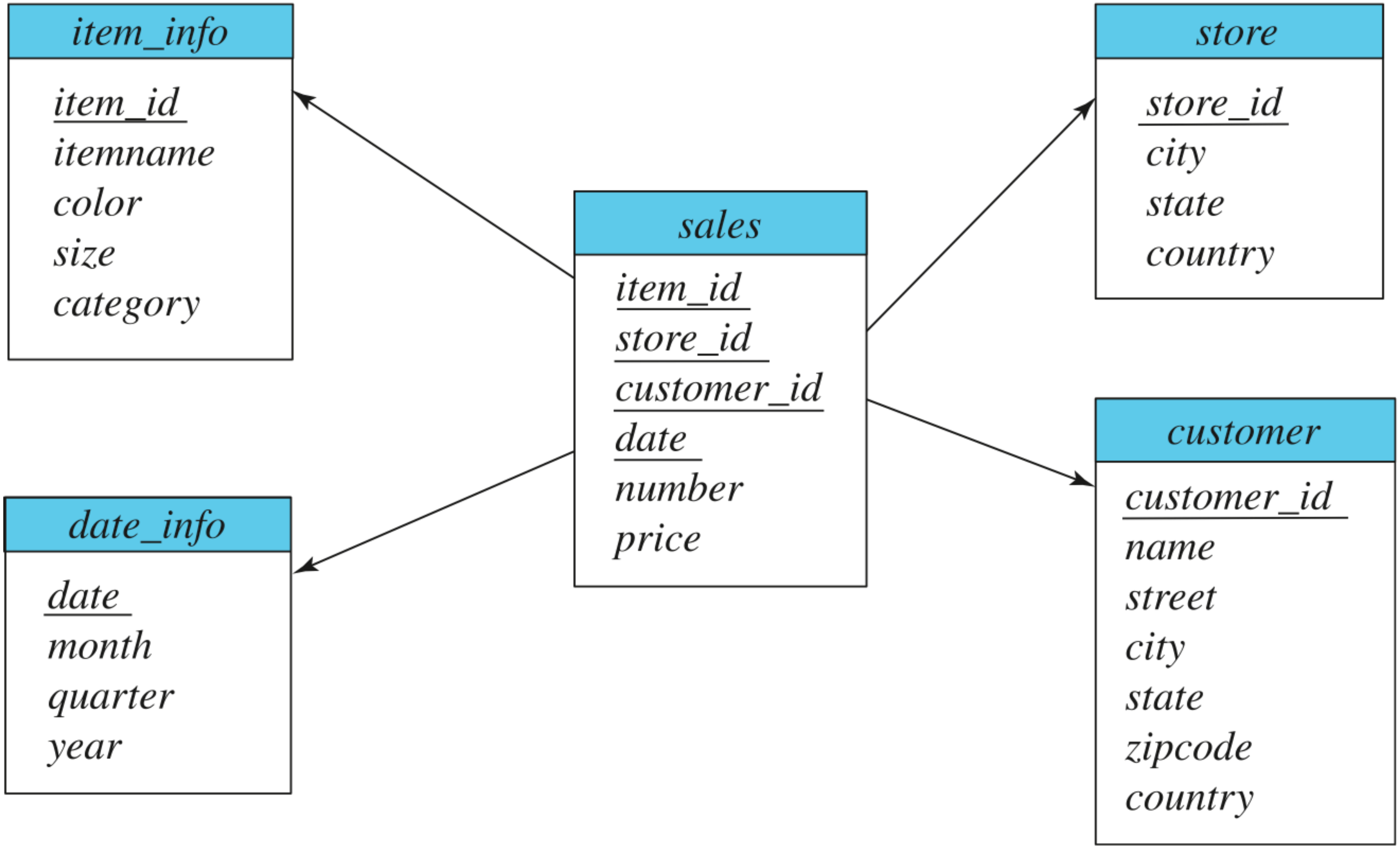
- Sales volume as a function of product, month, and region



Dimensions: Product, Location, Time
Hierarchical summarization paths



Data Warehouse Schema



Data Mining

- Data mining is the process of semi-automatically analyzing large databases to find useful patterns
- **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**
    - Given a new item whose class is unknown, predict to which class it belongs
  - **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

Classification Rules

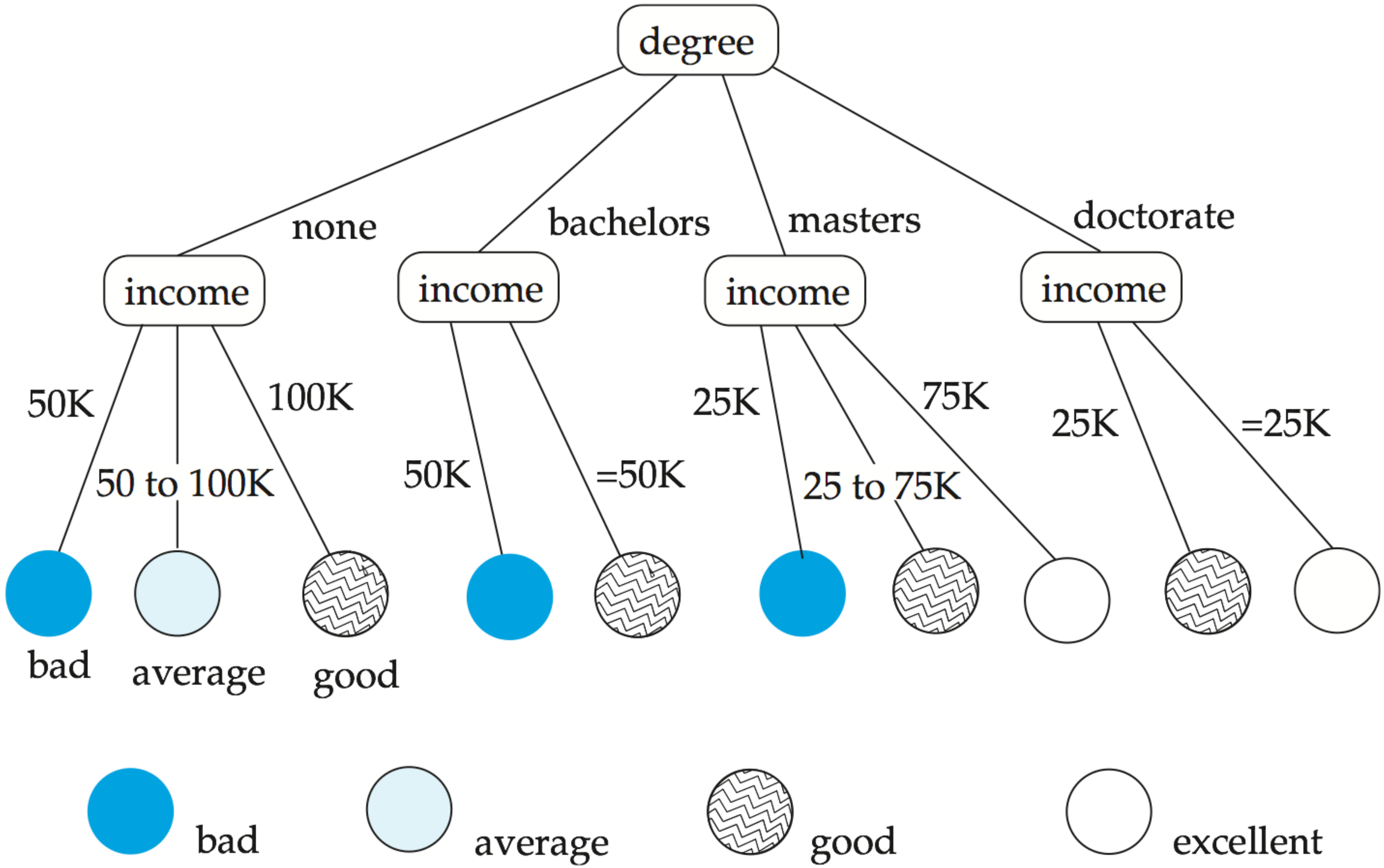
- Classification rules help assign new objects to classes.
  - E.g., given a new automobile insurance applicant, should he or she be classified as low risk, medium risk or high risk?
- Classification rules for above example could use a variety of data, such as educational level, salary, age, etc.
  - $\forall$ person P, P.degree = masters **and** P.income > 75,000

    $\Rightarrow$ P.credit = excellent
  - $\forall$ person P, P.degree = bachelors **and**

    (P.income $\geq$ 25,000 and P.income $\leq$ 75,000)

    $\Rightarrow$ P.credit = good
- Rules are not necessarily exact: there may be some misclassifications
- Classification rules can be shown compactly as a decision tree.

Decision Tree



Construction of Decision Trees

- **Training set**: a data sample in which the classification is already known.
- **Greedy** top down generation of 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.

Best Splits

- Pick best attributes and conditions on which to partition
- The purity of a set S of training instances can be measured quantitatively in several ways.
  - Notation: number of classes = *k*, number of instances = |S|, fraction of instances in class $i = p_i$.
- The **Gini** measure of purity is defined as

[

$$\text{Gini}(S) = 1 - \sum_{i-1}^{k} p^2_i$$

  - When all instances are in a single class, the Gini value is 0
  - It reaches its maximum (of 1 –1 /*k*) if each class the same number of instances.

Best Splits (Cont.)

- Another measure of purity is the **entropy** measure, which is defined as

$$\text{entropy}(S) = -\sum_{i-1}^{k} p_i \log_2 p_i$$

- When a set S is split into multiple sets Si, I=1, 2, …, r, we can measure the purity of the resultant set of sets as:

$$\text{purity}(S_1, S_2, \ldots.., S_r) = \sum_{i=1}^{r} \frac{|S_i|}{|S|} \text{purity}(S_i)$$

- The information gain due to particular split of S into S_i, i = 1, 2, …., r

Information-gain $(S, \{S_1, S_2, \ldots., S_r\}) = \text{purity}(S) - \text{purity}(S_1, S_2, \ldots S_r)$

Best Splits (Cont.)

- Measure of "cost" of a split:

  $$\text{Information-content}\ (S, \{S_1, S_2, \ldots\ldots, S_r\})) = -\sum_{i-1}^{r} \frac{|S_i|}{|S|} \log_2 \frac{|S_i|}{|S|}$$

- **Information-gain ratio** = $\dfrac{\text{Information-gain}\ (S, \{S_1, S_2, \ldots\ldots, S_r\})}{\text{Information-content}\ (S, \{S_1, S_2, \ldots\ldots, S_r\})}$

- The best split is the one that gives the maximum information gain ratio

Finding Best Splits

- Categorical attributes (with no meaningful order):
  - Multi-way split, one child for each value
  - Binary split: try all possible breakup of values into two sets, and pick the best
- Continuous-valued attributes (can be sorted in a meaningful order)
  - Binary split:
    - Sort values, try each as a split point
      - E.g., if values are 1, 10, 15, 25, split at ≤ 1, ≤ 10, ≤ 15
    - Pick the value that gives best split
  - Multi-way split:
    - A series of binary splits on the same attribute has roughly equivalent effect

Decision-Tree Construction Algorithm

Procedure *GrowTree* (S)
  Partition (S);

Procedure Partition (S)
  if (*purity* (S) > δ_p or $|S|$ < δ_s) **then**
    return;
  for each attribute A
    evaluate splits on attribute A;
  Use best split found (across all attributes) to partition
    S into $S_1, S_2, \ldots, S_r$,
  for $i = 1, 2, \ldots, r$
    Partition (S_i);

Other Types of Classifiers

- Neural net classifiers are studied in artificial intelligence and are not covered here
- 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

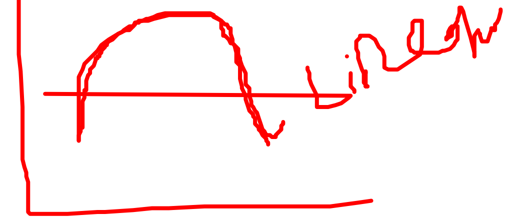
Naïve Bayesian Classifiers

- Bayesian classifiers require
  - computation of $p(d \mid c_j)$
  - precomputation of $p(c_j)$
  - $p(d)$ can be ignored since it is the same for all classes
- To simplify the task, **naïve Bayesian classifiers** assume attributes have independent distributions, and thereby estimate

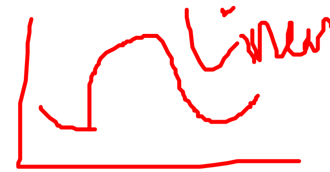
$$p(d \mid c_j) = p(d_1 \mid c_j) * p(d_2 \mid c_j) * \ldots * (p(d_n \mid c_j)$$

  - Each of the $p(d_i \mid c_j)$ can be estimated from a histogram on d_i values for each class c_j
    - the histogram is computed from the training instances
  - Histograms on multiple attributes are more expensive to compute and store

Regression



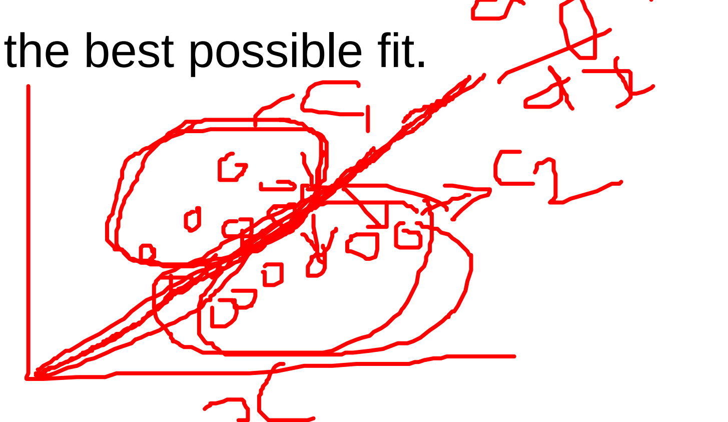
- Regression deals with the prediction of a value, rather than a class.
  - Given values for a set of variables, $X_1, X_2, \ldots, X_n$, we wish to predict the value of a variable Y.



- 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.

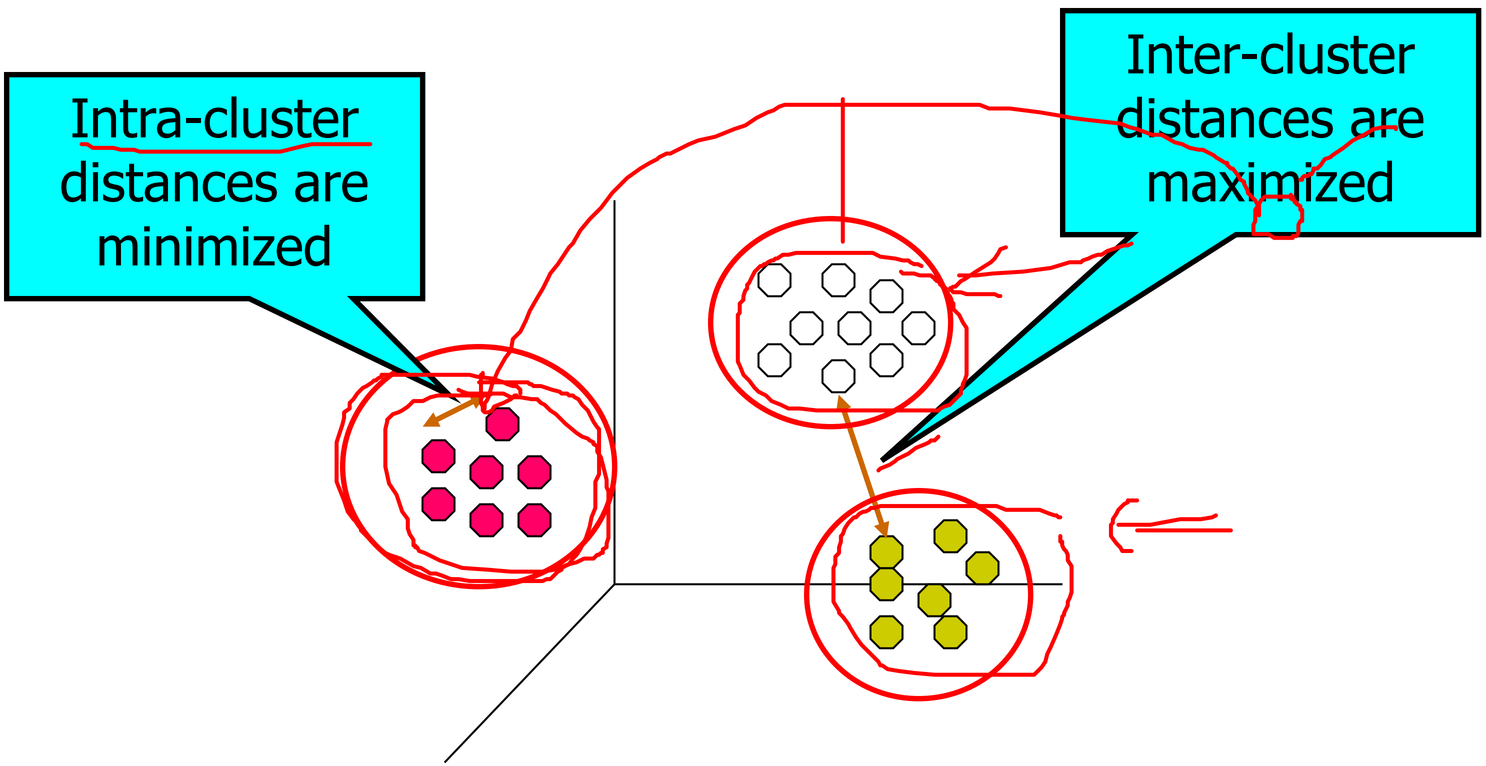


What is clustering?

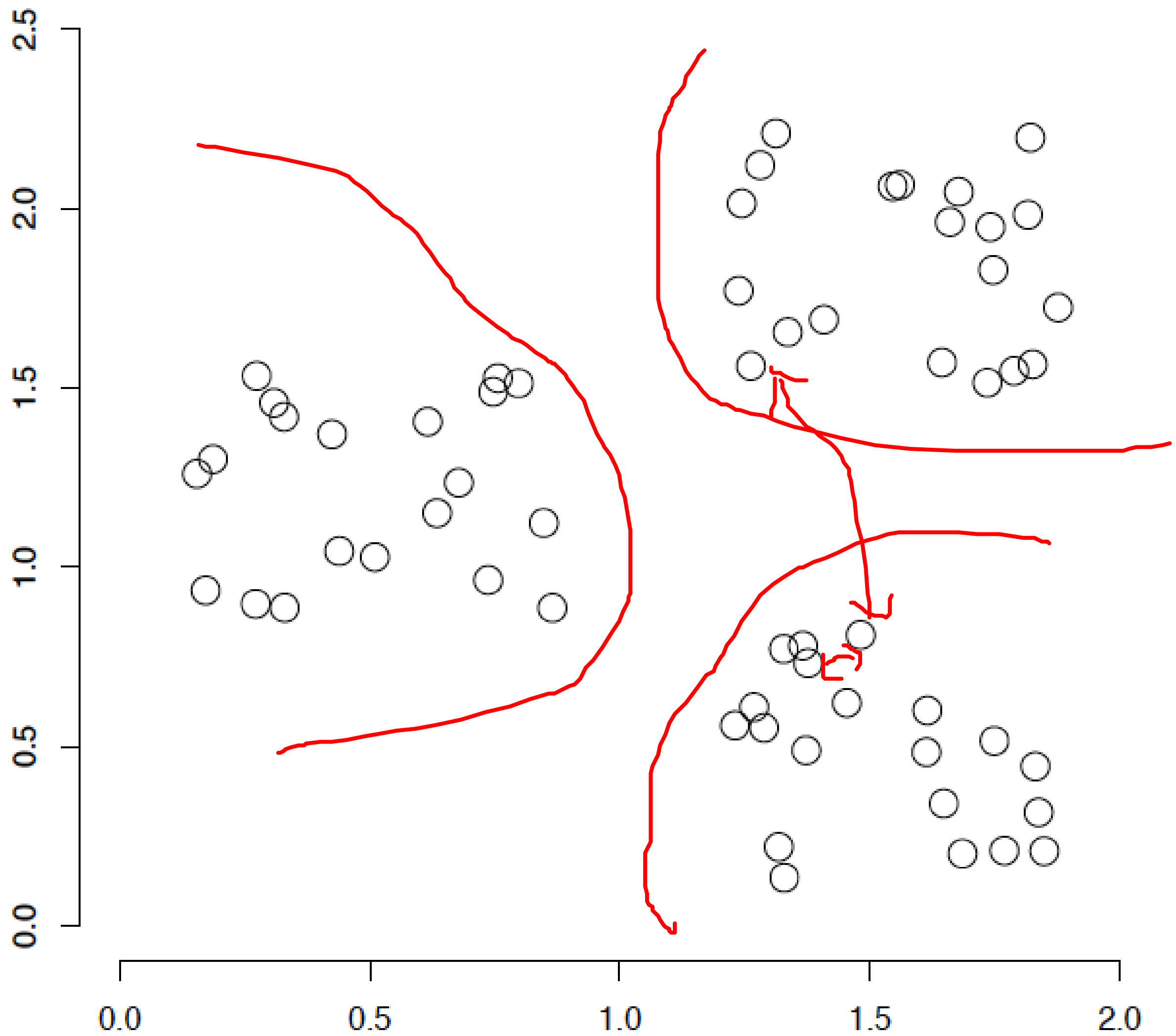
- Clustering: the process of grouping a set of objects into classes of similar objects
  - Documents within a cluster should be similar.
  - Documents from different clusters should be dissimilar.
- The commonest form of *unsupervised learning*
    - Unsupervised learning = learning from raw data, as opposed to supervised data where a classification of examples is given
  - A common and important task that finds many applications in IR and other places

Cluster Analysis

- Finding groups of objects such that the objects in a group will be similar (or related) to one another and different from (or unrelated to) the objects in other groups



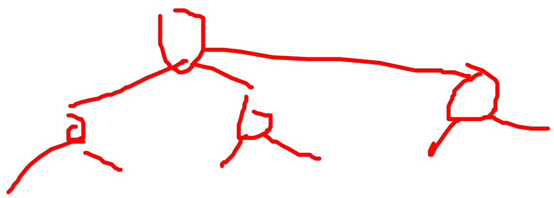
A data set with clear cluster structure



- How would you design an algorithm for finding the three clusters in this case?

Types of Clusterings

- A clustering is a set of clusters
- Important distinction between hierarchical and partitional sets of clusters
- Partitional Clustering
  - A division data objects into non-overlapping subsets (clusters) such that each data object is in exactly one subset
- Hierarchical clustering
  - A set of nested clusters organized as a hierarchical tree

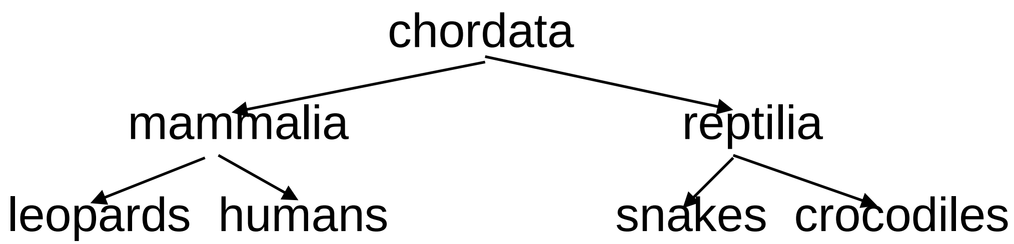


Clustering

- 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
- Has been studied extensively in statistics, but on small data sets
  - Data mining systems aim at clustering techniques that can handle very large data sets
  - E.g., the Birch clustering algorithm (more shortly)

Hierarchical Clustering

- Example from biological classification
  - (the word classification here does not mean a prediction mechanism)



- Other examples: Internet directory systems (e.g., Yahoo, more on this later)
- **Agglomerative clustering algorithms**
  - Build small clusters, then cluster small clusters into bigger clusters, and so on
- **Divisive clustering algorithms**
  - Start with all items in a single cluster, repeatedly refine (break) clusters into smaller ones

Clustering Algorithms

- Clustering algorithms have been designed to handle very large datasets
- E.g., the **Birch algorithm**
  - Main idea: use an in-memory R-tree to store points that are being clustered
  - Insert points one at a time into the R-tree, merging a new point with an existing cluster if is less than some δ distance away
  - If there are more leaf nodes than fit in memory, merge existing clusters that are close to each other
  - At the end of first pass we get a large number of clusters at the leaves of the R-tree
    - Merge clusters to reduce the number of clusters