Chapter 4

Data & Storage

A computer does more than just computation. In particular, a computer can also store and retrieve large amounts of data efficiently. In this chapter, we want to understand some of the key ingredients when it comes to dealing with data and storage.

4.1 Dictionary

We manage a library and want to be able to quickly tell whether we carry a given book or not. We need the capability to insert, delete, and search books.

Definition 4.1 (Dictionary). A dictionary is a data structure that manages a set of objects. Each object is uniquely identified by its key. The relevant operations are:

- search: find an object with a given key
- insert: put an object into the set
- delete: remove an object from the set

Remarks:

- There are alternative names for dictionary, e.g. key-value store, associative array, map, or just set.
- If the dictionary only offers search, it is called static; if it also offers insert and delete, it is dynamic.
- When discussing the algorithms, we will often ignore that we actually have a set of objects, each of which is identified by a unique key, and just talk about the set of keys. With regard to the library example, books are globally uniquely identified by a key called ISBN. Whenever we say we insert/delete/search a key, we can just drag the key’s object along.
- The classic data structure for dictionaries is a binary search tree.

4.2 Hashing

In this section we use hashing to implement an efficient dictionary.

Definition 4.4 (Universe, Key Set, Hash Table, Buckets). We consider a universe $U$ containing all possible keys. We want to maintain a subset of this universe, the key set $N \subseteq U$ with $|N| = n$, where $|N| \ll |U|$. We will use a hash table $M$, i.e. an array $M$ with $m$ buckets $M[0], M[1], \ldots, M[m-1]$. 

Remarks:

- The standard library of almost every widely used programming language provides hash tables, sometimes by another name. In C++, they are called unordered_map, in Python dictionary, in Java HashMap.
• The translation from virtual memory to physical memory uses a piece of hardware called translation lookaside buffer (TLB), which is a hardware implementation of a hash table. It has a fixed size and acts like a cache for frequently looked up virtual addresses.

• Compilers make use of hash tables to manage the symbol table.

**Definition 4.5 (Hash Function).** Given a universe $U$ and a hash table $M$, a hash function is a function $h: U \rightarrow M$. Given some key $k \in U$, we call $h(k)$ the hash of $k$.

Remarks:

• A hash function should be fast to compute and distribute hashes nicely, e.g. $h(k) = k \mod m$ for a key $k \in \mathbb{Z}$; in contrast to Chapter 3, we do not care whether a hash function is one-way.

• If we use ISBN mod $m$ as our library hash function, can we insert/delete/search books in constant time?!

• What if two keys $k \neq k'$ have $h(k) = h(k')$?

**Definition 4.6 (Collision).** Given a hash function $h: U \rightarrow M$, two distinct keys $k, k' \in U$ produce a collision if $h(k) = h(k')$.

Remarks:

• Since keys may experience collisions, the key must be stored in the bucket.

• There are competing objectives we want to optimize for when hashing. On the one hand, we want to make the hash table small since we want to save memory. On the other hand, small tables will have more collisions. How likely is it to get a collision for a given $n$ and $m$?

**Theorem 4.7 (Birthday Problem).** If we throw a fair $m$-sided die $n \leq m$ times, let $D$ be the event that all throws show different numbers. Then $D$ satisfies

$$P[D] \leq \exp \left( -\frac{n(n-1)}{2m} \right).$$

**Proof.** We have that

$$P[D] = \prod_{i=1}^{n-1} \left( 1 - \frac{1}{m} \right) = \exp \left( \sum_{i=0}^{n-1} \ln \left( 1 - \frac{1}{m} \right) \right).$$

We can use that $\ln(1 + x) \leq x$ for all $x > -1$ and the monotonicity of $e^x$:

$$P[D] = \exp \left( \sum_{i=0}^{n-1} \ln \left( 1 - \frac{1}{m} \right) \right) \leq \exp \left( \sum_{i=0}^{n-1} -\frac{i}{m} \right) = \exp \left( -\frac{n(n-1)}{2m} \right).$$

• Theorem 4.7 is called the “birthday problem” since traditionally, people use birthdays for illustration: In order to have a chance of at least 50% that two people in a group share a birthday, we only need 23 people.

• If we insert more than roughly $n \approx \sqrt{m}$ keys into a hash table, the probability of a collision approaches 1 quickly. In other words, unless we are willing to use at least $n \approx m^2$ space for our hash table, we will need a good strategy for resolving collisions.

• Theorem 4.7 assumes totally random hash functions — for non-random distributions of hashes, we might have more collisions. In particular, if we fix a hash function, then we can always end up with a key set that differs from many collisions. E.g., if many books have an ISBN that ends in 000, then ISBN mod 1000 is a terrible hash function.

• Maybe we can use modulo, but with a different $m$?

• However, for any hash function there are bad key sets.

• On the other hand, for every key set there are good hash functions! How do we efficiently pick a good hash function, i.e. one that is likely to distribute hashes well?

**Definition 4.8 (Universal Family).** Let $H \subset \{ h : U \rightarrow M \}$ be a family of hash functions from $U$ to $M$. If for all pairs of distinct keys $k \neq k' \in U$, the probability of a collision is $P[h(k) = h(k')] \leq \frac{1}{m}$ when we choose $h \in \mathcal{H}$ uniformly, then $\mathcal{H}$ is called a universal family (of hash functions).

Remarks:

• In other words: if we choose a hash function from a universal family, we can expect the hashes to be distributed well, regardless of the key set.

• We cannot just pick a random function from $U$ to $M$ because there are $|M|^{|U|}$ many, so we need $|U| \log |M|$ bits to encode such a random function. That is even more bits than keys in our huge universe $U$.

**Lemma 4.9.** For prime $m$, $a \in \{0, \ldots, m-1\}$, $\delta \in \{1, \ldots, b-1\}$, and $b \leq m$, the linear function $f_{\delta}(a) := a \cdot \delta \mod m$ is a bijection.

**Proof.** Suppose there are integers $a, a'$ with $0 \leq a < a' < m$ such that $f_{\delta}(a) = f_{\delta}(a') \mod m$. Then, there exists an integer $k$ such that $a' - a = \delta \cdot k \mod m$, which implies that $m | \delta(a' - a)$. Since $\delta$ is relative prime to $m$, we have $m | (a' - a)$, thus $a = a' \mod m$ or $a = a'$.

**Theorem 4.10 (Universal Hashing).** Let $m$ be prime and $s \in \mathbb{N}$. Let $U = \{0, \ldots, b-1\}^s$ and let $M = \{0, \ldots, m-1\}$ with $b \leq m$. For a key $k = (k_0, \ldots, k_{s-1}) \in U$ and coefficient tuple $a = (a_0, \ldots, a_{s-1}) \in (0, \ldots, m-1)^s$, define $h_a(k_0, \ldots, k_{s-1}) = \sum_{i=0}^{s-1} a_i \cdot k_i \mod m$. 
Then \( H := \{h_a : a \in \{0, \ldots, m - 1\}\} \) is a universal family of hash functions.

**Proof.** Let \( (h_0, \ldots, h_{m-1}) = k \neq k' = (k'_0, \ldots, k'_{m-1}) \in U \). Using \( \delta_i = k'_i - k_i \), we get

\[
\begin{align*}
    h_a(k') - h_a(k) &= \sum_{i=0}^{m-1} a_i \cdot k'_i - \sum_{i=0}^{m-1} a_i \cdot k_i \\
    &\equiv \sum_{i=0}^{m-1} a_i \cdot \delta_i \mod m.
\end{align*}
\]

The terms with \( \delta_i = 0 \) are 0, and so we can ignore them. Let \( X := \{i \in \{0, \ldots, m - 1\} : \delta_i \neq 0\} \) be the non-empty set of the indices of the non-zero terms, with \( x = |X| \). There are \( m^x \) possibilities to choose the coefficients \( \{a_i : i \in X\} \).

So how many of these possibilities will have a conflict, i.e., a sum of 0? If we choose \( x - 1 \) coefficients arbitrarily, then the last coefficient can always render the sum 0, as according to Lemma 4.9 the last coefficient can add any value \( \{0, \ldots, m - 1\} \) to the sum. In other words, \( m^{x-1} \) sums are 0. Therefore, our chance of randomly picking an \( a \) that produces a collision is \( \frac{m^x - 1}{m^x} = \frac{1}{m} \).

**Remarks:**

- Theorem 4.10 gives us a general method for picking hash functions from a universal family in an efficient manner. We simply choose a prime number \( m \) and uniformly at random some factors \( a_0, \ldots, a_r \).

- In practice, hash tables perform really well, and if we detect that we had bad luck in choosing our hash function, we just choose a new one and rehash our table with the new function — this is called rehashing.

### 4.3 Static Hashing

**How can we state the tradeoff between space and collisions more precisely?**

**Definition 4.11 (Number of Collisions).** Given a hash function \( h : U \to M \) and a key set \( N \subseteq U \), define the number of collisions that \( h \) produces on \( N \) as

\[
C(h, N) := \left| \{(k, k') \subseteq N : k \neq k', h(k) = h(k')\} \right|.
\]

**Lemma 4.12 (Space vs. Collisions).** We want a hash function \( h \) which produces less than \( c \) collisions, i.e., \( C(h, N) < c \), with \( n = |N| \). If \( h \) comes from a universal family, a hash table size \( m = \lceil \frac{n(n-1)}{2} \rceil \) works.

**Proof.** There are \( \binom{n}{2} \) pairs of distinct keys in \( N \), and each pair produces a collision with probability at most \( 1/m \) since \( h \) is chosen from a universal family. Using the linearity of expectation we can bound the number of expected collisions:

\[
E[C] \leq \binom{n}{2} \cdot \frac{1}{m} = \frac{n(n-1)}{2m}.
\]

We choose \( m \) such that \( 2 \cdot E[C] \leq c \):

\[
2 \cdot E[C] \leq c \Leftrightarrow \frac{n(n-1)}{m} \leq c \Leftrightarrow \frac{n(n-1)}{c} \leq m.
\]

Now we use the Markov inequality which states that for any random variable \( X \) that only takes on non-negative integer values, we have \( P(X > c) \leq \frac{E[X]}{c} \). Hence, we have \( P(C < c | C) \leq \frac{c}{n} \). In other words, to find a hash function with \( C < c \) we only need to sample 2 hash functions in expectation.

**Remarks:**

- According to Theorem 4.12, if we want no collisions, we set \( c = 1 \) and choose \( m = \lceil \frac{n(n-1)}{2} \rceil = n(n-1) \).

- Similarly, if we can tolerate \( n \) collisions, we find that a hash table of size \( m = n - 1 \) suffices.

- Algorithm 4.13 defines perfect static hashing, which applies the result of Theorem 4.12.

#### Algorithm 4.13: Perfect Static Hashing

```python
# Compute primary hash table N and secondary hash tables N_i
def perfect_static_hashing(W):
    # N = fixed set (list) of keys
    n = len(W)
    N = {None} * n
    h = None
    h2 = {None} * n
    while True:
        h = from_universal_family(n) # h : N -> range(n)
        if C(h, W) < n: break # C counts the number of collisions
        for i in range(n):
            N_i = [x for x in W if h(x) == i]
            n_i = len(N_i)
            M[i] = {None} * (n_i + (n_i - 1))
            while True:
                h2[i] = from_universal_family(len(M[i]))
                if C(h2[i], N_i) < 1: break
        return N, h, h2
```

**Remarks:**

- In the first stage, we find a hash function \( h \) with at most \( n \) collisions in linear space according to Theorem 4.12.

- In the second stage, we find a hash function \( h_i \) per bucket \( i \) without collisions by using an amount of space that is quadratic in the number of keys in the bucket \( n_i \) as per Theorem 4.12.
**Theorem 4.14 (Perfect Static Hashing).** Algorithm 4.13 returns a collision-free data structure of with a total size ($M$ and all $M_i$) less than $3n$.

**Proof.** The data structure is collision-free because of the $i$ condition in the inner while loop. Bucket $i$ is of size $n_i(n_i - 1) = 2\binom{n}{2}$ holds $n_i$ keys that produced \( \binom{n}{2} \) collisions. Since the total number of collisions is less than $n$ (if $i$ condition in the first while loop), and each bucket is of size twice its collisions, the total size of all buckets is less than $2n$. The size of the primary table $M$ is $n$, so together the total size of the data structure is less than $n + 2n = 3n$.

**Remarks:**
- We now have a hashing algorithm that can be built in linear space and expected linear time, and offers worst-case constant time search for a static set $N$.
- But what about a dynamic dictionary?

### 4.4 Dynamic Hashing

**Definition 4.15 (Hashing with Chaining).** In hashing with chaining, every bucket $M_i[j]$ stores a pointer to a secondary data structure that manages all keys $k$ with $h(k) = i$. Insertion, search, and deletion of $k$ are all relegated to those data structures. In the simplest implementation, we use a list for each bucket.

**Remarks:**
- Algorithm 4.13 is an instance of hashing with chaining with the $M_i$ being the secondary data structures managing the buckets.
- The Java standard library uses hashing with chaining to resolve collisions.

**Definition 4.16 (Load Factor).** The fraction $\frac{n}{M} = \alpha$ is called the load factor of the hash table.

**Remarks:**
- The performance of all three operations (insert/delete/search) depends on the load factor for all collision resolution strategies.
- Hashing with chaining allows for a load factor $\alpha > 1$ since the size of the table is the number of secondary data structures; performance deteriorates with growing $\alpha$.
- If we use linked lists as secondary structures and use a hash function chosen from a universal family, the cost for an unsuccessful search is $1 + \alpha$ in expectation, while that for a successful search is roughly $1 + \frac{\alpha}{c}$.
- If we use one of the strategies of this section and $\alpha$ grows too large, we should rehash with a bigger $m$ in order to remain efficient. In the Java standard library, if a hash table surpasses a load factor of 0.75, it is rehashed into a hash table with twice the size of the old one.

**Algorithm 4.18: Hashing with Probing: Search**

```python
def search(self, k):
    i = 0
    while i < self.size:
        j = self.h(i, k) % self.size # j = h_i(k)
        key_value = self.M[j]
        if key_value == None: return None
        elif key_value[0] == k: return key_value[1]
        i += 1
    return None
```

**Remarks:**
- Algorithm 4.18 defines how to search for a key in hashing with probing. The search is successful if the $i$ condition is satisfied. If the preceding $i$ is satisfied (or None returned at the end) the search is unsuccessful.
- To insert a key, we adapt Algorithm 4.18: with an unsuccessful search where $i$ was satisfied, we insert in the empty bucket. Therefore, the cost of an insert is roughly the cost of an unsuccessful search. An unsuccessful search where the loop finished triggers a rehash.
- Table 4.19 describes three different types of hashing with probing, each with the approximate time that a successful or unsuccessful search takes in expectation. More generally, linear probing uses some linear function $h_i(k) = h(k) + i$ for some $c \neq 0$, and quadratic probing uses some quadratic function $h_i(k) = h(k) + ci + di^2$ with $d \neq 0$. As long as we guarantee that $h_i(k)$ is integer for all $i \in [m]$, the constants $c$ and $d$ can be rational.

<table>
<thead>
<tr>
<th>Probing</th>
<th>$h_i(k)$</th>
<th>$\approx$ cost successful</th>
<th>$\approx$ cost unsuccessful</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear</td>
<td>$h(k) + i$</td>
<td>$\frac{1}{2} \left( 1 + \frac{1}{\alpha} \right)$</td>
<td>$\frac{1}{2} \left( 1 + \frac{1}{\alpha} \right)$</td>
</tr>
<tr>
<td>Quadratic</td>
<td>$h(k) + i^2$</td>
<td>$\frac{1}{2} \left( 1 + \frac{1}{\alpha} \right)$</td>
<td>$\frac{1}{2} \left( 1 + \frac{1}{\alpha} \right)$</td>
</tr>
<tr>
<td>Double hashing</td>
<td>$h_1(k) + i \cdot h_2(k)$</td>
<td>$\frac{1}{2} \left( 1 + \frac{1}{\alpha} \right)$</td>
<td>$\frac{1}{2} \left( 1 + \frac{1}{\alpha} \right)$</td>
</tr>
</tbody>
</table>

**Table 4.19:** Different types of hashing with probing together with the expected number of probes per search, where $\alpha$ is the load factor of the table. For hashing with probing, we need $\alpha \leq 1$ since we must have $n \leq m$. Each of $h, h_1, h_2$ is a hash function drawn from a universal family.
4.5 CUCKOO HASHING

Remarks:
• What is the reason for the different costs in Table 4.19?
• Linear probing suffers from so-called primary clustering: the probing sequences are simplistic; if two probing sequences meet in the same bucket \( j \), they will continue to collide in buckets \( j + 1, j + 2, \ldots \).
• Quadratic probing does not suffer from primary clustering, but it is subject to secondary clustering: if two keys have the same hash, then their probing sequences are identical.
• The form of quadratic probing defined in Table 4.19 has one additional issue: the probing sequence of a key does not necessarily cover the whole table. Assume \( n = 7 \) buckets and \( b(k) = 0 \), then the probing sequence of \( k \) is \((0, 1, 4, 2, 2, 4, 1)\) — buckets 3, 5, 6 do not appear.
• Double hashing does not suffer from either version of clustering. One can show that if the hash functions \( h_1 \) and \( h_2 \) used in double hashing are independently drawn from a universal family, then double hashing performs as well as an idealized hash function that assigns hashes uniformly at random.

4.5 Cuckoo Hashing

So far, the cost of all operations for dynamic key sets has been given in expected time cost. There are algorithms that allow us to do better and give us worst case guarantees on some of the operations. Two widely known possibilities to achieve this are called dynamic perfect hashing and cuckoo hashing.

Cuckoo hashing uses two hash tables, and as such provide two possible buckets \( M_1[h_1(k)] \) or \( M_2[h_2(k)] \) for each key \( k \).
If one of the two buckets is empty, simply place \( k \) there.
If both buckets are occupied by other keys, \( k \) is anyway inserted in one of the two possible buckets, replacing some key \( k_1 \) that currently resides in this bucket.
The kicked out key \( k_1 \) moves to its other bucket, potentially kicking out the currently resident key \( k_2 \); this is repeated recursively until an empty bucket is found.
If this recursion loops or takes too long (logarithmic in the table size), the hash table is rebuilt using two new hash functions.

Algorithm 4.20: Cuckoo Hashing: Insert

Remarks:
• Search and delete only need to check two buckets to figure out whether a given key is in the table, and so those operations are worst case constant time.
• One can show that the expected insert cost in cuckoo hashing is constant as long as the load factor \( \alpha \) is below 0.5.
• Cuckoo hashing gets its name from cuckoo birds: they lay their eggs into the nests of other birds, and once the cuckoo chicks hatch, they push the other eggs/chicks out of the nest.
• The idea behind cuckoo hashing is to use the “power of two choices”, which can be roughly described as: if you can choose between two resources and use the one that is less busy, you gain efficiency.
• To adapt perfect static hashing to a dynamic setting where we can also handle insertions and deletions, all we have to do is choose the size of \( M_i \) twice as large as in Algorithm 4.13, and rehash appropriately: Whenever \( C(h_i, N_i) > 0 \) for some bucket \( i \), we rehash that bucket until there are no collisions. Once some bucket reaches \( n_i^2 = |M_i| \), due to insertions, we rehash the entire table. This leaves us with expected constant time insert and delete, and worst case constant time search.
• To keep the table linear-sized, we rehash everything after every \( m \) updates (inserts or deletes).

4.6 Key-Value Databases

Definition 4.21 (Key-Value Database System). The concept of dictionaries is used in key-value database systems. The server maintains the dictionary and clients can insert and query the stored data using the keys.

Remarks:
• Popular key-value databases are Redis and Memcached. They are often used for caching in web services. Dynamically generated documents or results of queries to other databases can be stored temporarily to allow fast access to often requested data.
• The data is often kept in main memory to speed up the access and only duplicated to disk to recover the database in case of a system failure.
• Depending on the used database, different data types can be stored in the value. This can be an integer, a string, or even an array.
• Document databases are an extension of simple key-value database systems. The value has to be in a format that the database understands, such as a JSON or XML document. These databases allow queries on the content of the documents. MongoDB and CouchDB are popular document databases.
4.7 Relational Databases

However, most databases offer queries beyond simple key searches. Questions like “What is the movie with the largest cast?” or “How many directors have directed more than ten movies?” should be answered without first writing a new program. Relational databases can store large amounts of structured data and answer possibly complex questions about it.

Definition 4.22 (Table, Row, Column, Database). A table consists of rows, so that each row (data record) contains the same fields, i.e., kinds of entries. When the rows of a table are written line by line, the fields form the columns of the table. Each column is referred to by a descriptive name, and is associated with the type of the respective field, e.g., integer, floating point, string, or a date. A database is a collection of tables.

Remarks:

- In the database context, tables are also called relations, because the entries in each row are related to each other, namely by belonging to the same row.

<table>
<thead>
<tr>
<th>movies</th>
</tr>
</thead>
<tbody>
<tr>
<td>title</td>
</tr>
<tr>
<td>------</td>
</tr>
<tr>
<td>12 Angry Men</td>
</tr>
<tr>
<td>Raiders of the Lost Ark</td>
</tr>
<tr>
<td>War of the Worlds</td>
</tr>
<tr>
<td>Manos: The Hands of Fate</td>
</tr>
</tbody>
</table>

Figure 4.23: A database containing a single table called “movies” storing the title, director, and year of release for each movie.

Remarks:

- Databases as we study them are accessed using the so-called structured query language (SQL). Thus they are referred to as SQL or relational databases.
- MySQL and PostgreSQL are two popular open source SQL database systems.
- SQL database systems typically run as a daemon process on some server. Client applications connect to the server and authenticate themselves via username and password. Therefore, multiple users accessing the same database may result in concurrency issues. Some form of concurrency control is necessary!

4.8 SQL Basics

Definition 4.24 (SQL Data Types). SQL defines the following types of columns.

- CHARACTER(m) and CHARACTER VARYING(m) for fixed and variable length strings of (maximum) length \( m \),
- BIT(m) and BIT VARYING(m) for fixed and variable length bit strings of (maximum) length \( m \),
- NUMERIC, DECIMAL, INTEGER, and SMALLINT for fixed point and integer numbers,
- FLEX, REAL, and DOUBLE PRECISION for floating point numbers,
- DATE, TIME, and TIMESTAMP for dates in time, or
- INTERVAL for ranges of time.

Remarks:

- The range of each type includes the special value NULL. Note that NULL is different from the string ’NULL’, the empty string, and from the number 0 (zero). NULL indicates that the row has no value for the corresponding field.
- Many database systems implement more types, e.g., geographic coordinates, IP addresses, geometric objects, or large integers.
- All SQL statements end with a semicolon. The SQL language is case insensitive, but by convention keywords are often typed in upper case.
- The SQL-92 specification is over 600 pages long, newer versions of the standard even longer. To add insult to injury there are lots of vendor specific “SQL dialects”, i.e., modifications and extensions. However, the basic set of commands for creating, manipulating, and querying tables are largely the same across database implementations.

CREATE DATABASE database-name;

Additional parameters allow to set database-specific options, e.g., user-based permissions, or default character sets for text strings. How a database is opened depends on the implementation.

CREATE TABLE table-name (field-name type, field-name type, . . .);

To enforce that all rows have a value for a particular field, one can add NOT NULL to the type when creating the table. Fields have a default value, which is NULL if not specified by adding DEFAULT value to the type description.
Remarks:

- There are also GUI and web-based client applications (that execute locally or on an http-server, respectively) and offer access to the database in a more intuitive manner than the classic command line tools. Examples for PostgreSQL are pgAdmin, DataGrip and DBBeaver.
- Such tools are especially helpful for creating the databases and tables and often support multiple database systems. They also feature importing data from various formats, e.g., CSV files, instead of using SQL statements to populate the tables.

```
INSERT INTO table-name (field-name, ... ) VALUES (value, ...);
```

Values must be listed in the same order as the corresponding field names. When a field name (and thus its value) is omitted the field’s default value is assumed. When the list of field names is omitted the field’s values must be listed in the same order that was used when creating the table. To insert more than one row in one statement, multiple rows may be separated by commas.

```
SELECT * FROM movies;
SELECT * FROM movies WHERE director = 'Spielberg, Steven';
SELECT title FROM movies WHERE year BETWEEN 1990 AND 1999;
SELECT * FROM movies WHERE title IS NULL OR director IS NULL;
SELECT title, director FROM movies WHERE title LIKE '%the%';
```

Listing 4.25: Querying the movies table.

```
SELECT aggregate, . . . ;
Functions for aggregation include AVG to compute the average of a certain field, MIN and MAX for the minimum and maximum value, SUM for the sum of a field, and COUNT to count the number of occurrences. In an aggregation, the keyword DISTINCT indicates that only distinct values should be considered.
```

```
SELECT director, COUNT(title) FROM movies GROUP BY director;
SELECT director, COUNT(title) FROM movies GROUP BY director HAVING COUNT(title) > 10;
SELECT year, director, COUNT(title) FROM movies GROUP BY director, year ORDER BY year DESC, director ASC;
```

Listing 4.26: Aggregation with SQL.

```
SELECT field-name | aggregate, . . . GROUP BY field-name,. . . ;
```

Aggregations may be partitioned using the group-by clause. Similar to before, the query result can only include aggregates and fields by which the result is partitioned.

```
UPDATE movies SET title = 'Star Wars Episode IV: A New Hope'
WHERE title = 'Star Wars';
DELETE FROM movies WHERE title = '';
```

Listing 4.27: Grouping and sorting.

```
UPDATE table SET field-name = value,... WHERE condition;
```

Functions for aggregation include AVG to compute the average of a certain field, MIN and MAX for the minimum and maximum value, SUM for the sum of a field, and COUNT to count the number of occurrences. In an aggregation, the keyword DISTINCT indicates that only distinct values should be considered.

```
SELECT director, COUNT(title) FROM movies GROUP BY director;
SELECT director, COUNT(title) FROM movies GROUP BY director HAVING COUNT(title) > 10;
SELECT year, director, COUNT(title) FROM movies GROUP BY director, year ORDER BY year DESC, director ASC;
```

Listing 4.28: Updating and removing rows.

```
DELETE FROM table-name WHERE condition;
```

Removes all rows fulfilling the condition from the table.

4.9 Modeling

The way our example table from Figure 4.23 is designed results in lots of duplicate data—the director’s name is stored anew for each row, and two directors with the same name cannot be distinguished. The situation worsens when we
want to store the cast of each movie. Clearly the way we modeled our data can be improved. Entity-Relationship (ER) diagrams are a tool to find good representations for data.

**Definition 4.29** (ER Diagram). Rectangles denote entities (tables), and diamonds with edges to entities indicate relations between those entities. On such an edge, the number 1 or the letter n denotes whether the corresponding entity takes part once or arbitrarily many times in the relation. Entities and relations can have attributes (columns) with a name, drawn as ellipses. Italicsized attributes are key attributes which must be unique for each such entity.

![Figure 4.30: Model for a movie database. Movies and directors are in a 1-to-n relation: Each movie is directed by 1 director, and a director may work on many movies. Movies and actors are in a n-to-n relation, which has an additional attribute: An actor may appear in many movies, and each appearance is associated with a character in that movie, played by that actor.](image)

**Remarks:**
- It is standard practice to assign a so-called key attribute, often named `id`, to every entity.
- What do ER diagrams have to do with SQL? Primarily, ER diagrams are for conceptually modeling the kind of data and relations one wishes to store. They can be translated into databases, but not in a unique way.
- A close relative of the ER diagram is the Unified Modeling Language (UML). UML is used to represent the tables of a database (or classes of object-oriented software) accurately, with detailed information, e.g. fields.
- Each entity corresponds to a table with the corresponding attributes as columns. An n-to-n relation is represented by a table with columns for each attribute, and a column for the key attribute of each entity in the relation.

![Figure 4.31: The actor table and a table capturing the acting relation.](image)

![Figure 4.32: The movie and director tables using the new database layout. The director table simply maps ids to director names. Since the directing relationship is 1-to-n, it can be represented by adding a column to the movies table that stores the director for each movie.](image)

**Remarks:**
- The same scheme can be used for 1-to-1 and 1-to-n relations. However, one may also include the relation in the table storing the entity on the 1-side.
- Similarly, a 1-to-1 relation can be turned into an attribute of one of the entities.
- Tables dedicated to capturing relations are often called join tables.

### 4.10 Joins

How can we access the data, which is now scattered across multiple tables?
SELECT `movie.title`, `director.name` AS `director`, `movie.year`
FROM `movie`
INNER JOIN `director` ON `movie.director_id` = `director.id`;

Listing 4.33: Example query that returns the table depicted in Figure 4.34.

SELECT ... FROM `left-table` INNER JOIN `right-table` ON condition;
Returns all rows that can be formed from a row in the left-table and a row in the right-table that satisfy the specified condition.

<table>
<thead>
<tr>
<th>movie.title</th>
<th>director</th>
<th>movie.year</th>
</tr>
</thead>
<tbody>
<tr>
<td>12 Angry Men</td>
<td>Sidney Lumet</td>
<td>1957</td>
</tr>
<tr>
<td>Raiders of the Lost Ark</td>
<td>Steven Spielberg</td>
<td>1981</td>
</tr>
<tr>
<td>War of the Worlds</td>
<td>Steven Spielberg</td>
<td>2005</td>
</tr>
<tr>
<td>Manos: The Hands of Fate</td>
<td>Harold P. Warren</td>
<td>1966</td>
</tr>
<tr>
<td>...</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 4.34: The result returned by the query in Listing 4.33.

Remarks:
- In a query, one can create aliases for field and table names using the AS keyword, see Listing 4.33.
- The result of a JOIN clause can be ordered, fields can be aggregated and grouped, and conditions can be added using WHERE clauses.
- For example, we can combine joins and aggregations to answer our initial question of which movie has the largest cast.

SELECT `movie.title`, COUNT(*) AS `cast_size`
FROM `acting` INNER JOIN `movie` ON `acting.movie_id` = `movie.id`
GROUP BY `movie.id` ORDER BY `cast_size` DESC LIMIT 10;

Listing 4.35: Finding the 10 movies with the largest cast.

Remarks:
- The query from Listing 4.35 uses a LIMIT clause to return only the ten first entries of the sorted results.
- An INNER JOIN where the condition is TRUE returns the Cartesian product of both tables. This special case can also be obtained with the CROSS JOIN clause.
- An inner join will only return those rows of one table that have a matching row (that satisfies the condition) in the other table. For example, in Listing 4.33, a director with id 5 would not appear in the result if there are no movies which have director_id=5.
- If you want unmatched rows to appear in the result, you need to use an OUTER JOIN.

SELECT `movie.title`, `director.name` AS `director`, `movie.year`
FROM `movie`
RIGHT OUTER JOIN `director` ON `movie.director_id` = `director.id`;

Listing 4.36: Example query that returns the table depicted in Figure 4.37.

<table>
<thead>
<tr>
<th>movie.title</th>
<th>director</th>
<th>movie.year</th>
</tr>
</thead>
<tbody>
<tr>
<td>12 Angry Men</td>
<td>Sidney Lumet</td>
<td>1957</td>
</tr>
<tr>
<td>Raiders of the Lost Ark</td>
<td>Steven Spielberg</td>
<td>1981</td>
</tr>
<tr>
<td>War of the Worlds</td>
<td>Steven Spielberg</td>
<td>2005</td>
</tr>
<tr>
<td>Manos: The Hands of Fate</td>
<td>Harold P. Warren</td>
<td>1966</td>
</tr>
<tr>
<td>NULL</td>
<td>Jon Doe</td>
<td>NULL</td>
</tr>
<tr>
<td>NULL</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 4.37: The result returned by the query in Algorithm 4.36. The right outer join includes all rows from the inner join (see Figure 4.34) and, additionally, all entries from the directors table for which there is no matching entry in the movies table. In our example, “director” Jon Doe has not directed any movies, hence the movie title and year column are filled with NULL values.

SELECT ... FROM `left-table` | `RIGHT` | `FULL` OUTER JOIN `right-table` ON condition;
Returns all rows from the inner join. In addition, a LEFT or RIGHT OUTER JOIN also returns all rows from the left or right table that have no
matching row on the opposite table, respectively. The fields in unmatched rows that cannot be filled from the other table are filled with NULL values. A FULL OUTER JOIN returns both of the above.

Remarks:
- A LEFT OUTER JOIN in Listing 4.36 would include the movies with no director instead of the directors who have not directed any movie.
- Queries may use more than one JOIN clause.

```
SELECT movie.title
FROM actor INNER JOIN acting
ON actor.actor_id = acting.actor_id AND actor.name = 'Harrison Ford'
RIGHT OUTER JOIN movie ON acting.movie_id = movie.id
WHERE acting.actor_id IS NULL;
```

Listing 4.38: Finding all movies that Harrison Ford did not appear in.

Remarks:
- The conditions for the first join in Listing 4.38 ensure that only movies with Harrison Ford are taken into account for the second OUTER JOIN. That second join in turn delivers all movies that cannot be matched, yielding a NULL entry for the actor_id for movies without Harrison Ford.

4.11 Keys & Constraints

What is stopping us from inserting a row in the acting table that contains an actor_id or a movie_id that does not exist? Or from creating a director with a duplicate id?

Definition 4.39 (Key). In a table, a column (or set of columns) is a unique key if the corresponding values uniquely identify the rows within the table. The primary key of a table is a designated unique key. A foreign key is a column (or set of columns) that references the primary key of another table.

Remarks:
- SQL databases can automatically enforce these constraints. For example, a row containing a foreign key can only be inserted if it references an existing primary key. Vice versa, a row may only be removed if its primary key is not referenced by any foreign key.

```
ALTER TABLE table ADD PRIMARY KEY (field-name, ...);
```

Sets the specified fields as the primary key for the table. Any two rows must differ in at least one of the specified fields. The entries in these fields must not be NULL.

```
ALTER TABLE left-table ADD FOREIGN KEY (field-name, ...)
REFERENCES right-table;
```

Ensures that the values in the specified fields in the left table are the primary key of a row in the right table.

Remarks:
- Constraints for new tables can also be set using CREATE TABLE.
- Other ALTER TABLE queries add different constraints (e.g., checking that an integer field contains only certain values), remove constraints, and change the name, type or default value of fields.
- To ensure that checking constraints and searching for data is fast, database systems rely on index data structures.

```
CREATE INDEX directorid ON director USING HASH (id);
```

Listing 4.41: Adding a hash table index to our database.

Remarks:
- The director associated with a movie is now found quickly when performing a join.
- Some database systems automatically create index data structures to speed up queries that involve frequently used fields.
- Index data structures have a name—"directorid" in Listing 4.41. This is for referencing it later, e.g., if one decides to delete the index.
INDEXING

• Hash tables scatter the data across the storage (volatile or persistent), and it is likely that every access incurs overhead. Many database queries require scanning through ranges of the data sequentially. For example, when searching the movies from 2000–2005. Thus, accessing supposedly closeby rows requires accessing items at many different places.

• B+ trees are a data structure designed to minimize the amount of I/O operations for both searching and scanning.

```sql
CREATE INDEX movieyear ON movies USING BTREE (year);
```

Listing 4.42: Adding a B+ tree index to our database.

Definition 4.43 (B+ Tree). A B+ Tree of order b is a rooted search tree mapping keys to rows. B+ trees are balanced, i.e., all leaf nodes are at the same depth.

Every non-leaf node has between \(\lceil b/2 \rceil\) and \(b\) children. A non-leaf node \(v\) with \(k\) children contains exactly \(k - 1\) keys, in sorted order. The \(i\)th key of a non-leaf node \(v\) is identical to the smallest key in the subtree rooted at \(v\)’s \((i + 1)\)st child.

Leaf nodes contain all keys inserted into the tree, together with a pointer which points to the row associated with that key. Every leaf has pointers to at least \(\lceil (b - 1)/2 \rceil\) and at most \(b - 1\) table rows. Additionally, every leaf \(w\) has a pointer which points to its next sibling \(w'\).

![Example B+ Tree of order \(b = 4\).](image)

Figure 4.44: Example B+ tree of order \(b = 4\).

Remarks:

• The root node is a special case—it may have as little as 2 children if it is not a leaf. If it is a leaf, it may have only one pointer to a table row.

The order \(b\) is sometimes called branching factor. To reduce the number of necessary I/O operations, \(b\) is chosen so that all data necessary to store a node is the size of one page on disk.

Finding the row for some key \(k\) in a B+ tree works similar to a binary search tree.

When inserting a key \(k\), we have to check if the leaf \(v\) that should contain \(k\) is already full (i.e., already contains \(b - 1\) keys). In that case \(v\), and possibly predecessors of \(v\) that contain too many keys, need to be split using B+SplitUp.

If the root node is split into two nodes \(v, v'\), then a new root \(r\) containing key \(k\) and \(v\) and \(v'\) as children is created, and the recursion stops.

Inserting a key \(k\) is now performed by first making room using B+SplitUp if necessary, and then inserting \(k\) at the leaf.

```python
1 def B+Insert(self, k, r):
2     # Search for k to find the leaf v at which k must be inserted
3     v = self.search(k)
4     if len(v) == b-1:
5         B+SplitUp(v, k)
6     else:
7         Insert key k with row r into node v
```

Algorithm 4.45: B+Insert

Remarks:

• Vice versa, when deleting a key, nodes with too few keys need to be filled up or removed from the tree.

• The properties of B+ trees ensure that every node has at least one sibling. Thus, the merge operation always has two nodes to work with.

• If no keys can be “borrowed” from a sibling, the merge may propagate until the last two children of the root node are merged into one node. In that case the root node is replaced by the merged node, decreasing the height of the tree by 1.

```python
1 def B+Delete(self, k):
2     # Search for k to find the leaf v containing k
3     v = self.search(k)
4     Remove k from v
```

Algorithm 4.46: B+Delete
Algorithm 4.46: B+Delete

Remarks:
- The height of a B+ tree is changed only when inserting a new or removing an old root node. Therefore, all leaf nodes are always at the same depth, thus ensuring the balanced property.
- A B+ tree containing $n$ keys has height at most $O(\log_b n)$.
- It may happen that many nodes contain as little as $\frac{b}{2}$ keys, wasting memory and I/O operations. B* trees ensure that nodes contain at least $\frac{2}{3}b$ keys by cleverly “trading” entries with neighboring nodes when they contain too many or too few keys.

4.13 Transactions

Definition 4.47 (Transaction). A database transaction is a sequence of statements that is executed atomically, i.e., the transaction appears to be instantaneous to an observer.

Remarks:
- Why would we need transactions? Consider a bank managing customer’s accounts using a database system. Alice wants to calculate the liquid assets, and Bob wants to make a money transfer:

```sql
-- Alice’s statement:
SELECT SUM(balance) FROM accounts;
-- Bob’s statements:
UPDATE accounts SET balance=balance-100 WHERE customer = 'Bob';
UPDATE accounts SET balance=balance+100 WHERE customer = 'Jim';
```

Listing 4.48: Concurrency issues in databases.

Remarks:
- Assuming that the database system uses multiple threads or processes to process queries, Alice’s query may be CHF 100 short.
- To execute the queries atomically, both Alice and Bob can use transactions.

BEGIN TRANSACTION; statement1; . . . ; END TRANSACTION;

Executes the statements atomically.

Remarks:
- One way to implement transactions is to keep track of all fields read from and written to (the read- and write-set, respectively). Then, before a transaction ends, the database system checks whether another transaction wrote to any value in the read-set. If the read-set is unchanged, the write-set can be applied atomically, e.g., by using a global lock.
- SQL offers different so-called isolation levels. The isolation level defines when writes of one transaction become visible to others. The above technique implements the repeatable reads level, ensuring that read values were committed before and are not written by another transaction.
- Consider some transaction $A$ that selects all years between 1999 and 2004. What happens if another transaction $B$ concurrently inserts an entry for the year 2000? In the repeatable reads isolation level, $A$ may not see $B$’s data if $B$’s insert is scheduled after $A$ read all other entries for the year 2000, and $A$ would still be allowed to finish.
- Repeatable reads do not ensure atomicity . . .
- The highest isolation level is called serializable. This level ensures that the transactions behave “as if they were executed in some sequential order”, possibly at the cost of low concurrency.

4.14 Programming with Databases

How do you write an application that relies on a SQL database to store data? Should you construct the necessary SQL statements by manipulating strings, send them to the SQL server, and then parse the result?

Remarks:
- Writing such a SQL client is one possibility, but this is error-prone: The compiler used for the application will not be able to detect errors made in the SQL statements. Moreover, the declarative SQL most likely does not mix well with the programming language chosen for the application.
- One way to mitigate these issues in object oriented programming languages is object/relational mapping.

Definition 4.49 (Object/Relational Mapping). Object/Relational Mapping (ORM) is a design pattern used in object oriented programming to store objects in and retrieve them from relational (SQL) databases.

Remarks:
- In the simplest case, an ORM simply maps a class to a table. An object then corresponds to a row, and the object’s attributes correspond to the row’s fields.
• The ORM takes care of storing and retrieving object in the database and performs type conversions where necessary. It provides object oriented abstractions for database queries involving WHERE and other clauses. ORMs also remove boilerplate code, i.e., setting up the SQL connection, error handling, data conversion, etc.

• Popular ORMs include SQLAlchemy for Python, ActiveRecord for Ruby, Hibernate for Java, and the Entity Framework for .NET.

• The ORM needs to know how it should translate between objects and rows. For that, many ORM implementations allow to specify the database layout using object oriented methods. Many ORM mappers also support creating the database using the object oriented specification.

• Some concepts from object oriented programming are difficult to model with database concepts, and vice versa. The problems arising from combining these two paradigms are called the Object-relational impedance mismatch.

Chapter Notes

Dictionaries based on search trees are useful for providing additional operations such as nearest neighbor queries or range queries, where we want to find all keys in a certain range. Binary search trees were first published by three independent groups in 1960 and 1962 (for references, see Knuth [18]). The first instance of a self-balancing search tree that guarantees logarithmic cost for insert/search/delete is the AVL-tree, named so after its inventors Adelson-Velski and Landis [1]. For multidimensional keys, e.g., geographic data or images, there are specialized tree structures such as k-d trees [3] or BK-trees [5].

Hashing has a long history and was initially used and validated based on empirical results. One of the first publications was Peterson’s 1957 article [20] where he defined an idealized version of probing and empirically analyzed linear probing. Universal hashing was introduced two decades later by Carter and Wegman in 1979 [6]. Perfect static hashing was invented in 1984 by Fredman et al. [13] and is sometimes also referred to as FKS hashing after its inventors. Its dynamization by Dietzfelbinger et al. took another decade until 1994 [12]. A comprehensive study on perfect hashing by Czech et al. was compiled in 1997 [11]. Cuckoo hashing is a comparatively recent algorithm; it was introduced by Pagh and Rodler in 2001 [19].

There have been a number of other developments regarding hashing since the late 1970s; for an overview, see Knuth [18], in particular the section on History at the end of chapter 6.4. For a neat visualization of hashing with probing, see [14] online.

The power of two choices paradigm has found widespread application and analysis in load balancing scenarios. It was initially studied from the perspective of a balls-into-bins game where we want to minimize the maximum number of balls in any bin, and to do this we can pick two random bins and put the next ball into the least full of the two bins. Richa et al. [21] compiled an excellent survey on the earliest sources and numerous applications of this paradigm.

### Bibliography


