Chapter 9
Peer-to-Peer Data Management

In this chapter, we discuss the data management issues in the "modern" peer-to-peer (P2P) data management systems. We intentionally use the phrase "modern" to differentiate these from the early P2P systems that were common prior to client/server computing. As indicated in Chap. 1, early work on distributed DBMSs had primarily focused on P2P architectures where there was no differentiation between the functionality of each site in the system. So, in one sense, P2P data management is quite old—if one simply interprets P2P to mean that there are no identifiable "servers" and "clients" in the system. However, the "modern" P2P systems go beyond this simple characterization and differ from the old systems that are referred to by the same name in a number of important ways, as mentioned in Chap. 1.

The first difference is the massive distribution in current systems. While the early systems focused on a few (perhaps at most tens of) sites, current systems consider thousands of sites. Furthermore, these sites are geographically very distributed, with possible clusters forming at certain locations.

The second is the inherent heterogeneity of every aspect of the sites and their autonomy. While this has always been a concern of distributed databases, coupled with massive distribution, site heterogeneity and autonomy take on added significance, disallowing some of the approaches from consideration.

The third major difference is the considerable volatility of these systems. Distributed DBMSs are well-controlled environments, where additions of new sites or the removal of existing sites are done very carefully and rarely. In modern P2P systems, the sites are (quite often) people's individual machines and they join and leave the P2P system at will, creating considerable hardship in the management of data.

In this chapter, we focus on this modern incarnation of P2P systems. In these systems, the following requirements are:

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- **Autonomy.** An autonomous peer should be able to join or leave the system at any time without restriction. It should also be able to control the data it stores and which other peers can store its data (e.g., some other trusted peers).
- **Query expressiveness.** The query language should allow the user to describe the desired data at the appropriate level of detail. The simplest form of query is key lookup, which is only appropriate for finding files. Keyword search with ranking of results is appropriate for searching documents, but for more structured data, an SQL-like query language is necessary.
- **Efficiency.** The efficient use of the P2P system resources (bandwidth, computing power, storage) should result in lower cost, and, thus, higher throughput of queries, i.e., a higher number of queries can be processed by the P2P system in a given time interval.
- **Quality of service.** This refers to the user-perceived efficiency of the system, such as completeness of query results, data consistency, data availability, and query response time.
- **Fault-tolerance.** Efficiency and quality of service should be maintained despite the failures of peers. Given the dynamic nature of peers that may leave or fail at any time, it is important to properly exploit data replication.
- **Security.** The open nature of a P2P system gives rise to serious security challenges since one cannot rely on trusted servers. With respect to data management, the main security issue is access control which includes enforcing intellectual property rights on data contents.

A number of different uses of P2P systems have been developed for sharing computation (e.g., SETI@home), communication (e.g., ICQ), or data (e.g., BitTorrent, Gnutella, and Kazaa). Our interest, naturally, is on data sharing systems. Popular systems such as BitTorrent, Gnutella, and Kazaa are quite limited when viewed from the perspective of database functionality. First, they provide only file level sharing with no sophisticated content-based search/query facilities. Second, they are single-application systems that focus on performing one task, and it is not straightforward to extend them for other applications/functions. In this chapter, we discuss the research activities towards providing proper database functionality over P2P infrastructures. Within this context, data management issues that must be addressed include the following:

- Data location: peers must be able to refer to and locate data stored in other peers.
- Query processing: given a query, the system must be able to discover the peers that contribute relevant data and efficiently execute the query.
- Data integration: when shared data sources in the system follow different schemas or representations, peers should still be able to access that data, ideally using the data representation used to model their own data.
- Data consistency: if data is replicated or cached in the system, a key issue is to maintain the consistency between these duplicates.

Figure 9.1 shows a reference architecture for a peer participating in a data sharing P2P system. Depending on the functionality of the P2P system, one or more of the

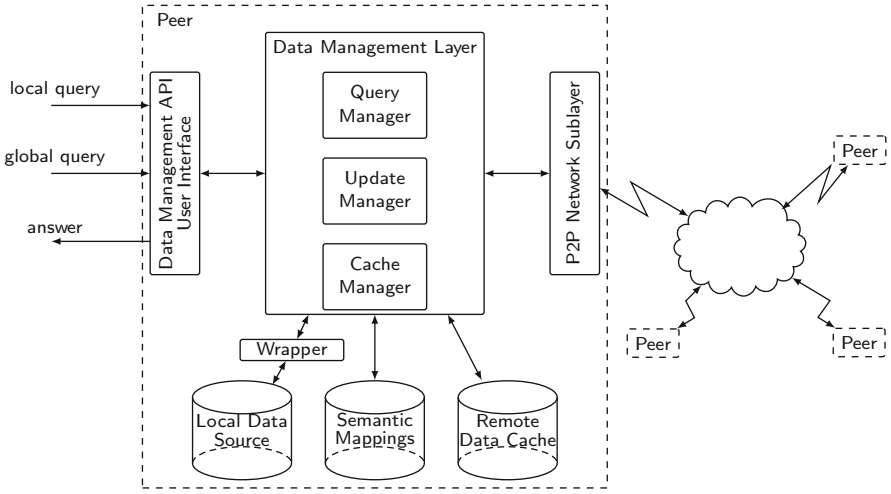


Fig. 9.1 Peer reference architecture

components in the reference architecture may not exist, may be combined together, or may be implemented by specialized peers. The key aspect of the proposed architecture is the separation of the functionality into three main components: (1) an interface used for submitting the queries; (2) a data management layer that handles query processing and metadata information (e.g., catalogue services); and (3) a P2P infrastructure, which is composed of the P2P network sublayer and P2P network. In this chapter, we focus on the P2P data management layer and P2P infrastructure.

Queries are submitted using a user interface or data management API and handled by the data management layer. They may refer to data stored locally or globally in the system. The query request is processed by a query manager module that retrieves semantic mapping information from a repository when the system integrates heterogeneous data sources. This semantic mapping repository contains metainformation that allows the query manager to identify peers in the system with data relevant to the query and to reformulate the original query in terms that other peers can understand. Some P2P systems may store the semantic mapping in specialized peers. In this case, the query manager will need to contact these specialized peers or transmit the query to them for execution. If all data sources in the system follow the same schema, neither the semantic mapping repository nor its associated query reformulation functionality is required.

Assuming a semantic mapping repository, the query manager invokes services implemented by the P2P network sublayer to communicate with the peers that will be involved in the execution of the query. The actual execution of the query is influenced by the implementation of the P2P infrastructure. In some systems, data is sent to the peer where the query was initiated and then combined at this peer. Other systems provide specialized peers for query execution and coordination. In either case, result data returned by the peers involved in the execution of the query

may be cached locally to speed up future executions of similar queries. The cache manager maintains the local cache of each peer. Alternatively, caching may occur only at specialized peers.

The query manager is also responsible for executing the local portion of a global query when data is requested by a remote peer. A wrapper may hide data, query language, or any other incompatibilities between the local data source and the data management layer. When data is updated, the update manager coordinates the execution of the update between the peers storing replicas of the data being updated.

The P2P network infrastructure, which can be implemented as either structured or unstructured network topology, provides communication services to the data management layer.

In the remainder of this chapter, we will address each component of this reference architecture, starting with infrastructure issues in Sect. 9.1. The problems of data mapping and the approaches to address them are the topics of Sect. 9.2. Query processing is discussed in Sect. 9.3. Data consistency and replication issues are discussed in Sect. 9.4. In Sect. 9.5, we introduce Blockchain, a P2P infrastructure for recording transactions efficiently, safely, and permanently.

9.1 Infrastructure

The infrastructure of all P2P systems is a P2P network, which is built on top of a physical network (usually the Internet); thus, it is commonly referred to as the *overlay network*. The overlay network may (and usually does) have a different topology than the physical network and all the algorithms focus on optimizing communication over the overlay network (usually in terms of minimizing the number of "hops" that a message needs to go through from a source node to a destination node—both in the overlay network). The distinction between the overlay network and the physical network may be a problem in that two nodes that are neighbors in the overlay network may, in some cases, be considerably far apart in the physical network. Therefore, the cost of communication within the overlay network may not reflect the actual cost of communication in the physical network. We address this issue at the appropriate points during the infrastructure discussion.

Overlay networks can be of two general types: pure and hybrid. *Pure overlay networks* (more commonly referred to as *pure P2P networks*) are those where there is no differentiation between any of the network nodes—they are all equal. In *hybrid P2P networks*, on the other hand, some nodes are given special tasks to perform. Hybrid networks are commonly known as *superpeer systems*, since some of the peers are responsible for "controlling" a set of other peers in their domain. The pure networks can be further divided into structured and unstructured networks. *Structured networks* tightly control the topology and message routing, whereas in *unstructured networks* each node can directly communicate with its neighbors and can join the network by attaching themselves to any node.

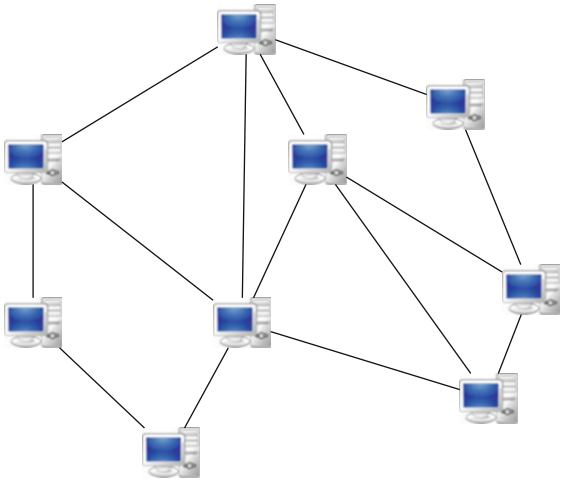


Fig. 9.2 Unstructured P2P network

9.1.1 Unstructured P2P Networks

Unstructured P2P networks refer to those with no restriction on data placement in the overlay topology. The overlay network is created in a nondeterministic (ad hoc) manner and the data placement is completely unrelated to the overlay topology. Each peer knows its neighbors, but does not know the resources that they have. Figure 9.2 shows an example unstructured P2P network.

Unstructured networks are the earliest examples of P2P systems whose core functionality remains file sharing. In these systems, replicated copies of popular files are shared among peers, without the need to download them from a centralized server. Examples of these systems are Gnutella, Freenet, Kazaa, and BitTorrent.

A fundamental issue in all P2P networks is the type of index to the resources that each peer holds, since this determines how resources are searched. Note that what is called "index management" in the context of P2P systems is very similar to catalog management that we studied in Chap. 2. Indexes are stored metadata that the system maintains. The exact content of the metadata differs in different P2P systems. In general, it includes, at a minimum, information on the resources and sizes.

There are two alternatives to maintaining indices: centralized, where one peer stores the metadata for the entire P2P system, and distributed, where each peer maintains metadata for resources that it holds. Again, the alternatives are identical to those for directory management.

The type of index supported by a P2P system (centralized or distributed) impacts how resources are searched. Note that we are not, at this point, referring to running queries; we are merely discussing how, given a resource identifier, the underlying P2P infrastructure can locate the relevant resource. In systems that maintain a centralized index, the process involves consulting the central peer to find the location

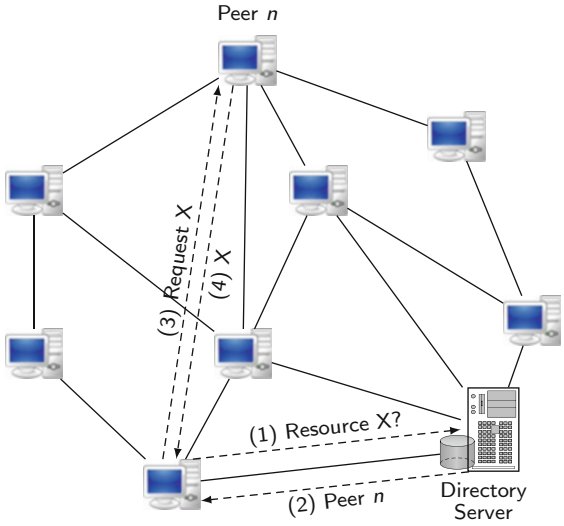


Fig. 9.3 Search over a centralized index. (1) A peer asks the central index manager for resource, (2) The response identifies the peer with the resource, (3) The peer is asked for the resource, (4) It is transferred

of the resource, followed by directly contacting the peer where the resource is located (Fig. 9.3). Thus, the system operates similar to a client/server one up to the point of obtaining the necessary index information (i.e., the metadata), but from that point on, the communication is only between the two peers. Note that the central peer may return a set of peers who hold the resource and the requesting peer may choose one among them, or the central peer may make the choice (taking into account loads and network conditions, perhaps) and return only a single recommended peer.

In systems that maintain a distributed index, there are a number of search alternatives. The most popular one is flooding, where the peer looking for a resource sends the search request to all of its neighbors on the overlay network. If any of these neighbors have the resource, they respond; otherwise, each of them forwards the request to its neighbors until the resource is found or the overlay network is fully spanned (Fig. 9.4).

Naturally, flooding puts very heavy demands on network resources and is not scalable—as the overlay network gets larger, more communication is initiated. This has been addressed by establishing a Time-to-Live (TTL) limit that restricts the number of hops that a request message makes before it is dropped from the network. However, TTL also restricts the number of nodes that are reachable.

There have been other approaches to address this problem. A straightforward method is for each peer to choose a subset of its neighbors and forward the request only to those. There are different ways to determine this subset. For example, the concept of random walks can be used where each peer chooses a neighbor at random

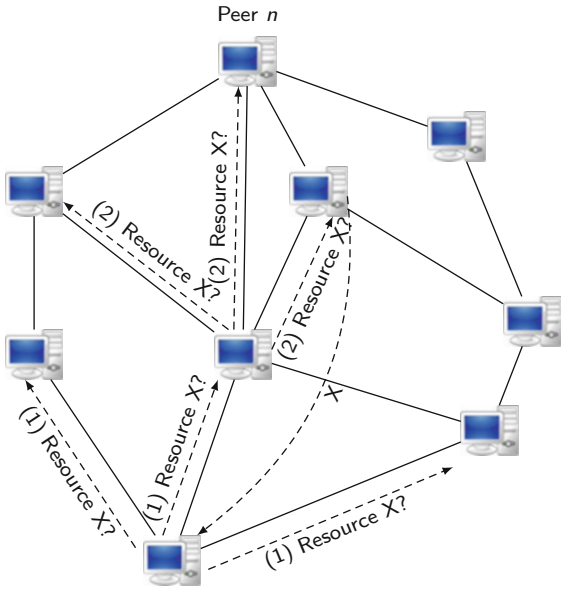


Fig. 9.4 Search over a Decentralized Index. (1) A peer sends the request for resource to all its neighbors, (2) Each neighbor propagates to its neighbors if it does not have the resource, (3) The peer who has the resource responds by sending the resource

and propagates the request only to it. Alternatively, each neighbor can maintain not only indices for local resources, but also for resources that are on peers within a radius of itself and use the historical information about their performance in routing queries. Still another alternative is to use similar indices based on resources at each node to provide a list of neighbors that are most likely to be in the direction of the peer holding the requested resources. These are referred to as routing indices and are used more commonly in structured networks, where we discuss them in more detail.

Another approach is to exploit *gossip protocols*, also known as *epidemic protocols*. Gossiping has been initially proposed to maintain the mutual consistency of replicated data by spreading replica updates to all nodes over the network. It has since been successfully used in P2P networks for data dissemination. Basic gossiping is simple. Each node in the network has a complete view of the network (i.e., a list of all nodes' addresses) and chooses a node at random to spread the request. The main advantage of gossiping is robustness over node failures since, with very high probability, the request is eventually propagated to all the nodes in the network. In large P2P networks, however, the basic gossiping model does not scale as maintaining the complete view of the network at each node would generate very heavy communication traffic. A solution to scalable gossiping is to maintain at each node only a partial view of the network, e.g., a list of tens of neighbor nodes. To gossip a request, a node chooses, at random, a node in its partial view and sends it

the request. In addition, the nodes involved in a gossip exchange their partial views to reflect network changes in their own views. Thus, by continuously refreshing their partial views, nodes can self-organize into randomized overlays that scale up very well.

The final issue that we would like to discuss with respect to unstructured networks is how peers join and leave the network. The process is different for centralized versus distributed index approaches. In a centralized index system, a peer that wishes to join simply notifies the central index peer and informs it of the resources that it wishes to contribute to the P2P system. In the case of a distributed index, the joining peer needs to know one other peer in the system to which it "attaches" itself by notifying it and receiving information about its neighbors. At that point, the peer is part of the system and starts building its own neighbors. Peers that leave the system do not need to take any special action, they simply disappear. Their disappearance will be detected in time, and the overlay network will adjust itself.

9.1.2 Structured P2P Networks

Structured P2P networks have emerged to address the scalability issues faced by unstructured P2P networks. They achieve this goal by tightly controlling the overlay topology and the placement of resources. Thus, they achieve higher scalability at the expense of lower autonomy as each peer that joins the network allows its resources to be placed on the network based on the particular control method that is used.

As with unstructured P2P networks, there are two fundamental issues to be addressed: how are the resources indexed, and how are they searched. The most popular indexing and data location mechanism that is used in structured P2P networks is a *distributed hash table* (DHT). DHT-based systems provide two APIs: put(key, data) and get(key), where key is an object identifier. Each key (k_i) is hashed to generate a peer id (p_i), which stores the data corresponding to object contents (Fig. 9.5).

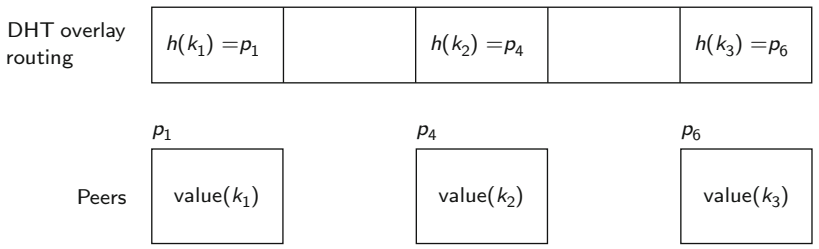


Fig. 9.5 DHT network

A straightforward approach could be to use the URI of the resource as the IP address of the peer that would hold the resource. However, one of the important design requirements is to provide a uniform distribution of resources over the overlay network and URIs/IP addresses do not provide sufficient flexibility. Consequently, *consistent hashing* techniques that provide uniform hashing of values are used to evenly place the data on the overlay. Although many hash functions may be employed for generating *virtual address mappings* for the resource, SHA-1 has become the most widely accepted *base*[1] hash function that supports both uniformity and security (by supporting data integrity for the keys). The actual design of the hash function may be implementation dependent and we will not discuss that issue any further.

Search (commonly called "lookup") over a DHT-based structured P2P network also involves the hash function: the key of the resource is hashed to get the id of the peer in the overlay network that is responsible for that key. The lookup is then initiated on the overlay network to locate the target node in question. This is referred to as the *routing protocol*, and it differs between different implementations and is closely associated with the overlay structure used. We will discuss one example approach shortly.

While all routing protocols aim to provide efficient lookups, they also try to minimize the *routing information* (also called *routing state*) that needs to be maintained in a routing table at each peer in the overlay. This information differs between various routing protocols and overlay structures, but it needs to provide sufficient directory-type information to route the put and get requests to the appropriate peer on the overlay. All routing table implementations require the use of maintenance algorithms in order to keep the routing state up-to-date and consistent. In contrast to routers on the Internet that also maintain routing databases, P2P systems pose a greater challenge since they are characterized by high node volatility and undependable network links. Since DHTs also need to support perfect recall (i.e., all the resources that are accessible through a given key have to be found), routing state consistency becomes a key challenge. Therefore, the maintenance of consistent routing state in the face of concurrent lookups and during periods of high network volatility is essential.

Many DHT-based overlays have been proposed. These can be categorized according to their *routing geometry* and *routing algorithm*. Routing geometry essentially defines the manner in which neighbors and routes are arranged. The routing algorithm corresponds to the routing protocol discussed above and is defined as the manner in which next-hops/routes are chosen on a given routing geometry. The more important existing DHT-based overlays can be categorized as follows:

- **Tree.** In the tree approach, the leaf nodes correspond to the node identifiers that store the keys to be searched. The height of the tree is $\log n$, where n is the number of nodes in the tree. The search proceeds from the root to the leaves by

[1] A base hash function is defined as a function that is used as a basis for the design of another hash function.

doing a longest prefix match at each of the intermediate nodes until the target node is found. Therefore, in this case, matching can be thought of as correcting bit values from left-to-right at each successive hop in the tree. A popular DHT implementation that falls into this category is Tapestry, which uses *surrogate routing* in order to forward requests at each node to the closest digit in the routing table. Surrogate routing is defined as routing to the *closest* digit when an exact match in the longest prefix cannot be found. In Tapestry, each unique identifier is associated with a node that is the root of a unique spanning tree used to route messages for the given identifier. Therefore, lookups proceed from the base of the spanning tree all the way to the root node of the identifier. Although this is somewhat different from traditional tree structures, Tapestry routing geometry is very closely associated with a tree structure and we classify it as such.

In tree structures, a node in the system has 2^{i-1} nodes to choose from as its neighbor from the subtree with whom it has $\log(n - i)$ prefix bits in common. The number of potential neighbors increases exponentially as we proceed further up in the tree. Thus, in total there are $n^{\log n/2}$ possible routing tables per node (note, however that, only one such routing table can be selected for a node). Therefore, the tree geometry has good neighbor selection characteristics that would provide it with fault-tolerance. However, routing can only be done through one neighboring node when sending to a particular destination. Consequently, the tree-structured DHTs do not provide any flexibility in the selection of routes.

- **Hypercube.** The hypercube routing geometry is based on d-dimensional Cartesian coordinate space that is partitioned into an individual set of zones such that each node maintains a separate zone of the coordinate space. An example of hypercube-based DHT is the Content Addressable Network (CAN). The number of neighbors that a node may have in a d-dimensional coordinate space is $2d$ (for the sake of discussion, we consider $d = \log n$). If we consider each coordinate to represent a set of bits, then each node identifier can be represented as a bit string of length $\log n$. In this way, the hypercube geometry is very similar to the tree since it also simply *fixes* the bits at each hop to reach the destination. However, in the hypercube, since the bits of neighboring nodes only differ in *exactly* one bit, each forwarding node needs to modify only a single bit in the bit string, which can be done in any order. Thus, if we consider the correction of the bit string, the first correction can be applied to any $\log n$ nodes, the next correction can be applied to any $(\log n) - 1$ nodes, etc. Therefore, we have $(\log n)!$ possible routes between nodes, which provides high route flexibility in the hypercube routing geometry. However, a node in the coordinate space does not have any choice over its neighbors' coordinates since adjacent coordinate zones in the coordinate space cannot change. Therefore, hypercubes have poor neighbor selection flexibility.
- **Ring.** The ring geometry is represented as a one-dimensional circular identifier space where the nodes are placed at different locations on the circle. The distance between any two nodes on the circle is the numeric identifier difference (clockwise) around the circle. Since the circle is one-dimensional, the data identifiers can be represented as single decimal digits (represented as binary bit strings) that map to a node that is closest in the identifier space to the given

decimal digit. Chord is a popular example of the ring geometry. Specifically, in Chord, a node whose identifier is a maintains information about $\log n$ other neighbors on the ring where the i^{th} neighbor is the node closest to $a + 2^{i-1}$ on the circle. Using these links (called *fingers*), Chord is able to route to any other node in $\log n$ hops.

A careful analysis of Chord's structure reveals that a node does not necessarily need to maintain the node closest to $a + 2^{i-1}$ as its neighbor. In fact, it can still maintain the $\log n$ lookup upper bound if any node from the range $[(a + 2^{i-1}), (a + 2^i)]$ is chosen. Therefore, in terms of route flexibility, it is able to select between $n^{\log n/2}$ routing tables for each node. This provides a great deal of neighbor selection flexibility. Moreover, for routing to any node, the first hop has $\log n$ neighbors that can route the search to the destination and the next node has $(\log n) - 1$ nodes, and so on. Therefore, there are typically $(\log n)!$ possible routes to the destination. Consequently, ring geometry also provides good route selection flexibility.

In addition to these most popular geometries, there have been many other DHT-based structured overlays that use different topologies.

DHT-based overlays are efficient in that they guarantee finding the node on which to place or find the data in $\log n$ hops, where n is the number of nodes in the system. However, they have several problems, in particular when viewed from the data management perspective. One of the issues with DHTs that employ consistent hashing functions for better distribution of resources is that two peers that are "neighbors" in the overlay network because of the proximity of their hash values may be geographically quite apart in the actual network. Thus, communicating with a neighbor in the overlay network may incur high transmission delays in the actual network. There have been studies to overcome this difficulty by designing *proximity-aware* or *locality-aware* hash functions. Another difficulty is that they do not provide any flexibility in the placement of data—a data item has to be placed on the node that is determined by the hash function. Thus, if there are P2P nodes that contribute their own data, they need to be willing to have data moved to other nodes. This is problematic from the perspective of node autonomy. The third difficulty is in that it is hard to run range queries over DHT-based architectures since, as is well-known, it is hard to run range queries over hash indices. There have been studies to overcome this difficulty that we discuss later.

These concerns have caused the development of structured overlays that do not use DHT for routing. In these systems, peers are mapped into the data space rather than the hash key space. There are multiple ways to partition the data space among multiple peers.

- **Hierarchical structure.** Many systems employ hierarchical overlay structures, including tree, balanced trees, randomized balance trees (e.g., skip list), and others. Specifically PHT and P-Grid employ a binary tree structure, where peers whose data share common prefixes cluster under common branches. Balanced trees are also widely used due to their guaranteed routing efficiency (the expected "hop length" between arbitrary peers is proportional to the tree height). For

instance, BATON, VBI-tree, and BATON* employ k-way balanced tree structure to manage peers, and data is evenly partitioned among peers at the leaf-level. In comparison, P-Tree uses a B-tree structure with better flexibility on tree structural changes. SkipNet and Skip Graph are based on the skip list, and they link peers according to a randomized balanced tree structure where the node order is determined by each node's data values.

- **Space-filling curve.** This architecture is usually used to linearize sort data in multidimensional data space. Peers are arranged along the space-filling curve (e.g., Hilbert curve) so that sorted traversal of peers according to data order is possible.
- **Hyperrectangle structure.** In these systems, each dimension of the hyperrectangle corresponds to one attribute of the data according to which an organization is desired. Peers are distributed in the data space either uniformly or based on data locality (e.g., through data intersection relationship). The hyperrectangle space is then partitioned by peers based on their geometric positions in the space, and neighboring peers are interconnected to form the overlay network.

9.1.3 Superpeer P2P Networks

Superpeer P2P systems are hybrid between pure P2P systems and the traditional client–server architectures. They are similar to client–server architectures in that not all peers are equal; some peers (called *superpeers*) act as dedicated serves for some other peers and can perform complex functions such as indexing, query processing, access control, and metadata management. If there is only one superpeer in the system, then this reduces to the client–server architecture. They are considered P2P systems, however, since the organization of the superpeers follows a P2P organization, and superpeers can communicate with each other in sophisticated ways. Thus, unlike client–server systems, global information is not necessarily centralized and can be partitioned or replicated across superpeers.

In a superpeer network, a requesting peer sends the request, which can be expressed in a high-level language, to its responsible superpeer. The superpeer can then find the relevant peers either directly through its index or indirectly using its neighbor superpeers. More precisely, the search for a resource proceeds as follows (see Fig. 9.6):

1. A peer, say Peer 1, asks for a resource by sending a request to its superpeer.
2. If the resource exists at one of the peers controlled by this superpeer, it notifies Peer 1, and the two peers then communicate to retrieve the resource. Otherwise, the superpeer sends the request to the other superpeers.
3. If the resource does not exist at one of the peers controlled by this superpeer, the superpeer asks the other superpeers. The superpeer of the node that contains the resource (say Peer n) responds to the requesting superpeer.

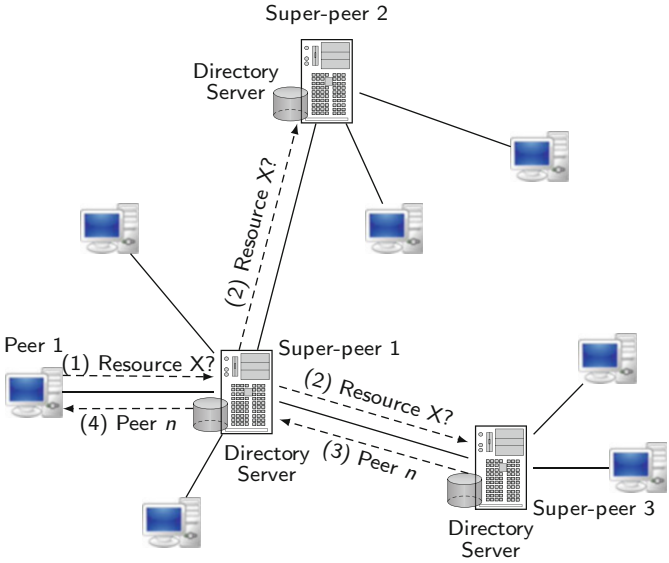


Fig. 9.6 Search over a superpeer system. (1) A peer sends the request for resource to all its superpeer, (2) The superpeer sends the request to other superpeers if necessary, (3) The superpeer one of whose peers has the resource responds by indicating that peer, (4) The superpeer notifies the original peer

4. Peer *n*'s identity is sent to Peer 1, after which the two peers can communicate directly to retrieve the resource.

The main advantages of superpeer networks are efficiency and quality of service (e.g., completeness of query results, query response time). The time needed to find data by directly accessing indices in a superpeer is very small compared with flooding. In addition, superpeer networks exploit and take advantage of peers' different capabilities in terms of CPU power, bandwidth, or storage capacity as superpeers take on a large portion of the entire network load. Access control can also be better enforced since directory and security information can be maintained at the superpeers. However, autonomy is restricted since peers cannot log in freely to any superpeer. Fault-tolerance is typically lower since superpeers are single points of failure for their subpeers (dynamic replacement of superpeers can alleviate this problem).

Examples of superpeer networks include Edutella and JXTA.

Requirements	Unstructured	Structured	Superpeer
Autonomy	Low	Low	Moderate
Query expressiveness	High	Low	High
Efficiency	Low	High	High
QoS	Low	High	High
Fault-tolerance	High	High	Low
Security	Low	Low	High

Fig. 9.7 Comparison of approaches

9.1.4 Comparison of P2P Networks

Figure 9.7 summarizes how the requirements for data management (autonomy, query expressiveness, efficiency, quality of service, fault-tolerance, and security) are possibly attained by the three main classes of P2P networks. This is a rough comparison to understand the respective merits of each class. Obviously, there is room for improvement in each class of P2P networks. For instance, fault-tolerance can be improved in superpeer systems by relying on replication and fail-over techniques. Query expressiveness can be improved by supporting more complex queries on top of structured networks.

9.2 Schema Mapping in P2P Systems

We discussed the importance of, and the techniques for, designing database integration systems in Chap. 7. Similar issues arise in data sharing P2P systems.

Due to specific characteristics of P2P systems, e.g., the dynamic and autonomous nature of peers, the approaches that rely on centralized global schemas no longer apply. The main problem is to support decentralized schema mapping so that a query expressed on one peer's schema can be reformulated to a query on another peer's schema. The approaches which are used by P2P systems for defining and creating the mappings between peers' schemas can be classified as follows: pairwise schema mapping, mapping based on machine learning techniques, common agreement mapping, and schema mapping using information retrieval (IR) techniques.

9.2.1 Pairwise Schema Mapping

In this approach, each user defines the mapping between the local schema and the schema of any other peer that contains data that are of interest. Relying on the transitivity of the defined mappings, the system tries to extract mappings between schemas that have no defined mapping.

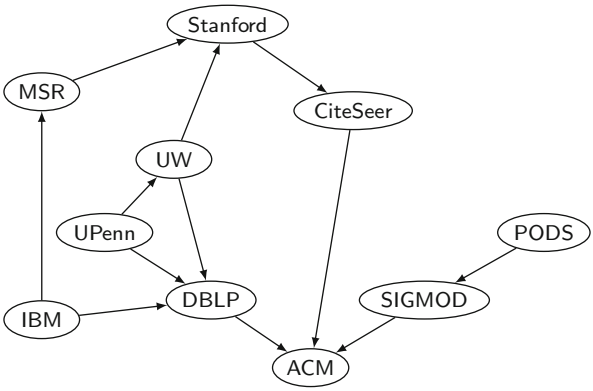


Fig. 9.8 An example of pairwise schema mapping in piazza

Piazza follows this approach (see Fig. 9.8). The data is shared as XML documents, and each peer has a schema that defines the terminology and the structural constraints of the peer. When a new peer (with a new schema) joins the system for the first time, it maps its schema to the schema of some other peers in the system. Each mapping definition begins with an XML template that matches some path or subtree of an instance of the target schema. Elements in the template may be annotated with query expressions that bind variables to XML nodes in the source.

The Local Relational Model (LRM) is another example that follows this approach. LRM assumes that the peers hold relational databases, and each peer knows a set of peers with which it can exchange data and services. This set of peers is called peer's *acquaintances*. Each peer must define semantic dependencies and translation rules between its data and the data shared by each of its acquaintances. The defined mappings form a semantic network, which is used for query reformulation in the P2P system.

Hyperion generalizes this approach to deal with autonomous peers that form acquaintances at runtime, using mapping tables to define value correspondences among heterogeneous databases. Peers perform local querying and update processing, and also propagate queries and updates to their acquainted peers.

PGrid also assumes the existence of pairwise mappings between peers, initially constructed by skilled experts. Relying on the transitivity of these mappings and using a gossip algorithm, PGrid extracts new mappings that relate the schemas of the peers between which there is no predefined schema mapping.

9.2.2 Mapping Based on Machine Learning Techniques

This approach is generally used when the shared data is defined based on ontologies and taxonomies as proposed for the semantic web. It uses machine learning

techniques to automatically extract the mappings between the shared schemas. The extracted mappings are stored over the network, in order to be used for processing future queries. GLUE uses this approach. Given two ontologies, for each concept in one, GLUE finds the most similar concept in the other. It gives well-founded probabilistic definitions to several practical similarity measures, and uses multiple learning strategies, each of which exploits a different type of information either in the data instances or in the taxonomic structure of the ontologies. To further improve mapping accuracy, GLUE incorporates commonsense knowledge and domain constraints into the schema mapping process. The basic idea is to provide classifiers for the concepts. To decide the similarity between two concepts X and Y, the data of concept Y is classified using X's classifier and vice versa. The number of values that can be successfully classified into X and Y represent the similarity between X and Y.

9.2.3 Common Agreement Mapping

In this approach, the peers that have a common interest agree on a common schema description for data sharing. The common schema is usually prepared and maintained by expert users. The APPA P2P system makes the assumption that peers wishing to cooperate, e.g., for the duration of an experiment, agree on a Common Schema Description (CSD). Given a CSD, a peer schema can be specified using views. This is similar to the LAV approach in data integration systems, except that queries at a peer are expressed in terms of the local views, not the CSD. Another difference between this approach and LAV is that the CSD is not a global schema, i.e., it is common to a limited set of peers with a common interest (see Fig. 9.9). Thus, the CSD does not pose scalability challenges. When a peer decides to share data, it needs to map its local schema to the CSD.

Example 9.1 Given two CSD relation definitions $\mathtt{R}_1$ and $\mathtt{R}_2$, an example of peer mapping at peer p is

$$p : \mathtt{R}(\mathtt{A}, \mathtt{B}, \mathtt{D}) \subseteq csd : \mathtt{R}_1(\mathtt{A}, \mathtt{B}, \mathtt{C}), csd : \mathtt{R}_2(\mathtt{C}, \mathtt{D}, \mathtt{E})$$

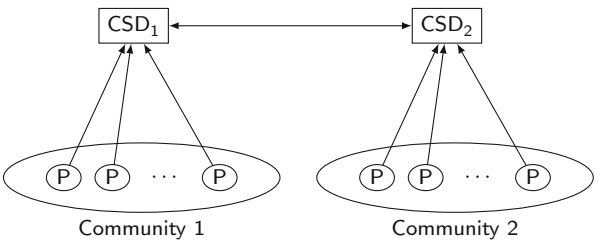


Fig. 9.9 Common agreement schema mapping in APPA

In this example, the relation R(A, B, D) that is shared by peer p is mapped to relations R_1(A, B, C), R_2(C, D, E) both of which are involved in the CSD. In APPA, the mappings between the CSD and each peer's local schema are stored locally at the peer. Given a query Q on the local schema, the peer reformulates Q to a query on the CSD using locally stored mappings. ♦

9.2.4 Schema Mapping Using IR Techniques

This approach extracts the schema mappings at query execution time using IR techniques by exploring the schema descriptions provided by users. PeerDB follows this approach for query processing in unstructured P2P networks. For each relation that is shared by a peer, the description of the relation and its attributes is maintained at that peer. The descriptions are provided by users upon creation of relations, and serve as a kind of synonymous names of relation names and attributes. When a query is issued, a request to find out potential matches is produced and flooded to the peers that return the corresponding metadata. By matching keywords from the metadata of the relations, PeerDB is able to find relations that are potentially similar to the query relations. The relations that are found are presented to the issuer of the query who decides whether or not to proceed with the execution of the query at the remote peer that owns the relations.

Edutella also follows this approach for schema mapping in superpeer networks. Resources in Edutella are described using the RDF metadata model, and the descriptions are stored at superpeers. When a user issues a query at a peer p, the query is sent to p's superpeer where the stored schema descriptions are explored and the addresses of the relevant peers are returned to the user. If the superpeer does not find relevant peers, it sends the query to other superpeers such that they search relevant peers by exploring their stored schema descriptions. In order to explore stored schemas, superpeers use the RDF-QEL query language, which is based on Datalog semantics and thus compatible with all existing query languages, supporting query functionalities that extend the usual relational query languages.

9.3 Querying Over P2P Systems

P2P networks provide basic techniques for routing queries to relevant peers and this is sufficient for supporting simple, exact-match queries. For instance, as noted earlier, a DHT provides a basic mechanism to efficiently look up data based on a key-value. However, supporting more complex queries in P2P systems, particularly in DHTs, is difficult and has been the subject of much recent research. The main types of complex queries which are useful in P2P systems are top-k queries, join queries, and range queries. In this section, we discuss the techniques for processing them.

9.3.1 Top-k Queries

Top-k queries have been used in many domains such as network and system monitoring, information retrieval, and multimedia databases. With a top-k query, the user requests k most relevant answers to be returned by the system. The degree of relevance (score) of the answers to the query is determined by a scoring function. Top-k queries are very useful for data management in P2P systems, in particular when the complete answer set is very large.

Example 9.2 Consider a P2P system with medical doctors who want to share some (restricted) patient data for an epidemiological study. Assume that all doctors agreed on a common Patient description in relational format. Then, one doctor may want to submit the following query to obtain the top 10 answers ranked by a scoring function over height and weight:

```
SELECT *
FROM   Patient P
WHERE  P.disease = "diabetes"
AND    P.height < 170
AND    P.weight > 160
ORDER BY scoring-function(height,weight)
STOP AFTER 10
```

The scoring function specifies how closely each data item matches the conditions. For instance, in the query above, the scoring function could compute the ten most overweight people. ♦

Efficient execution of top-k queries in P2P systems is difficult because of the scale of the network. In this section, we first discuss the most efficient techniques proposed for top-k query processing in distributed systems. Then, we present the techniques proposed for P2P systems.

9.3.1.1 Basic Techniques

An efficient algorithm for top-k query processing in centralized and distributed systems is the Threshold Algorithm (TA) . TA is applicable for queries where the scoring function is monotonic, i.e., any increase in the value of the input does not decrease the value of the output. Many of the popular aggregation functions such as Min, Max, and Average are monotonic. TA has been the basis for several algorithms, and we discuss these in this section.

Threshold Algorithm (TA)

TA assumes a model based on lists of data items sorted by their local scores. The model is as follows. Suppose we have m lists of n data items such that each data item has a local score in each list and the lists are sorted according to the local scores of their data items. Furthermore, each data item has an overall score that is computed based on its local scores in all lists using a given scoring function. For example, consider the database (i.e., three sorted lists) in Fig. 9.10. Assuming the scoring function computes the sum of the local scores of the same data item in all lists, the overall score of item d_1 is $30 + 21 + 14 = 65$.

Then the problem of top-k query processing is to find the k data items whose overall scores are the highest. This problem model is simple and general. Suppose we want to find the top-k tuples in a relational table according to some scoring function over its attributes. To answer this query, it is sufficient to have a sorted (indexed) list of the values of each attribute involved in the scoring function, and return the k tuples whose overall scores in the lists are the highest. As another example, suppose we want to find the top-k documents whose aggregate rank is the highest with respect to some given set of keywords. To answer this query, the solution is to have, for each keyword, a ranked list of documents, and return the k documents whose aggregate rank over all lists are the highest.

TA considers two modes of access to a sorted list. The first mode is sorted (or sequential) access that accesses each data item in their order of appearance in the list. The second mode is random access by which a given data item in the list is directly looked up, for example, by using an index on item id.

Given m sorted lists of n data items, TA (see Algorithm 9.1) goes down the sorted lists in parallel, and, for each data item, retrieves its local scores in all lists through random access and computes the overall score. It also maintains in a set Y, the k data

Position	List 1		List 2		List 3	
	Data Item	Local score s_1	Data Item	Local score s_2	Data Item	Local score s_3
1	d_1	30	d_2	28	d_3	30
2	d_4	28	d_6	27	d_5	29
3	d_9	27	d_7	25	d_8	28
4	d_3	26	d_5	24	d_4	25
5	d_7	25	d_9	23	d_2	24
6	d_8	23	d_1	21	d_6	19
7	d_5	17	d_8	20	d_{13}	15
8	d_6	14	d_3	14	d_1	14
9	d_2	11	d_4	13	d_9	12
10	d_{11}	10	d_{14}	12	d_7	11
...	...	...	...	...	...	...

Fig. 9.10 Example database with 3 sorted lists

Algorithm 9.1: Threshold Algorithm (TA)

```
Input: L_1, L_2, ..., L_m: m sorted lists of n data items
f: scoring function
Output: Y: list of top-k data items
begin
    j ← 1
    threshold ← 1
    min_overall_score ← 0
    while j ≠ n + 1 and min_overall_score < threshold do
        {Do sorted access in parallel to each of the m sorted lists}
        for i from 1 to m in parallel do
            {Process each data item at position j}
            for each data item d at position j in L_i do
                {access the local scores of d in the other lists through random access}
                overall_score(d) ← f(scores of d in each L_i)
            end for
        end for
        Y ← k data items with highest score so far
        min_overall_score ← smallest overall score of data items in Y
        threshold ← f(local scores at position j in each L_i)
        j ← j + 1
    end while
end
```

items whose overall scores are the highest so far. The stopping mechanism of TA uses a threshold that is computed using the last local scores seen under sorted access in the lists. For example, consider the database in Fig. 9.10. At position 1 for all lists (i.e., when only the first data items have been seen under sorted access) assuming that the scoring function is the sum of the scores, the threshold is $30 + 28 + 30$. At position 2, it is 84. Since data items are sorted in the lists in decreasing order of local score, the threshold decreases as one moves down the list. This process continues until k data items are found whose overall scores are greater than a threshold.

Example 9.3 Consider again the database (i.e., three sorted lists) shown in Fig. 9.10. Assume a top-3 query Q (i.e., $k = 3$), and suppose the scoring function computes the sum of the local scores of the data item in all lists. TA first looks at the data items which are at position 1 in all lists, i.e., d_1, d_2, and d_3. It looks up the local scores of these data items in other lists using random access and computes their overall scores (which are 65, 63, and 70, respectively). However, none of them has an overall score that is as high as the threshold of position 1 (which is 88). Thus, at position 1, TA does not stop. At this position, we have $Y = \{d_1, d_2, d_3\}$, i.e., the k highest scored data items seen so far. At positions 2 and 3, Y is set to $\{d_3, d_4, d_5\}$ and $\{d_3, d_5, d_8\}$, respectively. Before position 6, none of the data items involved in Y has an overall score higher than or equal to the threshold value. At position 6, the threshold value is 63, which is less than the overall score of the three data items involved in Y, i.e., $Y = \{d_3, d_5, d_8\}$. Thus, TA stops. Note that the contents of Y at position 6 are exactly the same as at position 3. In other words,

at position 3, Y already contains all top-k answers. In this example, TA does three additional sorted accesses in each list that do not contribute to the final result. This is a characteristic of TA algorithm in that it has a conservative stopping condition that causes it to stop later than necessary—in this example, it performs 9 sorted accesses and $18 = (9 * 2)$ random accesses that do not contribute to the final result. ♦

TA-Style Algorithms

Several TA-style algorithms, i.e., extensions of TAThreshold Algorithm, have been proposed for distributed top-k query processing. We illustrate these by means of the Three Phase Uniform Threshold (TPUT) algorithm that executes top-k queries in three round trips, assuming that each list is held by one node (which we call the *list holder*) and that the scoring function is sum. The TPUT algorithm executed by the query originator is detailed in Algorithm 9.2.

TPUT works as follows:

1. The query originator first gets from each list holder its k top data items. Let f be the scoring function, d be a received data item, and $s_i(d)$ be the local score of d in list L_i. Then the partial sum of d is defined as $psum(d) = \sum_{i=1}^{m} s_i^{'}(d)$, where $s_i'(d) = s_i(d)$ if d has been sent to the coordinator by the holder of L_i, else $s_i'(d) = 0$. The query originator computes the partial sums for all received data items and identifies the items with the k highest partial sums. The partial sum of the $k-$th data item (called *phase-1 bottom*) is denoted by λ_1.
2. The query originator sends a threshold value $\tau = \lambda_1/m$ to every list holder. In response, each list holder sends back all its data items whose local scores are not less than τ. The intuition is that if a data item is not reported by any node in this phase, its score must be less than λ_1, so it cannot be one of the top-k data items. Let Y be the set of data items received from list holders. The query originator computes the new partial sums for the data items in Y, and identifies the items with the k highest partial sums. The partial sum of the k-th data item (called phase-2 bottom) is denoted by λ_2. Let the upper bound score of a data item d be defined as $u(d) = \sum_{i=1}^{m} u_i(d)$, where $u_i(d) = s_i(d)$ if d has been received, else $u_i(d) = \tau$. For each data item $d \in D$, if $u(d)$ is less than λ_2, it is removed from Y. The data items that remain in Y are called top-k candidates because there may be some data items in Y that have not been obtained from all list holders. A third phase is necessary to retrieve those.
3. The query originator sends the set of top-k candidate data items to each list holder that returns their scores. Then, it computes the overall score, extracts the k data items with highest scores, and returns the answer to the user.

Example 9.4 Consider the first two sorted lists (List 1 and List 2) in Fig. 9.10. Assume a top-2 query Q, i.e., $k = 2$, where the scoring function is sum. Phase 1

Algorithm 9.2: Three Phase Uniform Threshold (TPUT)

Input: $L_1, L_2, \ldots, L_m$: m sorted lists of n data items, each at a different list holder
f: scoring function
Output: Y: list of top-k data items
begin
  {Phase 1}
  for *i from* 1 *to m in parallel* **do**
    $Y \leftarrow$ receive top-k data items from L_i holder
  end for
  $Z \leftarrow$ data items with the k highest partial sum in Y
  $\lambda_1 \leftarrow$partial sum of k-th data item in Z
  {Phase 2}
  for *i from* 1 *to m in parallel* **do**
    send λ_1/m to L_i's holder
    $Y \leftarrow$ all data items from L_i's holder whose local scores are not less than λ_1/m
  end for
  $Z \leftarrow$ data items with the k highest partial sum in Y
  $\lambda_2 \leftarrow$ partial sum of k-th data item in Z
  $Y \leftarrow Y -$ {data items in Y whose upper bound score is less than λ_2}
  {Phase 3}
  for *i from* 1 *to m in parallel* **do**
    send Y to L_i holder
    $Z \leftarrow$ data items from L_i's holder that are in both Y and L_i
  end for
  $Y \leftarrow k$ data items with highest overall score in Z
end

produces the sets $Y = \{d_1, d_2, d_4, d_6\}$ and $Z = \{d_1, d_2\}$. The $k-$th (i.e., second) data item is d_2, whose partial sum is 28. Thus we get $\lambda_1/2 = 28/2 = 14$. Let us now denote each data item d in Y as (d, score in List 1, score in List 2). Phase 2 produces

$Y = \{(d_1, 30, 21), (d_2, 0, 28), (d_3, 26, 14), (d_4, 28, 0), (d_5, 17, 24), (d_6, 14, 27), (d_7, 25, 25), (d_8, 23, 20), (d_9, 27, 23)\}$ and $Z = \{(d_1, 30, 21), (d_7, 25, 25)\}$. Note that d_9 could also have been picked instead of d_7 because it has same partial sum. Thus we get $\lambda_2/2$=50. The upper bound scores of the data items in Y are obtained as:

$$
\begin{aligned}
u(d_1) &= 30 + 21 = 51 \\
u(d_2) &= 14 + 28 = 42 \\
u(d_3) &= 26 + 14 = 40 \\
u(d_4) &= 28 + 14 = 42 \\
u(d_5) &= 17 + 24 = 41 \\
u(d_6) &= 14 + 27 = 41 \\
u(d_7) &= 25 + 25 = 50 \\
u(d_8) &= 23 + 20 = 43 \\
u(d_9) &= 27 + 23 = 50
\end{aligned}
$$

After removal of the data items in Y whose upper bound score is less than λ_2, we have $Y = \{d_1, d_7, d_9\}$. The third phase is not necessary in this case as all data items have all their local scores. Thus the final result is $Y = \{d_1, d_7\}$ or $Y = \{d_1, d_9\}$. ♦

When the number of lists (i.e., m) is high, the response time of TPUT is much better than that of the basic TA algorithm.

Best Position Algorithm (BPA)

There are many database instances over which TA keeps scanning the lists although it has seen all top-k answers (as in Example 9.3). Thus, it is possible to stop much sooner. Based on this observation, best position algorithms (BPA) that execute top-k queries much more efficiently than TA have been proposed. The key idea of BPA is that the stopping mechanism takes into account special positions in the lists, called the *best positions*. Intuitively, the best position in a list is the highest position such that any position before it has also been seen. The stopping condition is based on the overall score computed using the best positions in all lists.

The basic version of BPA (see Algorithm 9.3) works like TA, except that it keeps track of all positions that are seen under sorted or random access, computes best positions, and has a different stopping condition. For each list L_i, let P_i be the set of positions that are seen under sorted or random access in L_i. Let bp_i, the best position in L_i, be the highest position in P_i such that any position of L_i between 1 and bp_i is also in P_i. In other words, bp_i is best because we are sure that all positions of L_i between 1 and bpi have been seen under sorted or random access. Let $s_i(bp_i)$ be the local score of the data item that is at position bp_i in list L_i. Then, BPA's threshold is $f(s_1(bp_1), s_2(bp_2), \ldots, s_m(bp_m))$ for some function f.

Example 9.5 To illustrate basic BPA, consider again the three sorted lists shown in Fig. 9.10 and the query Q in Example 9.3.

1. At position 1, BPA sees the data items d_1, d_2, and d_3. For each seen data item, it does random access and obtains its local score and position in all the lists. Therefore, at this step, the positions that are seen in list L_1 are positions 1, 4, and 9, which are, respectively, the positions of d_1, d_3, and d_2. Thus, we have $P_1 = \{1, 4, 9\}$ and the best position in L_1 is $bp_1 = 1$ (since the next position is 4 meaning that positions 2 and 3 have not been seen). For L_2 and L_3 we have $P_2 = \{1, 6, 8\}$ and $P_3 = \{1, 5, 8\}$, so $bp_2 = 1$ and $bp_3 = 1$. Therefore, the best positions overall score is $\lambda = f(s_1(1), s_2(1), s_3(1)) = 30 + 28 + 30 = 88$. At position 1, the set of the three highest scored data items is $Y = \{d_1, d_2, d_3\}$, and since the overall score of these data items is less than λ , BPA cannot stop.
2. At position 2, BPA sees d_4, d_5, and d_6. Thus, we have $P_1 = \{1, 2, 4, 7, 8, 9\}$, $P_2 = \{1, 2, 4, 6, 8, 9\}$, and $P_3 = \{1, 2, 4, 5, 6, 8\}$. Therefore, we have $bp_1 = 2$, $bp_2 = 2$, and $bp_3 = 2$, so $\lambda = f(s_1(2), s_2(2), s_3(2)) = 28 + 27 + 29 = 84$. The overall score of the data items involved in $Y = \{d_3, d_4, d_5\}$ is less than 84, so BPA does not stop.

Algorithm 9.3: Best Position Algorithm (BPA)

```
Input: L_1, L_2, ..., L_m: m sorted lists of n data items
f: scoring function
Output: Y: list of top-k data items
begin
    j ← 1
    threshold ← 1
    min_overall_score ← 0
    for i from 1 to m in parallel do
        P_i ← ∅
    end for
    while j ≠ n + 1 and min_overall_score < threshold do
        {Do sorted access in parallel to each of the m sorted lists}
        for i from 1 to m in parallel do
            {Process each data item at position j}
            for each data item d at position j in L_i do
                {access the local scores of d in the other lists through random access}
                overall_score(d) ← f(scores of d in each L_i)
            end for
            P_i ← P_i ∪ {positions seen under sorted or random access}
            bp_i ← best position in L_i
        end for
        Y ← k data items with highest score so far
        min_overall_score ← smallest overall score of data items in Y
        threshold ← f(local scores at position bp_i in each L_i)
        j ← j + 1
    end while
end
```

3. At position 3, BPA sees d_7, d_8, and d_9. Thus, we have $P_1 = P_2 = \{1, 2, 3, 4, 5, 6, 7, 8, 9\}$ and $P_3 = \{1, 2, 3, 4, 5, 6, 7, 8, 10\}$. Thus, we have $bp_1 = 9$, $bp_2 = 9$, and $bp_3 = 8$. The best positions overall score is $\lambda = f(s_1(9), s_2(9), s_3(8)) = 11 + 13 + 14 = 38$. At this position, we have $Y = \{d_3, d_5, d_8\}$. Since the score of all data items involved in Y is higher than λ, BPA stops, i.e., exactly at the first position where BPA has all top-k answers.

Recall that over this database, TA stops at position 6. ♦

It has been proven that, for any set of sorted lists, BPA stops as early as TA, and its execution cost is never higher than TA. It has also been shown that the execution cost of BPA can be $(m - 1)$ times (where m is the number of sorted lists) lower than that of TA. Although BPA is quite efficient, it still does redundant work. One of the redundancies with BPA (and also TA) is that it may access some data items several times under sorted access in different lists. For example, a data item that is accessed at a position in a list through sorted access and thus accessed in other lists via random access may be accessed again in the other lists by sorted access at the next positions. An improved algorithm, BPA2, avoids this and is therefore much more efficient than BPA. It does not transfer the seen positions from list owners to

the query originator. Thus, the query originator does not need to maintain the seen positions and their local scores. It also accesses each position in a list at most once. The number of accesses to the lists done by BPA2 can be about $(m - 1)$ times lower than that of BPA.

9.3.1.2 Top-k Queries in Unstructured Systems

One possible approach for processing top-k queries in unstructured systems is to route the query to all the peers, retrieve all available answers, score them using the scoring function, and return to the user the k highest scored answers. However, this approach is not efficient in terms of response time and communication cost.

The first efficient solution that has been proposed is that of PlanetP, which is an unstructured P2P system. In PlanetP, a content-addressable publish/subscribe service replicates data across P2P communities of up to ten thousand peers. The top-k query processing algorithm works as follows. Given a query Q, the query originator computes a relevance ranking of peers with respect to Q, contacts them one by one in decreasing rank order, and asks them to return a set of their top-scored data items together with their scores. To compute the relevance of peers, a global fully replicated index is used that contains term-to-peer mappings. This algorithm has very good performance in moderate-scale systems. However, in a large P2P system, keeping the replicated index up-to-date may hurt scalability.

We describe another solution that was developed within the context of APPA, which is a P2P network-independent data management system. A fully distributed framework to execute top-k queries has been proposed that also addresses the volatility of peers during query execution, and deals with situations where some peers leave the system before finishing query processing. Given a top-k query Q with a specified TTL, the basic algorithm called Fully Decentralized Top-k (FD) proceeds as follows (see Algorithm 9.4):

1. **Query forward.** The query originator forwards Q to the accessible peers whose hop-distance from the query originator is less than TTL.
2. **Local query execution and wait.** Each peer p that receives Q executes it locally: it accesses the local data items that match the query predicate, scores them using a scoring function, selects the k top data items, and saves them as well as their scores locally. Then p waits to receive its neighbors' results. However, since some of the neighbors may leave the P2P system and never send a score-list to p, the wait time has a limit that is computed for each peer based on the received TTL, network parameters, and peer's local processing parameters.
3. **Merge-and-backward.** In this phase, the top scores are bubbled up to the query originator using a tree-based algorithm as follows. After its wait time has expired, p merges its k local top scores with those received from its neighbors and sends the result to its parent (the peer from which it received Q) in the form of a score-list. In order to minimize network traffic, FD does not bubble up the top data

Algorithm 9.4: Fully Decentralized Top-k (FD)

```
Input: Q: top-k query
f: scoring function
TTL: time to live
w: wait time
Output: Y: list of top-k data items
begin
    At query originator peer
    begin
        send Q to neighbors
        Final_score_list ← merge local score lists received from neighbors
        for each peer p in Final_score_list do
            Y ← retrieve top-k data items in p
        end for
    end
    for each peer that receives Q from a peer p do
        TTL ← TTL − 1
        if TTL > 0 then
            send Q to neighbors
        end if
        Local_score_list ← extract top-k local scores
        Wait a time w
        Local_score_list ← Local_score_list ∪ top-k received scores
        Send Local_score_list to p
    end for
end
```

items (which could be large), only their scores and addresses. A score-list is simply a list of k pairs (a, s), where a is the address of the peer owning the data item and s its score.

4. **Data retrieval.** After receiving the score-lists from its neighbors, the query originator forms the final score-list by merging its k local top scores with the merged score-lists received from its neighbors. Then it directly retrieves the k top data items from the peers that hold them.

The algorithm is completely distributed and does not depend on the existence of certain peers, and this makes it possible to address the volatility of peers during query execution. In particular, the following problems are addressed: peers becoming inaccessible in the merge-and-backward phase; peers that hold top data items becoming inaccessible in the data retrieval phase; late reception of score-lists by a peer after its wait time has expired. The performance evaluation of FD shows that it can achieve major performance gains in terms of communication cost and response time.

9.3.1.3 Top-k Queries in DHTs

As we discussed earlier, the main functionality of a DHT is to map a set of keys to the peers of the P2P system and lookup efficiently the peer that is responsible for a given key. This offers efficient and scalable support for exact-match queries. However, supporting top-k queries on top of DHTs is not easy. A simple solution is to retrieve all tuples of the relations involved in the query, compute the score of each retrieved tuple, and finally return the k tuples whose scores are the highest. However, this solution cannot scale up to a large number of stored tuples. Another solution is to store all tuples of each relation using the same key (e.g., relation's name), so that all tuples are stored at the same peer. Then, top-k query processing can be performed at that central peer using well-known centralized algorithms. However, the peer becomes a bottleneck and a single point of failure.

A solution has been proposed as part of APPA project that is based on TA (see Sect. 9.3.1.1) and a mechanism that stores the shared data in the DHT in a fully distributed fashion. In APPA, peers can store their tuples in the DHT using two complementary methods: tuple storage and attribute value storage. With tuple storage, each tuple is stored in the DHT using its identifier (e.g., its primary key) as the storage key. This enables looking up a tuple by its identifier similar to a primary index. Attribute value storage individually stores in the DHT the attributes that may appear in a query's equality predicate or in a query's scoring function. Thus, as in secondary indices, it allows looking up the tuples using their attribute values. Attribute value storage has two important properties: (1) after retrieving an attribute value from the DHT, peers can retrieve easily the corresponding tuple of the attribute value; (2) attribute values that are relatively "close" are stored at the same peer. To provide the first property, the key, which is used for storing the entire tuple, is stored along with the attribute value. The second property is provided using the concept of domain partitioning as follows. Consider an attribute a and let D_a be its domain of values. Assume that there is a total order $\prec$ on D_a (e.g., D_a is numeric). D_a is partitioned into n nonempty subdomains $d_1, d_2, \ldots, d_n$ such that their union is equal to D_a, the intersection of any two different subdomains is empty, and for each $v_1 \in d_i$ and $v_2 \in d_j$, if $i \prec j$, then we have $v_1 \prec v_2$. The hash function is applied on the subdomain of the attribute value. Thus, for the attribute values that fall in the same subdomain, the storage key is the same and they are stored at the same peer. To avoid attribute storage skew (i.e., skewed distribution of attribute values within subdomains), domain partitioning is done in such a way that attribute values are uniformly distributed in subdomains. This technique uses histogram-based information that describes the distribution of values of the attribute.

Using this storage model, the top-k query processing algorithm, called DHTop (see Algorithm 9.5), works as follows. Let Q be a given top-k query, f be its scoring function, and p_0 be the peer at which Q is issued. For simplicity, let us assume that f is a monotonic scoring function. Let scoring attributes be the set of attributes that are passed to the scoring function as arguments. DHTop starts at p_0 and proceeds in two phases: first it prepares ordered lists of candidate subdomains, and then it

Algorithm 9.5: DHT Top-k (DHTop)

```
Input: Q: top-k query;
f: scoring function;
A: set of m attributes used in f
Output: Y: list of top-k tuples
begin
    {Phase 1: prepare lists of attributes' subdomains}
    for each scoring attribute A_i in A do
        L_{A_i} ← all subdomains of A_i
        L_{A_i} ← L_{A_i} − subdomains which do not satisfy Q's condition
        Sort L_{A_i} in descending order of its subdomains
    end for
    {Phase 2: continuously retrieve attribute values and their tuples until finding k top
     tuples}
    Done ← false
    for each scoring attribute A_i in A in parallel do
        i ← 1
        while (i < number of subdomains of A) and not Done do
            send Q to peer p that maintains the attribute values of subdomain i in L_{A_i}
            Z ← A_i values (in descending order) from p that satisfy Q's condition,
              along with their corresponding data storage keys
            for each received value v do
                get the tuple of v
                Y ← k tuples with highest score so far
                threshold ← f(v_1, v_2, ..., v_m) such that v_i is the last value received
                  for attribute A_i in A
                min_overall_score ← smallest overall score of tuples in Y
                if min_overall_score ≤ threshold then
                    Done ← true
                end if
                i ← i + 1
            end for
        end while
    end for
end
```

continuously retrieves candidate attribute values and their tuples until it finds k top tuples. The details of the two steps are as follows:

1. For each scoring attribute $\mathtt{A}_i$, p_0 prepares the list of subdomains and sorts them in descending order of their positive impact on the scoring function. For each list, p_0 removes from the list the subdomains in which no member can satisfy Q's conditions. For instance, if there is a condition that enforces the scoring attribute to be equal to a constant, (e.g., $\mathtt{A}_i = 10$), then p_0 removes from the list all the subdomains except the subdomain to which the constant value belongs. Let us denote by $L_{\mathtt{A}_i}$ the list prepared in this phase for a scoring attribute $\mathtt{A}_i$.
2. For each scoring attribute $\mathtt{A}_i$, in parallel, p_0 proceeds as follows. It sends Q and $\mathtt{A}_i$ to the peer, say p, that is responsible for storing the values of the first subdomain of $L_{\mathtt{A}_i}$, and requests it to return the values of $\mathtt{A}_i$ at p. The values are

returned to p_0 in order of their positive impact on the scoring function. After receiving each attribute value, p_0 retrieves its corresponding tuple, computes its score, and keeps it if the score is one of the k highest scores yet computed. This process continues until k tuples are obtained whose scores are higher than a threshold that is computed based on the attribute values retrieved so far. If the attribute values that p returns to p_0 are not sufficient for determining the k top tuples, p_0 sends Q and $\mathtt{A}_i$ to the site that is responsible for the second subdomain of $L_{\mathtt{A}_i}$ and so on until k top tuples are found.

Let $\mathtt{A}_1, \mathtt{A}_2, \ldots, \mathtt{A}_m$ be the scoring attributes and $v_1, v_2, \ldots, v_m$ be the last values retrieved, respectively, for each of them. The threshold is defined to be $\tau = f(v_1, v_2, \ldots, v_m)$. A main feature of DHTop is that after retrieving each new attribute value, the value of the threshold decreases. Thus, after retrieving a certain number of attribute values and their tuples, the threshold becomes less than k of the retrieved data items and the algorithm stops. It has been analytically proven that DHTop works correctly for monotonic scoring functions and also for a large group of nonmonotonic functions.

9.3.1.4 Top-k Queries in Superpeer Systems

A typical algorithm for top-k query processing in superpeer systems is that of Edutella. In Edutella, a small percentage of nodes are superpeers and are assumed to be highly available with very good computing capacity. The superpeers are responsible for top-k query processing and the other peers only execute the queries locally and score their resources. The algorithm is quite simple and works as follows. Given a query Q, the query originator sends Q to its superpeer, which then sends it to the other superpeers. The superpeers forward Q to the relevant peers connected to them. Each peer that has some data items relevant to Q scores them and sends its maximum scored data item to its superpeer. Each superpeer chooses the overall maximum scored item from all received data items. For determining the second best item, it only asks one peer, the one that has returned the first top item, to return its second top-scored item. The superpeer selects the overall second top item from the previously received items and the newly received item. Then, it asks the peer which has returned the second top item and so on until all k top items are retrieved. Finally the superpeers send their top items to the superpeer of the query originator, to extract the overall k top items, and send them to the query originator. This algorithm minimizes communication between peers and superpeers since, after having received the maximum scored data items from each peer connected to it, each superpeer asks only one peer for the next top item.

9.3.2 Join Queries

The most efficient join algorithms in distributed and parallel databases are hash-based. Thus, the fact that a DHT relies on hashing to store and locate data can be naturally exploited to support join queries efficiently. A basic solution has been proposed in the context of the PIER P2P system that provides support for complex queries on top of DHTs. The solution is a variation of the parallel hash join algorithm (PHJ) (see Sect. 8.4.1) which we call PIERjoin. As in the PHJ algorithm, PIERjoin assumes that the joined relations and the result relations have a home (called *namespace* in PIER), which are the nodes that store horizontal fragments of the relation. Then it makes use of the put method for distributing tuples onto a set of peers based on their join attribute so that tuples with the same join attribute values are stored at the same peers. To perform joins locally, PIER implements a version of the symmetric hash join algorithm (see Sect. 8.4.1.2) that provides efficient support for pipelined parallelism. In symmetric hash join, with two joining relations, each node that receives tuples to be joined maintains two hash tables, one per relation. Thus, upon receiving a new tuple from either relation, the node adds the tuple into the corresponding hash table and probes it against the opposite hash table based on the tuples received so far. PIER also relies on the DHT to deal with the dynamic behavior of peers (joining or leaving the network during query execution) and thus does not give guarantees on result completeness.

For a binary join query Q (which may include select predicates), PIERjoin works in three phases (see Algorithm 9.6): multicast, hash, and probe/join.

1. **Multicast phase.** The query originator peer multicasts Q to all peers that store tuples of the join relations R and S, i.e., their homes.
2. **Hash phase.** Each peer that receives Q scans its local relation, searching for the tuples that satisfy the select predicate (if any). Then, it sends the selected tuples to the home of the result relation, using put operations. The DHT key used in the put operation is calculated using the home of the result relation and the join attribute.
3. **Probe/join phase.** Each peer in the home of the result relation, upon receiving a new tuple, inserts it in the corresponding hash table, probes the opposite hash table to find tuples that match the join predicate (and a select predicate if any), and constructs the result joined tuples. Recall that the "home" of a (horizontally partitioned) relation was defined in Chap. 4 as a set of peers where each peer has a different partition. In this case, the partitioning is by hashing on the join attribute. The home of the result relation is also a partitioned relation (using put operations) so it is also at multiple peers.

This basic algorithm can be improved in several ways. For instance, if one of the relations is already hashed on the join attributes, we may use its home as result home, using a variation of the parallel associative join algorithm (PAJ) (see Sect. 8.4.1), where only one relation needs to be hashed and sent over the DHT.

Algorithm 9.6: PIERjoin

Input: Q: join query over relations R and S on attribute A;
h: hash function;
H_{R}, H_{S}: homes of R and S
Output: T: join result relation;
H_{T}: home of T
begin
  {Multicast phase}
  At query originator peer send Q to all peers in H_{R} and H_{S}
  {Hash phase}
  for *each peer p in* H_{R} *that received Q in parallel* **do**
    for *each tuple* r *in* R_p *that satisfies the select predicate* **do**
      place r using $h(H_{\mathrm{T}}, \mathrm{A})$
    end for
  end for
  for *each peer p in* H_{S} *that received Q in parallel* **do**
    for *each tuple* s *in* S_p *that satisfies the select predicate* **do**
      place s using $h(H_{\mathrm{T}}, \mathrm{A})$
    end for
  end for
  {Probe/join phase}
  for *each peer p in* H_{T} *in parallel* **do**
    if *a new tuple i has arrived* **then**
      if *i is an* r *tuple* **then**
        probe s tuples in S_p using $h(\mathrm{A})$
      else
        probe r tuples in R_p using $h(\mathrm{A})$
      end if
      $\mathrm{T}_p \leftarrow \mathrm{r} \bowtie \mathrm{s}$
    end if
  end for
end

9.3.3 Range Queries

Recall that range queries have a **WHERE** clause of the form "attribute A in range $[a, b]$," with a and b being numerical values. Structured P2P systems, in particular, DHTs are very efficient at supporting exact-match queries (of the form "$\mathrm{A} = a$") but have difficulties with range queries. The main reason is that hashing tends to destroy the ordering of data that is useful in finding ranges quickly.

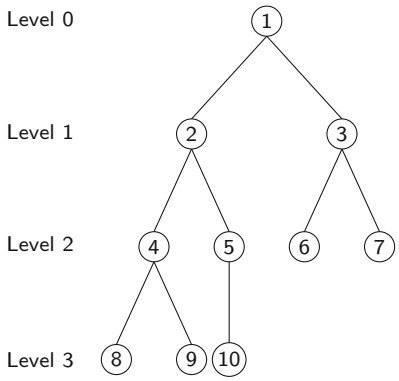
There are two main approaches for supporting range queries in structured P2P systems: extend a DHT with proximity or order-preserving properties, or maintain the key ordering with a tree-based structure. The first approach has been used in several systems. Locality sensitive hashing is an extension to DHTs that hashes similar ranges to the same DHT node with high probability. However, this method can only obtain approximate answers and may cause unbalanced loads in large networks.

The Prefix Hash Tree (PHT) is a tree-based distributed data structure that supports range queries over a DHT, by simply using the DHT lookup operation. The data being indexed are binary strings of length D. Each node has either 0 or 2 children, and a key k is stored at a leaf node whose label is a prefix of k. Furthermore, leaf nodes are linked to their neighbors. PHT's lookup operation on key k must return the unique leaf node $leaf(k)$ whose label is a prefix of k. Given a key k of length D, there are $D+1$ distinct prefixes of k. Obtaining $leaf(k)$ can be performed by a linear scan of these potential $D+1$ nodes. However, since a PHT is a binary tree, the linear scan can be improved using a binary search on prefix length. This reduces the number of DHT lookups from $(D+1)$ to $(\log\ D)$. Given two keys a and b such as $a \leq b$, two algorithms for range queries are supported, using PHT's lookup. The first one is sequential: it searches $leaf(a)$ and then scans sequentially the linked list of leaf nodes until the node $leaf(b)$ is reached. The second algorithm is parallel: it first identifies the node which corresponds to the smallest prefix range that completely covers the range $[a, b]$. To reach this node, a simple DHT lookup is used and the query is forwarded recursively to those children that overlap with the range $[a, b]$.

As in all hashing schemes, the first approach suffers from data skew that can result in peers with unbalanced ranges, which hurts load balancing. To overcome this problem, the second approach exploits tree-based structures to maintain balanced ranges of keys. The first attempt to build a P2P network based on a balanced tree structure is BATON (BAlanced Tree Overlay Network). We now present BATON and its support for range queries in more detail.

BATON organizes peers as a balanced binary tree (each node of the tree is maintained by a peer). The position of a node in BATON is determined by a (level, number) tuple, with level starting from 0 at the root, number starting from 1 at the root and sequentially assigned using in-order traversal. Each tree node stores links to its parent, children, adjacent nodes, and selected neighbor nodes that are nodes at the same level. Two routing tables: a *left routing table* and a *right routing table* store links to the selected neighbor nodes. For a node numbered i, these routing tables contain links to nodes located at the same level with numbers that are less (left routing table) and greater (right routing table) than i by a power of 2. The j^{th} element in the left (right) routing table at node i contains a link to the node numbered $i-2^{j-1}$ (respectively, $i+2^{j-1}$) at the same level in the tree. Figure 9.11 shows the routing table of node 6.

In BATON, each leaf and internal node (or peer) is assigned a range of values. For each link this range is stored at the routing table and when its range changes, the link is modified to record the change. The range of values managed by a peer is required to be to the right of the range managed by its left subtree and less than the range managed by its right subtree (see Fig. 9.12). Thus, BATON builds an effective distributed index structure. The joining and departure of peers are processed such that the tree remains balanced by forwarding the request upward in the tree for joins



Node 6: level 2, number=3
parent=3, leftchild=null, rightchild=null
leftadjacent=1, rightadjacent=3

Left routing table

	Node	Left Child	Right Child	Lower Bound	Upper Bound
0	5	10	null	LB5	UB5
1	4	8	9	LB4	UB4

Right routing table

	Node	Left Child	Right Child	Lower Bound	Upper Bound
0	7	null	null	LB7	UB7

Fig. 9.11 BATON structure-tree index and routing table of node 6

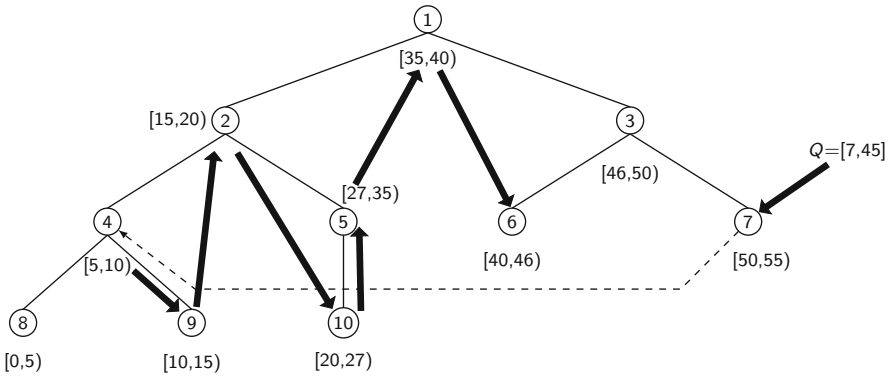


Fig. 9.12 Range query processing in BATON

and downward in the tree for leaves, thus with no more than $O(\log\ n)$ steps for a tree of n nodes.

A range query is processed as follows (Algorithm 9.7). For a range query Q with range $[a, b]$ submitted by node i, it looks for a node that intersects with the lower bound of the searched range. The peer that stores the lower bound of the range checks locally for tuples belonging to the range and forwards the query to its right adjacent node. In general, each node receiving the query checks for local tuples and contacts its right adjacent node until the node containing the upper bound of the range is reached. Partial answers obtained when an intersection is found are sent to the node that submits the query. The first intersection is found in $O(\log\ n)$ steps using an algorithm for exact-match queries. Therefore, a range query with X nodes covering the range is answered in $O(\log\ n + X)$ steps.

Algorithm 9.7: BatonRange

```
Input: Q: a range query in the form [a, b]
Output: T: result relation
begin
    {Search for the peer storing the lower bound of the range}
    At query originator peer
    begin
        find peer p that holds value a
        send Q to p
    end
    for each peer p that receives Q do
        T_p ← Range(p) ∩ [a, b]
        send T_p to query originator
        if Range(RightAdjacent(p)) ∩ [a, b] ≠ ∅ then
            let p be right adjacent peer of p
            send Q to p
        end if
    end for
end
```

Example 9.6 Consider the query Q with range [7, 45] issued at node 7 in Fig. 9.12. First, BATON executes an exact-match query looking for a node containing the lower bound of the range (see dashed line in the figure). Since the lower bound is in the range assigned to node 4, it checks locally for tuples belonging to the range and forwards the query to its adjacent right node (node 9). Node 9 checks for local tuples belonging to the range and forwards the query to node 2. Nodes 10, 5, 1, and 6 receive the query, they check for local tuples and contact their respective right adjacent node until the node containing the upper bound of the range is reached. ♦

9.4 Replica Consistency

To increase data availability and access performance, P2P systems replicate data. However, different P2P systems provide very different levels of replica consistency. The earlier, simple P2P systems such as Gnutella and Kazaa deal only with static data (e.g., music files) and replication is "passive" as it occurs naturally as peers request and copy files from one another (basically, caching data). In more advanced P2P systems where replicas can be updated, there is a need for proper replica management techniques. Unfortunately, most of the work on replica consistency has been done only in the context of DHTs. We can distinguish three approaches to deal with replica consistency: basic support in DHTs, data currency in DHTs, and replica reconciliation. In this section, we introduce the main techniques used in these approaches.

9.4.1 Basic Support in DHTs

To improve data availability, most DHTs rely on data replication by storing $(key, data)$ pairs at several peers by, for example, using several hash functions. If one peer is unavailable, its data can still be retrieved from the other peers that hold a replica. Some DHTs provide basic support for the application to deal with replica consistency. In this section, we describe the techniques used in two popular DHTs: CAN and Tapestry.

CAN provides two approaches for supporting replication. The first one is to use m hash functions to map a single key onto m points in the coordinate space, and, accordingly, replicate a single $(key, data)$ pair at m distinct nodes in the network. The second approach is an optimization over the basic design of CAN that consists of a node proactively pushing out popular keys towards its neighbors when it finds it is being overloaded by requests for these keys. In this approach, replicated keys should have an associated TTL field to automatically undo the effect of replication at the end of the overloaded period. In addition, the technique assumes immutable (read-only) data.

Tapestry is an extensible P2P system that provides decentralized object location and routing on top of a structured overlay network. It routes messages to logical endpoints (i.e., endpoints whose identifiers are not associated with physical location), such as nodes or object replicas. This enables message delivery to mobile or replicated endpoints in the presence of instability of the underlying infrastructure. In addition, Tapestry takes latency into account to establish each node's neighborhood. The location and routing mechanisms of Tapestry work as follows. Let o be an object identified by $id(o)$; the insertion of o in the P2P network involves two nodes: the server node (noted n_s) that holds o and the root node (noted n_r) that holds a mapping in the form $(id(o), n_s)$ indicating that the object identified by $id(o)$ is stored at node n_s. The root node is dynamically determined by a globally consistent deterministic algorithm. Figure 9.13a shows that when o is inserted into n_s, n_s publishes $id(o)$ at its root node by routing a message from n_s to n_r containing the mapping $(id(o), n_s)$. This mapping is stored at all nodes along the message path. During a location query, e.g., "$id(o)$?" in Fig. 9.13a, the message that looks for $id(o)$ is initially routed towards n_r, but it may be stopped before reaching it once a node containing the mapping $(id(o), n_s)$ is found. For routing a message to $id(o)$'s root, each node forwards this message to its neighbor whose logical identifier is the most similar to $id(o)$.

Tapestry offers the entire infrastructure needed to take advantage of replicas, as shown in Fig. 9.13b. Each node in the graph represents a peer in the P2P network and contains the peer's logical identifier in hexadecimal format. In this example, two replicas O_1 and O_2 of object O (e.g., a book file) are inserted into distinct peers ($O_1 \rightarrow$ peer 4228 and $O_2 \rightarrow$ peer $AA93$). The identifier of O_1 is equal to that of O_2 (i.e., 4378 in hexadecimal) as O_1 and O_2 are replicas of the same object O. When O_1 is inserted into its server node (peer 4228), the mapping $(4378, 4228)$ is routed from peer 4228 to peer 4377 (the root node for

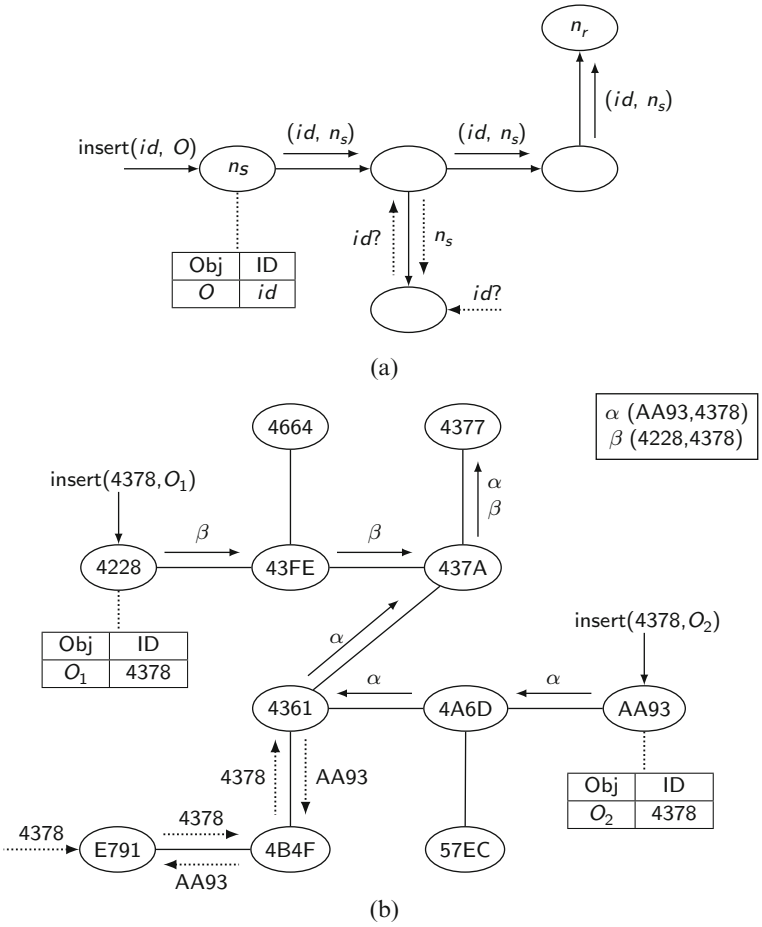


Fig. 9.13 Tapestry. (**a**) Object publishing. (**b**) Replica management

O_1's identifier). As the message approaches the root node, the object and the node identifiers become increasingly similar. In addition, the mapping (4378, 4228) is stored at all peers along the message path. The insertion of O_2 follows the same procedure. In Fig. 9.13b, if peer E791 looks for a replica of O, the associated message routing stops at peer 4361. Therefore, applications can replicate data across multiple server nodes and rely on Tapestry to direct requests to nearby replicas.

9.4.2 Data Currency in DHTs

Although DHTs provide basic support for replication, the mutual consistency of the replicas after updates can be compromised as a result of peers leaving the network or concurrent updates. Let us illustrate the problem with a simple update scenario in a typical DHT.

Example 9.7 Let us assume that the operation put(k, d_0) (issued by some peer) maps onto peers p_1 and p_2 both of which get to store data d_0. Now consider an update (from the same or another peer) with the operation put(k, d_1) that also maps onto peers p_1 and p_2. Assuming that p_2 cannot be reached (e.g., because it has left the network), only p_1 gets updated to store d_1. When p_2 rejoins the network later on, the replicas are not consistent: p_1 holds the current state of the data associated with k, while p_2 holds a stale state.

Concurrent updates also cause problems. Consider now two updates put(k, d_2) and put(k, d_3) (issued by two different peers) that are sent to p_1 and p_2 in reverse order, so that p_1's last state is d_2, while p_2's last state is d_3. Thus, a subsequent get(k) operation will return either stale or current data depending on which peer is looked up, and there is no way to tell whether it is current or not. ♦

For some applications (e.g., agenda management, bulletin boards, cooperative auction management, reservation management, etc.) that could take advantage of a DHT, the ability to get the current data is very important. Supporting data currency in replicated DHTs requires the ability to return a current replica despite peers leaving the network or concurrent updates. Of course, replica consistency is a more general problem, as discussed in Chap. 6, but the issue is particularly difficult and important in P2P systems, since there is considerable dynamism in the peers joining and leaving the system.

A solution has been proposed that considers both data availability and data currency. To provide high data availability, data is replicated in the DHT using a set of independent hash functions H_r, called *replication hash functions*. The peer that is responsible for key k with respect to hash function h at the current time is denoted by $rsp(k, h)$. To be able to retrieve a current replica, each pair $(k, data)$ is stamped with a logical timestamp, and for each $h \in H_r$, the pair $(k, newData)$ is replicated at $rsp(k, h)$, where $newData = \{data, timestamp\}$, i.e., newdata is composed of the initial data and the timestamp. Upon a request for the data associated with a key, we can return one of the replicas that are stamped with the latest timestamp. The number of replication hash functions, i.e., H_r, can be different for different DHTs. For instance, if in a DHT the availability of peers is low, a high value of H_r (e.g., 30) can be used to increase data availability.

This solution is the basis for a service called *Update Management Service* (UMS) that deals with efficient insertion and retrieval of current replicas based on timestamping. Experimental validation has shown that UMS incurs very little overhead in terms of communication cost. After retrieving a replica, UMS detects

whether it is current or not, i.e., without having to compare with the other replicas, and returns it as output. Thus, UMS does not need to retrieve all replicas to find a current one; it only requires the DHT's lookup service with put and get operations.

To generate timestamps, UMS uses a distributed service called *Key-based Timestamping Service* (KTS). The main operation of KTS is gen_ts(k), which, given a key k, generates a real number as a timestamp for k. The timestamps generated by KTS are *monotonic* such that if ts_i and ts_j are two timestamps generated for the same key at times t_i and t_j, respectively, $ts_j > ts_i$ if t_j is later than t_i. This property allows ordering the timestamps generated for the same key according to the time at which they have been generated. KTS has another operation denoted by *last_ts(k)*, which, given a key k, returns the last timestamp generated for k by KTS. At any time, gen_ts(k) generates at most one timestamp for k, and different timestamps for k are monotonic. Thus, in the case of concurrent calls to insert a pair $(k, data)$, i.e., from different peers, only the one that obtains the latest timestamp will succeed to store its data in the DHT.

9.4.3 Replica Reconciliation

Replica reconciliation goes one step further than data currency by enforcing mutual consistency of replicas. Since a P2P network is typically very dynamic, with peers joining or leaving the network at will, eager replication solutions (see Chap. 6) are not appropriate; lazy replication is preferred. In this section, we describe the reconciliation techniques used in OceanStore, P-Grid, and APPA to provide a spectrum of proposed solutions.

9.4.3.1 OceanStore

OceanStore is a data management system designed to provide continuous access to persistent information. It relies on Tapestry and assumes an infrastructure composed of untrusted powerful servers that are connected by high-speed links. For security reasons, data is protected through redundancy and cryptographic techniques. To improve performance, data is allowed to be cached anywhere in the network.

OceanStore allows concurrent updates on replicated objects and relies on reconciliation to assure data consistency. A replicated object can have multiple primary replicas and secondary replicas at different nodes. The primary replicas are all linked and cooperate among themselves to achieve replica mutual consistency by ordering updates. Secondary replicas provide a lesser degree of consistency in order to gain performance and availability. Thus, secondary replicas may be less up-to-date and can be in higher numbers than primary replicas. Secondary replicas communicate among themselves and primary replicase via an epidemic algorithm.

Figure 9.14 illustrates update management in OceanStore. In this example, R is the (only) replicated object, whereas R and R_{sec} denote, respectively, a primary and

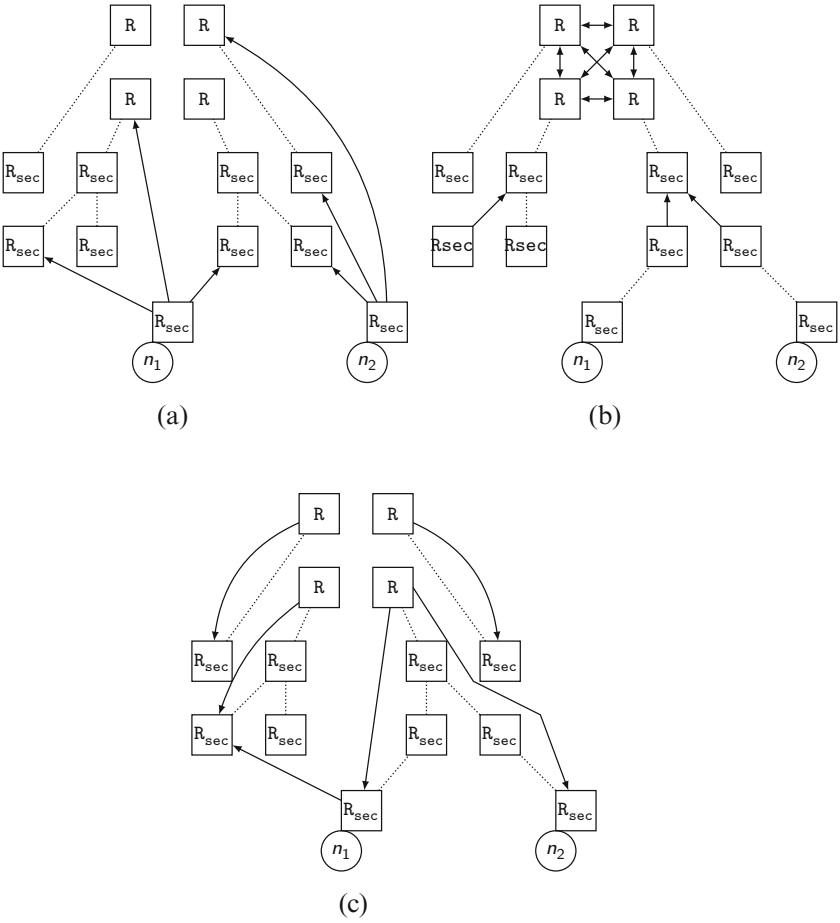


Fig. 9.14 OceanStore reconciliation. (**a**) Nodes n_1 and n_2 send updates to the master group of R and to several random secondary replicas. (**b**) The master group of R orders updates while secondary replicas propagate them epidemically. (**c**) After the master group agreement, the result of updates is multicast to secondary replicas

a secondary copy of R. The four nodes holding a primary copy are linked to each other (not shown in the figure). Dotted lines represent links between nodes holding primary or secondary replicas. Nodes n_1 and n_2 are concurrently updating R. Such updates are managed as follows. Nodes that hold primary copies of R, called the *master group of R*, are responsible for ordering updates. So, n_1 and n_2 perform tentative updates on their local secondary replicas and send these updates to the master group of R as well as to other random secondary replicas (see Fig. 9.14a). The tentative updates are ordered by the master group based on timestamps assigned by n_1 and n_2; at the same time, these updates are epidemically propagated among secondary replicas (Fig. 9.14b). Once the master group obtains an agreement, the

result of updates is multicast to secondary replicas (Fig. 9.14c), which contain both tentative[2] and committed data.

Replica management adjusts the number and location of replicas in order to serve requests more efficiently. By monitoring the system load, OceanStore detects when a replica is overwhelmed and creates additional replicas on nearby nodes to alleviate load. Conversely, these additional replicas are eliminated when they are no longer needed.

9.4.3.2 P-Grid

P-Grid is a structured P2P network based on a binary tree structure. A decentralized and self-organizing process builds P-Grid's routing infrastructure which is adapted to a given distribution of data keys stored by peers. This process addresses uniform load distribution of data storage and uniform replication of data to support availability.

To address updates of replicated objects, P-Grid employs gossiping, without strong consistency guarantees. P-Grid assumes that quasiconsistency of replicas (instead of full consistency which is too hard to provide in a dynamic environment) is enough.

The update propagation scheme has a push phase and a pull phase. When a peer p receives a new update to a replicated object `R`, it pushes the update to a subset of peers that hold replicas of `R`, which, in turn, propagate it to other peers holding replicas of `R`, and so on. Peers that have been disconnected and get connected again, peers that do not receive updates for a long time, or peers that receive a pull request but are not sure whether they have the latest update, enter the pull phase to reconcile. In this phase, multiple peers are contacted and the most up-to-date among them is chosen to provide the object content.

9.4.3.3 APPA

APPA provides a general lazy distributed replication solution that assures eventual consistency of replicas. It uses the IceCube action-constraint framework to capture the application semantics and resolve update conflicts.

The application semantics is described by means of constraints between update actions. An *action* is defined by the application programmer and represents an application-specific operation (e.g., a write operation on a file or document, or a database transaction). A *constraint* is the formal representation of an application invariant. For instance, the *predSucc*(a_1, a_2) constraint establishes causal ordering between actions (i.e., action a_2 executes only after a_1 has succeeded); the *mutuallyExclusive*(a_1, a_2) constraint states that either a_1 or a_2 can be executed. The aim of

[2]Tentative data is data that the primary replicas have not yet committed.

reconciliation is to take a set of actions with the associated constraints and produce a *schedule*, i.e., a list of ordered actions that do not violate constraints. In order to reduce the schedule production complexity, the set of actions to be ordered is divided into subsets called *clusters*. A cluster is a subset of actions related by constraints that can be ordered independently of other clusters. Therefore, the *global schedule* is composed by the concatenation of clusters' ordered actions.

Data managed by the APPA reconciliation algorithm are stored in data structures called *reconciliation objects*. Each reconciliation object has a unique identifier in order to enable its storage and retrieval in the DHT. Data replication proceeds as follows. First, nodes execute local actions to update a replica of an object while respecting user-defined constraints. Then, these actions (with the associated constraints) are stored in the DHT based on the object's identifier. Finally, reconciler nodes retrieve actions and constraints from the DHT and produce the global schedule, by reconciling conflicting actions based on the application semantics. This schedule is locally executed at every node, thereby assuring eventual consistency.

Any connected node can try to start reconciliation by inviting other available nodes to engage with it. Only one reconciliation can run at-a-time. The reconciliation of update actions is performed in 6 distributed steps as follows. Nodes at step 2 start reconciliation. The outputs produced at each step become the input to the next one.

- **Step 1—node allocation:** a subset of connected replica nodes is selected to proceed as reconcilers based on communication costs.
- **Step 2—action grouping:** reconcilers take actions from the action logs and put actions that try to update common objects into the same group since these actions are potentially in conflict. Groups of actions that try to update object R are stored in the *action log R* reconciliation object (L_R).
- **Step 3—cluster creation:** reconcilers take action groups from the action logs and split them into clusters of semantically dependent conflicting actions: two actions a_1 and a_2 are semantically independent if the application judges it safe to execute them together, in any order, even if they update a common object; otherwise, a_1 and a_2 are semantically dependent. Clusters produced in this step are stored in the cluster set reconciliation object.
- **Step 4—clusters extension:** user-defined constraints are not taken into account in cluster creation. Thus, in this step, reconcilers extend clusters by adding to them new conflicting actions, according to user-defined constraints.
- **Step 5—cluster integration:** cluster extensions lead to cluster overlapping (an overlap occurs when the intersection of two clusters results in a nonnull set of actions). In this step, reconcilers bring together overlapping clusters. At this point, clusters become mutually independent, i.e., there are no constraints involving actions of distinct clusters.
- **Step 6—cluster ordering:** in this step, reconcilers take each cluster from the cluster set and order the cluster's actions. The ordered actions associated with each cluster are stored in the *schedule* reconciliation object. The concatenation

of all clusters' ordered actions makes up the global schedule that is executed by all replica nodes.

At every step, the reconciliation algorithm takes advantage of data parallelism, i.e., several nodes perform simultaneously independent activities on a distinct subset of actions (e.g., ordering of different clusters).

9.5 Blockchain

Popularized by bitcoin and other cryptocurrencies, blockchain is a recent P2P infrastructure that can record transactions between two parties efficiently and safely. It has become a hot topic, subject to much hype and controversy. On the one hand, we find enthusiastic proponents such as Ito, Narula, and Ali claiming in 2017 that blockchain is a disruptive technology that "will do to the financial system what the Internet did to media." On the other hand, we find strong opponents, e.g., famous economist N. Roubini who calls blockchain in 2018 the most "overhyped and least useful technology in human history." As always, the truth is probably somewhere in between.

Blockchain was invented for bitcoin to solve the double spending problem of previous digital currencies without the need of a trusted, central authority. On January 3, 2009, Satoshi Nakamoto[3] created the first source block with a unique transaction of 50 bitcoins to himself. Since then, there have been many other blockchains such as Ethereum in 2013 and Ripple in 2014. The success has been significant and cryptocurrencies have been used a lot for money transfer or high-risk investment, e.g., initial coin offerings (ICOs) as an alternative to initial public offerings (IPOs). The potential advantages of using a blockchain-based cryptocurrency are the following:

- Low transaction fee (set by the sender to speed up processing), which is independent of the amount of money transferred;
- Fewer risks for merchants (no fraudulent chargebacks);
- Security and control (e.g., protection from identity theft);
- Trust through the blockchain, without any central authority.

However, cryptocurrencies have also been used a lot for scams and illegal activities (purchases on the dark web, money laundering, theft, etc.), which has triggered warnings from market authorities and beginning of regulation in some countries. Other problems are that it is:

- unstable: as there is no backing by a state or federal bank (unlike strong currencies like Dollar or Euro);

[3]Pseudo for the person or people who developed bitcoin, which generated much speculation about their true identity.

- unrelated to real economy, which fosters speculation;
- highly volatile, e.g., the exchange rate with a real currency (as set by cryptocurrency marketplaces) can greatly vary in a few hours;
- subject to severe crypto-bubble bursts, as in 2017.

Thus, there are pros and cons to blockchain-based cryptocurrencies. However, we should avoid restricting the blockchain to cryptocurrency, as there are many other useful applications. The original blockchain is a public, distributed ledger that can record and share transactions among a number of computers in a secure and permanent way. It is a complex distributed database infrastructure, combining several technologies such as P2P, data replication, consensus, and public key encryption. The term Blockchain 2.0 refers to new applications that can be programmed into the blockchain to go beyond transactions and enable exchange of assets without powerful intermediaries. Examples of such applications are smart contracts, persistent digital ids, intellectual property rights, blogging, voting, reputation, etc.

9.5.1 Blockchain Definition

Recording financial transactions between two parties has been traditionally done using an intermediary centralized ledger, i.e., a database of all transactions, controlled by a trusted authority, e.g., a clearing house. In a digital world, this centralized approach has several problems. First, it creates single points of failure and makes it an attractive target for attackers. Second, it favors concentration of actors such as big financial institutions. Third, complex transactions that require multiple intermediaries, typically with heterogeneous systems and rules, may be difficult and take time to execute.

A blockchain is essentially a distributed ledger shared among a number of participant nodes in a P2P network. It is organized as an append-only, replicated database of blocks. Blocks are digital containers for transactions and are secured through public key encryption. The code of each new block is built on that of the preceding block, which guarantees that it cannot be tampered with. The blockchain is viewed by all participants that maintain database copies in multimaster mode (see Chap. 6) and collaborate through consensus in validating the transactions in the blocks. Once validated and recorded in a block, a transaction cannot be modified or deleted, making the blockchain tamper-proof. The participant nodes may not fully trust each other and some may even behave in malicious (Byzantine) manner, i.e., give different values to different observer nodes. Thus, in the general case, i.e., public blockchain as in bitcoin, the blockchain must tolerate Byzantine failures.

Note that the objective of a typical P2P data structure such as a DHT is to provide fast and scalable lookup. The purpose of a blockchain is quite different, i.e., to manage a continuously growing list of blocks in a secure and tamper-proof manner. But scalability is not an objective as the blockchain is not partitioned across P2P nodes.

Compared with the centralized ledger approach, the blockchain can bring the following advantages:

- Increased trust in transactions and value exchange, by trusting the data, not the participants.
- Increased reliability (no single point of failure) through replication.
- Built-in security through chaining of blocks and public key encryption.
- Efficient and cheaper transactions between participants, in particular, compared with relying on a long chain of intermediaries.

Blockchains can be used in two different kinds of markets: public, e.g., cryptocurrency, public auction, where anybody can join in, and private, e.g., supply chain management, healthcare, where participants are known. Thus, an important distinction to make is between public and private (also called permissioned) blockchains.

A public blockchain (like bitcoin) is an open P2P nonpermissioned network and can be very large scale. Participants are unknown and untrusted, and can join and leave the network without notification. They are typically pseudonymized which makes it possible to track a participant's entire transaction history and sometimes even to identify the participant.

A private blockchain is a closed permissioned network, so its scale is typically much smaller than a public blockchain. Control is regulated to ensure that only identified, approved participants can validate transactions. Access to blockchain transactions can be restricted to authorized participants, which increases data protection. Although the underlying infrastructure can be the same, the main difference between public and private blockchain is who (person, group, or company) is allowed to participate in the network and who controls it.

9.5.2 Blockchain Infrastructure

In this section, we introduce the blockchain infrastructure as originally proposed for bitcoin, focusing on the process of transaction processing. Participant nodes are called *full nodes* to distinguish from other nodes, e.g., lightweight client nodes that handle digital wallets. When a new full node joins the network, it synchronizes with known nodes using Domain Name System (DNS) to obtain a copy of the blockchain. Then, it can create transactions and become a "miner," i.e., participate in the validation of blocks called "mining" process.

Transaction processing is done in three main steps:

1. Creating a transaction after two users have agreed on transaction information exchange: wallet addresses, public keys, etc.
2. Grouping of transactions in a block and linking with a previous block.
3. Validation of the block (and of the transactions) using "mining," addition of the validated block in the blockchain and replication in the network.

In the rest of this section, we present each step in more detail.

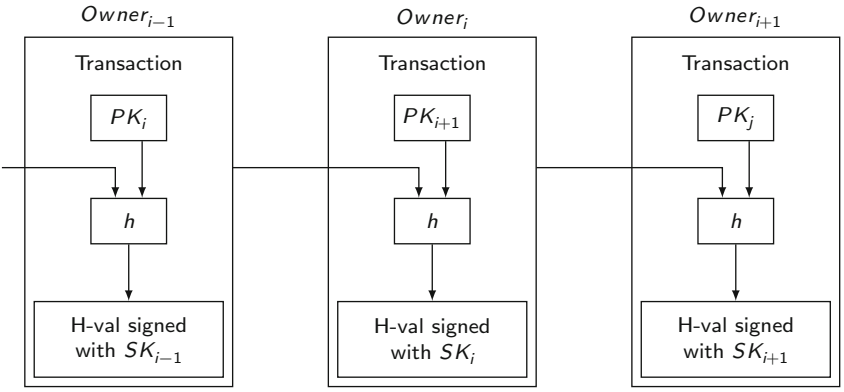


Fig. 9.15 Chaining of transactions

9.5.2.1 Creating a Transaction

Let us consider a bitcoin transaction between a coin owner and a coin recipient that receives the money. The transaction is secured with public key encryption and digital signature. Each owner has a public and private key. The coin owner signs the transaction by

- creating a hash digest of a combination of the previous transaction (with which it receives the coins) and of the public key of the next owner;
- signing the hash digest with its private key.

This signature is then appended to the end of the transaction, thus making a chain of transactions between all owners (see Fig. 9.15). Then, the coin owner publishes the transaction in the network by multicasting it to all other nodes. Given the public key of the coin owner who created the transaction, any node in the network can verify the transaction's signature.

9.5.2.2 Grouping Transactions into Blocks

Double spending is a potential flaw in a digital cash scheme in which the same single digital token can be spent more than once. Unlike physical cash, a digital token consists of a digital file that can be duplicated or falsified.

Each miner node (which maintains a copy of the blockchain) receives the transactions that get published, validates them, and groups them into blocks. To accept a transaction and include it in a block, the miners follow some rules such as checking that the inputs are valid and that a coin is not double-spent (spent more than once) as a result of an attack (see 51% attack next). It may be possible that a malicious miner tries to accept a transaction that violates some rules and include it in a block. In this case, the block will not obtain the consensus of other miners

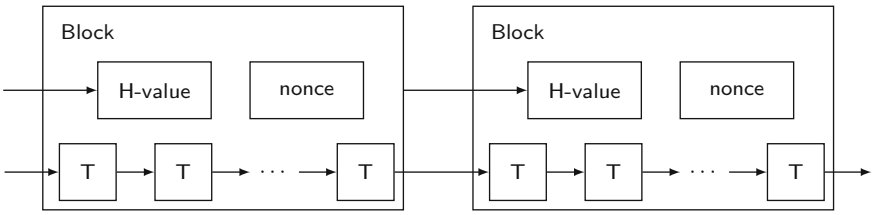


Fig. 9.16 Chaining of blocks

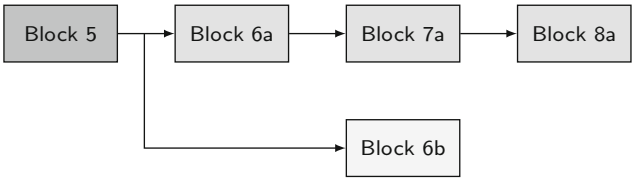


Fig. 9.17 Longest chain rule

that follow the rules and will not be accepted and included in the blockchain. Thus, if a majority of miners follow the rule, the system works. As shown in Fig. 9.16, each new block is built on a previous block of the chain by producing a hash digest ($h-$value) of the previous block's address, thus protecting the block from tampering or change. The current size of a bitcoin block is 1 Megabyte, reflecting a compromise between efficiency and security.

A problem that can arise is an accidental or intentional fork. As different blocks are validated in parallel by different nodes, one node can see several candidate chains at any time. For instance, in Fig. 9.17, a node may see blocks 7a and 6b, both originated from block 5. The solution is to apply the longest chain rule, i.e., choose the block which is in the longest chain. In the example of Fig. 9.17, the block 7a will be chosen to build the next block 7b. The rationale for this rule is to minimize the number of transactions that need to be resubmitted. For instance, transactions in Block 6b have to be resubmitted by the client (who will see that the block has not been validated). Thus, transactions in a validated block are only provisionally validated and confirmation must be awaited. Each new block accepted in the chain after the validation of the transaction is considered as a confirmation. Bitcoin considers a transaction mature after 6 confirmations (1 hour on average). In Fig. 9.17, transaction maturity is illustrated by the darkness of the boxes (Block 6b is lighter because its transactions will not be confirmed).

In addition to accidental forks, there are also intentional forks, which are useful to add new features to the blockchain code base (protocol changes) or to reverse the effects of hacking or catastrophic bugs. Two kinds of fork are possible: *soft fork* versus *hard fork*. A soft fork is backward compatible: the old software recognizes blocks created with new rules as valid. However, it makes it easy for attackers. A famous occurrence of a hard fork is that of the Ethereum blockchain in 2016, after

an attack against a complex smart contract for venture capital. Ethereum forked but without momentum from the community managing the software, thus leading to two blockchains: (new) Ethereum and (old) Ethereum Classic. Note that the battle has been more philosophical and ethical than technical.

9.5.2.3 Block Validation by Consensus

Since blocks are being produced in parallel by competing nodes, a consensus is needed to validate and add them to the blockchain. Note that in the general case of the public blockchain where participants are unknown, traditional consensus protocols such as Paxos (see Sect. 5.4.5) are not applicable. The consensus protocol of the bitcoin blockchain is based on *mining*.[4] We can summarize the consensus protocol as follows:

1. Miner nodes compete (as in a lottery) to produce new blocks. Using much computing power, each miner tries to produce a nonce (number used once) for the block (see Fig. 9.16).
2. Once a miner has found the nonce, it adds the block to the blockchain and multicasts it to all network nodes.
3. Other nodes verify the new block, by checking the nonce (which is easy).
4. Since many nodes try to be the first to add a block to the blockchain, a lottery-based reward system selects one of the competing blocks, based on some probability, and the winner gets paid, e.g., 12.5 bitcoins today (originally 50). This increases the money supply.

Mining is designed to be difficult. The more mining power the network has, the harder it is to compute the nonce. This allows controlling the injection of new blocks ("inflation") in the system, on average 1 block every 10 minutes. The mining difficulty consists in producing a Proof of Work (PoW), i.e., a piece of data that is difficult to calculate but easy to verify, to calculate the nonce. PoW was first proposed to prevent DoS attacks. The bitcoin blockchain uses the Hashcash PoW, which is based on the SHA-256 hash function. The goal is to produce a value v such that $h(f(block, v)) < T$, where

1. h is the SHA-256 hash function;
2. f is a function that combines v with information in the block, so the nonce cannot be precomputed;
3. T is a target value shared by all nodes and reflects the size of the network;
4. v is a 256-bit number starting with n zero bits.

The average effort to produce the PoW is exponential in the number of zero bits required, i.e., the probability of success is low and can be approximated as $1/2^n$.

[4]The term is used by analogy to gold mining as the process of bringing out coins that exist in the protocol's design.

This advantages powerful nodes, which now use big clusters of GPUs. However, verification is very simple and can be done by executing a single hash function.

A potential problem with PoW based mining is the *51% attack*, which enables the attacker to invalidate valid transactions and double spend funds. To do so, the attacker (a miner or miner coalition) must hold more than 50% of the total computing power for mining. It then becomes possible to modify a received chain (e.g., by removing a transaction) and produce a longer chain that will be selected by the majority according to the longest chain rule.

9.5.3 Blockchain 2.0

The first generation blockchain, pioneered by bitcoin, enables recording of transactions and exchange of cryptocurrencies without powerful intermediaries. Blockchain 2.0 is a major evolution of the paradigm to go beyond transactions and enable exchange of all kinds of assets. Pioneered by Etherum, it makes blockchain programmable, allowing application developers to build APIs and services directly on the blockchain.

Critical characteristics of the applications are that asset and value are exchanged (through transactions), there are multiple participants, possibly unknown to each other, and trust (in the data) is critical. There are many applications of Blockchain 2.0 in many industries, e.g., financial services and micropayments, digital rights, supply chain management, healthcare record keeping, Internet of Things (IoT), food provenance. Most of these applications can be supported by a private blockchain. In this case, the major advantages are increased privacy and control, and more efficient transaction validation since participants are trusted and there is no need to produce a PoW.

An important capability that can be supported in Blockchain 2.0 is smart contracts. A smart contract is a self-executing contract, with code that embeds the terms and conditions of a contract. An example of simple smart contract is a service contract between two parties, one that requests the service with an associated payment, and the other that fulfills the service and once executed gets the payment. In a blockchain, contracts can be partially or fully executed without human interaction and involve many participants, e.g., IoT devices. A major advantage of having smart contracts in the blockchain is that the code, which implements the contract, becomes visible to all for verification. However, once on a blockchain the contract cannot be changed. From a technical point of view, the main challenge is to produce bug-free code, which would best be done using code verification.

An important collaborative initiative to produce open source blockchains and related tools is the Hyperledger project of the Linux Foundation that was started in 2015 by IBM, Intel, Cisco, and others. The major frameworks are:

- Hyperledger Fabric (IBM, digital Asset): a permissioned blockchain infrastructure with smart contracts, configurable consensus, and membership services.

- Sawtooth (Intel): a novel consensus mechanism, "Proof of Elapsed Time," that builds on trusted execution environments.
- Hyperledger Iroha (Soramitsu): based on Hyperledger Fabric, with a focus on mobile applications.

9.5.4 Issues

Blockchain is often advertised as a disruptive technology for recording transactions and verifying records, with much impact on the finance industry. In particular, the ability to program applications and business logic in the blockchain opens up many possibilities for developers, e.g., smart contracts. Some proponents, e.g., cypherpunk activists, even consider it as a potential disruptive power that will establish a sense of democracy and equality, where individuals and small businesses will be able to compete with corporate powers.

However, there are important limitations, in particular in the case of the public blockchain, as is the most general infrastructure. The limitations are:

- Complexity and scalability, in particular, difficult evolution of operating rules that require forking the blockchain.
- Ever increasing chain size and high energy consumption (with PoW).
- Potential for a 51% attack.
- Low privacy as users are only pseudonymized. For instance, making a transaction with a user may reveal all its other transactions.
- Unpredictable duration of transactions, from a few minutes to days.
- Lack of control and regulation, which makes it hard for states to watch and tax transactions.
- Security concerns: if a private key is lost or stolen, an individual has no recourse.

To address these limitations, several research issues in distributed systems, software engineering, and data management can be identified:

- Scalability and security of the public blockchain. This issue has triggered renewed interest on consensus protocols, with more efficient alternatives to PoW: proof-of-stake, proof-of-hold, proof-of-use, proof-of-stake/time. Furthermore, there are other performance bottlenecks beside consensus. However, a major issue remains the trade-off between performance and security. Bitcoin-NG is a new generation blockchain with two types of blocks: key blocks that include PoW, a reference to previous block, and mining reward, which makes PoW computing more efficient; and microblocks that include transactions, but no PoW.
- Smart contract management, including code certification and verification, contract evolution (change propagation), optimization, and execution control.
- Blockchain and data management. As a blockchain is merely a distributed database structure, it can be improved by drawing from design principles of database systems. For instance, a declarative language could make it easier

to define, verify, and optimize complex smart contracts. BigchainDB is a new DBMS that applies distributed database concepts, in particular, a rich transaction model, role-based access control, and queries, to support a scalable blockchain. Understanding the performance bottlenecks also requires benchmarking. BLOCKBENCH is a benchmarking framework for understanding the performance of private blockchains against data processing workloads.

- Blockchain interoperability. There are many blockchains, each with different protocols and APIs. The Blockchain Interoperability Alliance (BIA) has been established to define standards in order to promote cross-blockchain transactions.

9.6 Conclusion

By distributing data storage and processing across autonomous peers in the network, P2P systems can scale without the need for powerful servers. Today, major data sharing applications such as BitTorrent, eDonkey, or Gnutella are used daily by millions of users. P2P has also been successfully used to scale data management in the cloud, e.g., DynamoDB key-value store (see Sect. 11.2.1). However, these applications remain limited in terms of database functionality.

Advanced P2P applications such as collaborative consumption (e.g., car sharing) must deal with semantically rich data (e.g., XML or RDF documents, relational tables, etc.). Supporting such applications requires significant revisiting of distributed database techniques (schema management, access control, query processing, transaction management, consistency management, reliability, and replication). When considering data management, the main requirements of a P2P data management system are autonomy, query expressiveness, efficiency, quality of service, and fault-tolerance. Depending on the P2P network architecture (unstructured, structured DHT, or superpeer), these requirements can be achieved to varying degrees. Unstructured networks have better fault-tolerance but can be quite inefficient because they rely on flooding for query routing. Hybrid systems have better potential to satisfy high-level data management requirements. However, DHT systems are best for key-based search and could be combined with superpeer networks for more complex searching.

Most of the work on data sharing in P2P systems has initially focused on schema management and query processing, in particular to deal with semantically rich data. However, more recently with blockchain, there has been much more work on update management, replication, transactions, and access control, yet over relatively simple data. P2P techniques have also received some attention to help scaling up data management in the context of Grid Computing or to help protecting data privacy in the context of information retrieval or data analytics.

Research on P2P data management is having renewed interest in two major contexts: blockchain and edge computing. In the context of blockchain, the major research issues, which we discussed at length at the end of Sect. 9.5, have to do with scalability and security of the public blockchain (e.g., consensus protocols), smart

contract management, in particular, using declarative query languages, benchmarking, and blockchain interoperability. In the context of edge computing, typically with IoT devices, mobile edge servers could be organized as a P2P network to offload data management tasks. Then, the issues are at the crossroads of mobile and P2P computing.

9.7 Bibliographic Notes

Data management in "modern" P2P systems is characterized by massive distribution, inherent heterogeneity, and high volatility. The topic is fully covered in several books including [Vu et al. 2009, Pacitti et al. 2012]. A shorter survey can be found in [Ulusoy 2007]. Discussions on the requirements, architectures, and issues faced by P2P data management systems are provided in [Bernstein et al. 2002, Daswani et al. 2003, Valduriez and Pacitti 2004]. A number of P2P data management systems are presented in [Aberer 2003].

In unstructured P2P networks, the problem of flooding is handled using one of two methods as noted. Selecting a subset of neighbors to forward requests is due to Kalogeraki et al. [2002]. The use of random walks to choose the neighbor set is proposed by Lv et al. [2002], using a neighborhood index within a radius is due to Yang and Garcia-Molina [2002], and maintaining a resource index to determine the list of neighbors most likely to be in the direction of the searched peer is proposed by Crespo and Garcia-Molina [2002]. The alternative proposal to use epidemic protocol is discussed in [Kermarrec and van Steen 2007] based on gossiping that is discussed in [Demers et al. 1987]. Approaches to scaling gossiping are given in [Voulgaris et al. 2003].

Structured P2P networks are discussed in [Ritter 2001, Ratnasamy et al. 2001, Stoica et al. 2001]. Similar to DHTs, dynamic hashing has also been successfully used to address the scalability issues of very large distributed file structures [Devine 1993, Litwin et al. 1993]. DHT-based overlays can be categorized according to their routing geometry and routing algorithm [Gummadi et al. 2003]. We introduced in more details the following DHTs: Tapestry[Zhao et al. 2004], CAN [Ratnasamy et al. 2001], and Chord [Stoica et al. 2003]. Hierarchical structured P2P networks that we discussed and their source publications are the following: PHT [Ramabhadran et al. 2004], P-Grid [Aberer 2001, Aberer et al. 2003a], BATON [Jagadish et al. 2005], BATON* [Jagadish et al. 2006], VBI-tree [Jagadish et al. 2005], P-Tree [Crainiceanu et al. 2004], SkipNet [Harvey et al. 2003], and Skip Graph [Aspnes and Shah 2003]. Schmidt and Parashar [2004] describe a system that uses space-filling curves for defining structure, and Ganesan et al. [2004] propose one based on hyperrectangle structure.

Examples of superpeer networks include Edutella [Nejdl et al. 2003] and JXTA.

A good discussion of the issues of schema mapping in P2P systems can be found in [Tatarinov et al. 2003]. Pairwise schema mapping is used in Piazza [Tatarinov et al. 2003], LRM [Bernstein et al. 2002], Hyperion [Kementsietsidis et al. 2003],

and PGrid [Aberer et al. 2003b]. Mapping based on machine learning techniques is used in GLUE [Doan et al. 2003b]. Common agreement mapping is used in APPA [Akbarinia et al. 2006, Akbarinia and Martins 2007] and AutoMed [McBrien and Poulovassilis 2003]. Schema mapping using IR techniques is used in PeerDB [Ooi et al. 2003] and Edutella [Nejdl et al. 2003]. Semantic query reformulation using pairwise schema mappings in social P2P systems is addressed in [Bonifati et al. 2014].

An extensive survey of query processing in P2P systems is provided in [Akbarinia et al. 2007b] and has been the basis for writing Sections 9.2 and 9.3. An important kind of query in P2P systems is top-k queries. A survey of top-k query processing techniques in relational database systems is provided in [Ilyas et al. 2008]. An efficient algorithm for top-k query processing is the Threshold Algorithm (TA) which was proposed independently by several researchers [Nepal and Ramakrishna 1999, Güntzer et al. 2000, Fagin et al. 2003]. TA has been the basis for several algorithms in P2P systems, in particular in DHTs [Akbarinia et al. 2007a]. A more efficient algorithm than TA is the Best Position Algorithm [Akbarinia et al. 2007c]. Several TA-style algorithms have been proposed for distributed top-k query processing, e.g., TPUT[Cao and Wang 2004].

Top-k query processing in P2P systems has received much attention: in unstructured systems, e.g., PlanetP [Cuenca-Acuna et al. 2003] and APPA [Akbarinia et al. 2006]; in DHTs, e.g., APPA [Akbarinia et al. 2007a]; and in superpeer systems, e.g., Edutella [Balke et al. 2005]. Solutions to P2P join query processing are proposed in PIER [Huebsch et al. 2003]. Solutions to P2P range query processing are proposed in locality sensitive hashing [Gupta et al. 2003], PHT [Ramabhadran et al. 2004], and BATON [Jagadish et al. 2005].

The survey of replication in P2P systems by Martins et al. [2006b] has been the basis for Sect. 9.4. A complete solution to data currency in replicated DHTs, i.e., providing the ability to find the most current replica, is given in [Akbarinia et al. 2007d]. Reconciliation of replicated data is addressed in OceanStore [Kubiatowicz et al. 2000], P-Grid [Aberer et al. 2003a], and APPA [Martins et al. 2006a, Martins and Pacitti 2006, Martins et al. 2008]. The action-constraint framework has been proposed for IceCube [Kermarrec et al. 2001].

P2P techniques have also received attention to help scaling up data management in the context of Grid Computing [Pacitti et al. 2007] or edge/mobile computing [Tang et al. 2019], or to help protecting data privacy in data analytics [Allard et al. 2015].

Blockchain is a relatively recent, polemical topic, featuring enthusiastic proponents [Ito et al. 2017] and strong opponents, e.g., famous economist N. Roubini [Roubini 2018]. The concepts are defined in the pioneering paper on the bitcoin blockchain [Nakamoto 2008]. Since then, many other blockchains for other cryptocurrencies have been proposed, e.g., Etherum and Ripple. Most of the initial contributions have been made by developers, outside the academic world. Thus, the main source of information is on web sites, white papers, and blogs. Academic research on blockchain has recently started. In 2016, Ledger, the first academic journal dedicated to various aspects (computer science, engineering, law,

economics, and philosophy) related to blockchain technology was launched. In the distributed system community, the focus has been on improving the security or performance of the protocols, e.g., Bitcoin-NG [Eyal et al. 2016]. In the data management community, we can find useful tutorials in major conferences, e.g., [Maiyya et al. 2018], survey papers, e.g., [Dinh et al. 2018], and system designs such as BigchainDB. Understanding the performance bottlenecks also requires benchmarking, as shown in BLOCKBENCH [Dinh et al. 2018].

Exercises

Problem 9.1 What is the fundamental difference between P2P and client–server architectures? Is a P2P system with a centralized index equivalent to a client–server system? List the main advantages and drawbacks of P2P file sharing systems from different points of view:

- end-users;
- file owners;
- network administrators.

Problem 9.2 (**) A P2P overlay network is built as a layer on top of a physical network, typically the Internet. Thus, they have different topologies and two nodes that are neighbors in the P2P network may be far apart in the physical network. What are the advantages and drawbacks of this layering? What is the impact of this layering on the design of the three main types of P2P networks (unstructured, structured, and superpeer)?

Problem 9.3 (*) Consider the unstructured P2P network in Fig. 9.4 and the bottom-left peer that sends a request for resource. Illustrate and discuss the two following search strategies in terms of result completeness:

- flooding with TTL=3;
- gossiping with each peer has a partial view of at most 3 neighbors.

Problem 9.4 (*) Consider Fig. 9.7, focusing on structured networks. Refine the comparison using the scale 1–5 (instead of low, moderate, high) by considering the three main types of DHTs: tree, hypercube, and ring.

Problem 9.5 (**) The objective is to design a P2P social network application, on top of a DHT. The application should provide basic functions of social networks: register a new user with her profile; invite or retrieve friends; create lists of friends; post a message to friends; read friends' messages; post a comment on a message. Assume a generic DHT with put and get operations, where each user is a peer in the DHT.

Problem 9.6 (**) Propose a P2P architecture of the social network application, with the (key, data) pairs for the different entities which need be distributed.

Describe how the following operations: create or remove a user; create or remove a friendship; read messages from a list of friends. Discuss the advantages and drawbacks of the design.

Problem 9.7 (**) Same question, but with the additional requirement that private data (e.g., user profile) must be stored at the user peer.

Problem 9.8 Discuss the commonalities and differences of schema mapping in multidatabase systems and P2P systems. In particular, compare the local-as-view approach presented in Chap. 7 with the pairwise schema mapping approach in Sect. 9.2.1.

Problem 9.9 (*) The FD algorithm for top-k query processing in unstructured P2P networks (see Algorithm 9.4) relies on flooding. Propose a variation of FD where, instead of flooding, random walk or gossiping is used. What are the advantages and drawbacks?

Problem 9.10 (*) Apply the TPUT algorithm (Algorithm 9.2) to the three lists of the database in Fig. 9.10 with k=3. For each step of the algorithm, show the intermediate results.

Problem 9.11 (*) Same question applied to Algorithm DHTop (see Algorithm 9.5).

Problem 9.12 (*) Algorithm 9.6 assumes that the input relations to be joined are placed arbitrarily in the DHT. Assuming that one of the relations is already hashed on the join attributes, propose an improvement of Algorithm 9.6.

Problem 9.13 (*) To improve data availability in DHTs, a common solution is to replicate $(k, data)$ pairs at several peers using several hash functions. This produces the problem illustrated in Example 9.7. An alternative solution is to use a nonreplicated DHT (with a single hash function) and have the nodes replicating (k, data) pairs at some of their neighbors. What is the effect on the scenario in Example 9.7? What are the advantages and drawbacks of this approach, in terms of availability and load balancing?

Problem 9.14 (*) Discuss the commonalities and differences of public versus private (permissioned) blockchain. In particular, analyze the properties that need be provided by the transaction validation protocol.