Multi-Tenant Cloud Data Services: State-of-the-Art, Challenges and Opportunities

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ABSTRACT

Enterprises are moving their business-critical workloads to public clouds at an accelerating pace. Multi-tenancy is a crucial tenet for cloud data service providers allowing them to provide services in cost-effective manner by sharing of resources among tenants of the service. In this tutorial we review architectures of today's cloud data services and identify trends and challenges that arise in multi-tenant cloud data services. We discuss techniques that have been developed for enabling elasticity, providing SLAs, ensuring performance isolation, and reducing cost. We conclude with open research problems in cloud data services.

CCS CONCEPTS

• **Information systems → DBMS engine architectures**; **Database query processing**; **Record and buffer management**; **Autonomous database administration**.

KEYWORDS

Cloud data service, multi-tenancy, disaggregation, serverless, resource management

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1 INTRODUCTION

The worldwide public cloud database services market is growing rapidly. The wave of cloud adoption is being driven by digital transformation projects within enterprises that are migrating their applications to the cloud. Major cloud vendors that offer public cloud database services include Alibaba Cloud, Amazon Web Services (AWS), Google Cloud Platform, IBM Cloud, Microsoft Azure, and Oracle Cloud. Cloud database services offer improved manageability compared to on-premises database systems by taking away the burden of managing hardware, virtual machines (VMs), and storage. They handle tasks such as patching and upgrades of the operating system and DBMS, ensuring high availability and disaster recovery, automated backups, point-in-time recovery and even some facets of performance tuning [129].

An overview of the classes of database services available in the cloud are shown in Figure 1[1]. Relational online transaction processing (OLTP) services, e.g., Amazon Aurora [158], Azure SQL Hyperscale [17], and Google Cloud Spanner [32] enable enterprises to run their operational workloads. In addition to traditional SQL-based OLTP services, a new class of operational cloud data services with key-value, document and graph data models has become popular. Examples of such NoSQL services are Google BigTable [37], Amazon Dynamo DB [61], Azure Cosmos DB [1], MongoDB Atlas [127] and Apache Cassandra. Data analytics services (see [39] for a survey) help enterprises to transform and shape data from operational and external sources for use in subsequent analysis, as well as run batch and interactive SQL queries. Examples of cloud services that support Extract-Transform-Load (ETL), interactive and batch SQL queries include AWS Redshift [26], Azure Synapse [28], Google BigQuery [78], Snowflake [52] as well as Spark-based [175] services such as Databricks. Finally, another class of online analytic processing (OLAP) services support ad-hoc interactive analysis over multi-dimensional data, and stream processing services enable near real-time data analytics on operational data.

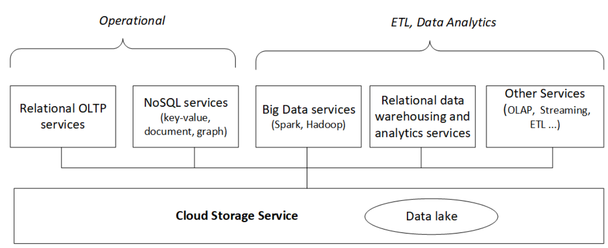

Figure 1: Classes of cloud data services

Three major factors are leading to the re-architecting and redesign of databases in the cloud: *disaggregation*, *multi-tenancy* and *serverless*. Disaggregation has been driven by the need to scale compute and storage independently of each other. Designing cloud databases with independent compute and storage tiers on modern data center architectures raises new challenges. Second, in the on-premises setting the customer owns all hardware resources (servers, networks, storage). However, in the cloud, multiple databases from different customers (a.k.a. *tenants*), share computing resources of the cloud provider including CPU, memory and disk (SSD) resources as well as the data center network. Multi-tenancy is crucial since dedicating hardware for each tenant is simply not cost effective, and sharing resources across tenants enables cloud providers to

[1]Figures in this tutorial have been adopted from [129].

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sharply lower the cost of providing the service. Finally, customers traditionally need to provision a database in the cloud by choosing a fixed set of resources up front; and they pay for those resources regardless of actual usage. Recently, *serverless* databases, which offer a pay-for-use consumption model have gained traction. Tenants no longer need to provision resources for peak usage ahead of time. Rather, the cloud provider acquires and releases resources in response to demands of the database workload, and tenants only pay for resources that their workloads actually use. Thus, today's cloud vendors not only face the challenges of ensuring the traditional demands of enterprise databases such as performance, high-availability, and durability, they must also meet new requirements demanded by serverless, while adhering to the foundational cloud tenets of disaggregation and multi-tenancy.

Scope and goals of the tutorial: In this tutorial we describe key architectures and techniques developed both in industry and research to address the above challenges, and present open problems in the area. We discuss virtualization technology for achieving multi-tenancy and its impact on isolation and consolidation, quality of service (i.e., SLOs and SLAs) and pricing models provided by cloud services, techniques for multi-tenant resource management and improving efficiency, and the new challenges raised by the serverless database paradigm. A detailed outline of the tutorial and the topics covered therein are described in Section 2. Since challenges and open problems are a major focus of the tutorial, in Section 3 we call out the open problems we plan to discuss. This tutorial is based on the survey article [129].

Target Audience and Duration: The intended audience is both academic researchers as well as engineers in the database industry. The tutorial will be largely self-contained for a database audience, and we will include introductory material for attendees not familiar with public cloud architectures.

2 TOPICS COVERED IN THE TUTORIAL

2.1 Architectures

The architectures of cloud data services have been deeply impacted by the design of data centers. Data centers are comprised of a large number of clusters of commodity machines connected to each other over fast, high-bandwidth networks [3], and organized into availability zones and regions. The need for independently scaling compute and storage has led to disaggregated architectures for all types of cloud data services: OLTP, data analytic and NoSQL. For OLTP services such as [2, 32, 158], we describe how their architectures have evolved to achieve high-availability, durability, performance and its impact on cost. We discuss and compare architectures of data analytic services [26, 28, 52, 78, 175] along key dimensions such as shared nothing vs. shared data, pre-loaded data vs. in-situ querying, interactive vs. batch querying capabilities, and the sophistication of query optimization. Finally, we review architectures of NoSQL services such as [1, 37, 61, 127] and compare their data models and consistency vs. performance trade-offs.

2.2 Multi-Tenancy

Multi-tenancy is a key tenet for public cloud data service providers since it allows consolidation of tenants (i.e. databases) by sharing resources, which reduces cost. In general, the greater the degree of consolidation – i.e. the number of databases that are hosted on a single server or cluster – the greater is the reduction in cost. In order to achieve good performance and security for tenants while achieving a high degree of consolidation, cloud service providers need to *virtualize* the available hardware resources. The strength of performance and security isolation and the degree of consolidation achieved depend primarily on the virtualization technology used, and are usually at odds with one another.

In the context of cloud databases, a wide variety of virtualization technology are used – see Figure 2. These include virtual machines (VMs) [141], operating system constructs, e.g. CGroups in Linux and Job Objects in Windows, containers (e.g. Docker) or even logical constructs implemented inside the application or database system (DBMS) for isolating tenants [133, 166]. The choice of virtualization technology is crucial since it influences the following key factors:

- Degree of consolidation: The higher up in the stack virtualization is supported, the greater the degree of consolidation achievable, leading to lower cost for the service provider.
- Degree of isolation: The lower down in the stack the virtualization logic is supported, the greater is the security and performance isolation achievable across tenants.
- Ease of provisioning: The time taken to create a new database or upsize/downsize resource limits for a database is important for many applications. Such provisioning is simpler in logical virtualization technology implemented higher up in the stack.
- Impact of failures: Cloud database services experience planned and unplanned failures. For example, DBMS, operating system and hypervisor software need to be patched and upgraded from time-to-time. Sometimes there are unplanned failures due to failed hardware (e.g. disk) or software (e.g. bug in DBMS code). Depending on the virtualization technology used, a single failure may affect only one tenant or many tenants.

We review each of these virtualization technologies and comment on their effectiveness for each of the above key factors.

2.3 Quality of Service and Pricing Models

In on-premises scenarios, customers provision their own hardware and have full control over the resources of their machines and enterprise network. This control enables them to provide certain quality of service (QoS) to users. These QoS guarantees are also referred to as Service level agreements (SLAs) with customers or internal Service Level Objectives (SLOs) [102] which are not made visible to customers. In contrast, in multi-tenant cloud data services, such QoS guarantees are not automatic since the cloud provider shares the resources of a machine and the data center network with multiple tenants.

Some cloud data services attempt to provide SLAs or SLOs. One common guarantee provided by most cloud data services is on *availability* of the service. End-to-end performance SLAs in terms of throughput and latency are typically not provided by cloud data

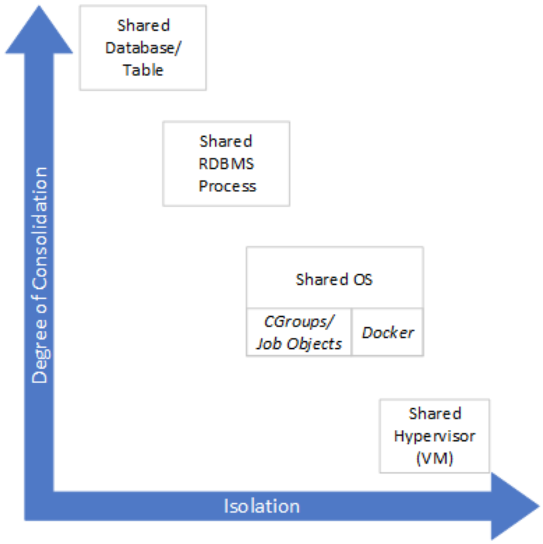
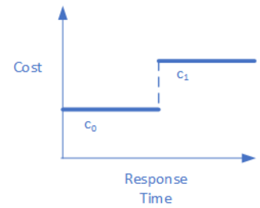
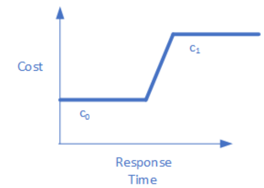


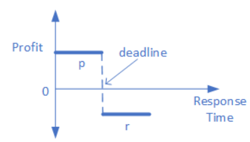
Figure 2: Virtualization technology in databases. Trade-offs in Consolidation vs. Isolation.



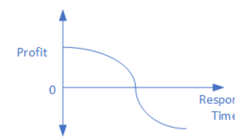
(a) Step function SLA



(b) Piece-wise linear SLA



(c) SLA that models deadlines



(d) SLA that models continuous drop in value over time

Figure 3: Performance SLAs

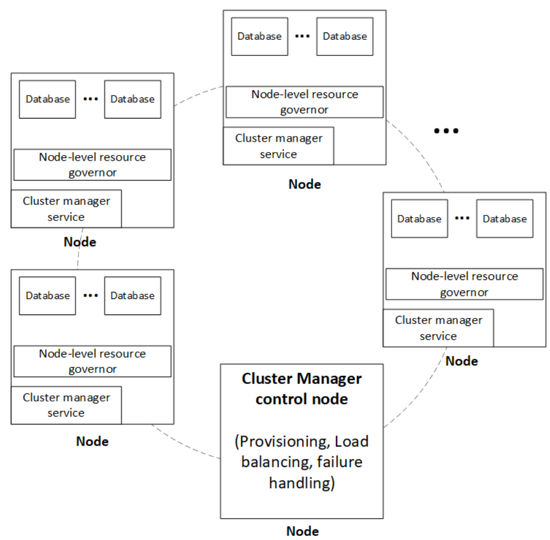


Figure 4: Resource management infrastructure

services. Key-value stores offer a much more limited API and do provide SLAs on latency and throughput. However, services with richer APIs such as SQL only provide guarantees of a minimum amount of resources available for the tenant, and not on latency or throughput.

In general, guaranteeing a higher quality of service requires the service provider to reserve more resources for the workload, and hence incurs a higher cost due to unutilized resources. Therefore, service providers use pricing models such as spot pricing and pre-emptible instances to incentivize customers to use cheaper services with weak or no quality of service guarantees, thereby allowing them to sell capacity that would otherwise go unutilized.

In this tutorial, we review some of the key factors that give rise to variations in quality of service and pricing. We also review models of SLAs and pricing in today's commercial cloud data services as well as other models proposed in the research literature (e.g., some examples of SLAs we will cover are shown in Figure 3 [43, 44, 56, 130, 170, 171]).

2.4 Multi-Tenant Resource Management

Effective management of resources plays a critical role in achieving high availability, good performance, scalability, and efficiency in a multi-tenant cloud data service. Servers in a data center are organized into *clusters*, which are a logical collection of nodes (i.e., machines). Figure 4 shows the typical infrastructure for resource management in a cloud database, where the tasks of managing resources is divided between two infrastructure components: the *cluster manager* and *node-level resource governor*.

The cluster manager (e.g., Kubernetes [89], Service Fabric [103]), is a distributed system infrastructure that is responsible for managing the collection of nodes in the cluster including key decisions such as placement of databases onto nodes, handling failures of nodes and databases, and balancing utilization across nodes in the cluster by moving databases while ensuring minimal impact on availability and performance e.g., [46, 57, 68, 163]. In data warehousing and Big Data analytic systems, when a query or job executes, decisions need to be made on how many nodes to execute the query on and with what amount of resources; and the necessary resources must then be acquired. We review such cluster-level resource management techniques for data analytics briefly [5, 49, 81].

On each node, when multiple databases execute and share resources such as CPU, I/O and memory on the node, a node-level resource governor ensures that databases do not suffer from *noisy neighbor* problems that can adversely affect SLOs. We will review mechanisms that have been developed for *performance isolation* in cloud data services [56, 85, 130, 131, 164].

In the techniques described above it is important to have good estimates of the resources required for a database or query/job.

We review the body of work on *resource estimation* for database workloads. These solutions leverage different techniques such as analytical models that use knowledge of database query processing [6, 41, 118], statistical techniques [168, 169, 177], machine learning, [7, 64, 72, 139], and combinations of the above [55, 115].

Finally, we review techniques that can help improve efficiency and thereby reduce cost both for cloud providers. In particular, we discuss techniques for more efficient use of resources in multi-tenant environments [33, 85, 131, 154, 162] which enables higher packing density of databases and reduced capital expenditure [56, 113, 130].

2.5 Serverless Databases

In the past few years, there has been increasing interest from industry and academia in *serverless computing*. The promise of serverless computing is compelling for cloud database customers. First, it reduces the burden of provisioning resources, since a serverless database can leverage the elasticity of the cloud to handle variable loads by automatically acquiring and releasing the required resources on-demand. Second, unlike in the traditional provisioned model, in a serverless consumption model, the customer only pays for resources that they use. This model is similar to a utility such as electricity where customers are billed only for power they actually consume. An example of such a pricing model in Microsoft Azure SQL Serverless Database is shown in Figure 5. When the database is in an active state, customers pay for a (small) minimum amount of resources or the actual resource usage, whichever is higher, (shown by the green shaded area). Customers pay nothing for compute when the database is in a paused state.

Serverless databases are particularly well suited for use cases where the resources needed to run the workload can vary substantially over time or cannot be accurately estimated in advance. One example is a line-of-business OLTP application in an enterprise with sporadic and bursty workload over the course of a week. Another scenario for data analytics is a resource-intensive query that would be too slow to execute with the fixed amount of resources that were provisioned up front.

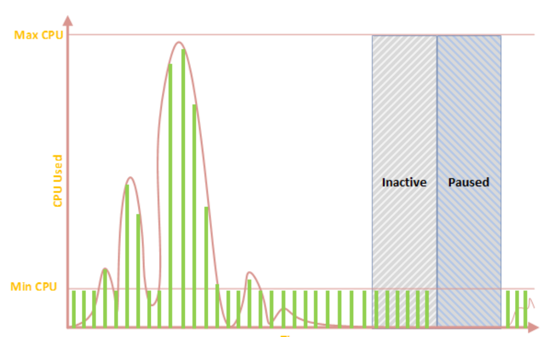


Figure 5: Example pricing model in a serverless database

We will highlight unique challenges for serverless databases, review examples of two commercial database services (one OLTP service and one data analytic service) and describe techniques developed in industry [5, 10, 11, 30, 78] and research [87, 101, 149] for serverless databases.

3 CHALLENGES AND OPEN PROBLEMS

Describing challenges and open problems facing multi-tenant cloud data services is a major focus of the tutorial. Below, we provide some examples of problem areas as well as specific problems we highlight in the tutorial.

3.1 Disaggregation

Separation of compute and storage has been a major driver of architectural changes in cloud data services. One area of active research in the systems and database communities is whether *memory disaggregation* can bring similar benefits by independently scaling CPU and memory. We also see *functional* disaggregation by components. For example, some of today's cloud data analytic services (e.g., Snowflake) use a multi-tenant metadata service that is separate from the query processing service. Similarly, cloud OLTP services (e.g. Azure SQL Hyperscale) employ caching and logging services that are separate from the compute and storage. Studying the benefits of such functional disaggregation for cloud data services has the potential to influence future architectures.

3.2 Caching

Services in all three workload categories: OLTP, Data analytics and NoSQL have developed architectures where the compute tier and the storage tier are separated. While such separation makes it much easier to scale compute resources independently, in response to workload demand, and thereby reduce cost, it simultaneously degrades performance. Hence cloud data services resort to aggressive caching strategies in the compute tier (or resort to adding intermediate caching tiers) to regain performance. Such caching, in turn, raises the cost of the service. Therefore, the one major challenge in caching is to effectively address the performance-cost trade-off. Furthermore, traditional caching techniques need to be made multi-tenant aware in order to be cost-effective.

The lack of our ability to move critical database state – particularly caches – efficiently across machines in a data center hurts user experience, for example, resulting in cold restarts. If database state can be migrated quickly and automatically, it makes it possible for cloud data services to improve performance, increase efficiency and lower cost. Hence improvements in this technology, including cache migration, and database live migration are important areas of work.

3.3 Optimizing Use of Cloud Services

We are seeing a proliferation of choices available to customers who want to run their applications on the cloud. There are different classes of services with different performance, availability and pricing characteristics. For example, provisioned vs. serverless databases vs. spot instances. Therefore it becomes important to help enterprises make decisions as to which offering to choose for their workloads. Software-as-a-service offerings for CRM and ERP (e.g. Salesforce, Microsoft Dynamics) are some of the largest users of cloud database services. The benefits of optimizing usage of cloud databases by choosing the appropriate class of database services for their workloads are therefore amplified for SaaS application vendors.

There are also opportunities for intermediary platforms that layer on top of cloud data services and expose value-added functionality. One example is the ability to use a collection of spot/preemtible compute to create a reliable enough but cheaper compute for batch data analytic jobs (e.g., [92]).

3.4 Auto Tuning

While auto-tuning databases is crucial in on-premises and cloud databases, there are potential opportunities that are uniquely enabled in the cloud. For example, cloud data service vendors have access to telemetry of many different databases and workloads of their customers. There is an opportunity to leverage this rich history, without compromising data privacy and compliance constraints, to aid in auto-tuning their services. An instance of such a problem is calibrating the cost model used by the query optimizer based on the specific machine (SKU) that the database runs on. The availability of large scale telemetry of optimizer estimates and actual execution costs from multiple databases running on various hardware SKUs in the data center can be a valuable asset that is not available in a traditional on-premises setting. Another aspect of the cloud is the relatively easy access to extra resources (at a certain cost). In the auto-tuning context, it is possible to leverage such resources to perform controlled A-B testing for a new database configuration, e.g, to evaluate if the new configuration indeed translates to better performance – without affecting performance of the production database.

3.5 Impact of new hardware

Data centers these days already have new hardware such as network based offload technology (e.g., RDMA), storage technologies such as SSD (now mainstream), FPGAs, GPUs, and non-volatile memory (NVRAM). These technologies have the potential for significant disruption and acceleration in the software stack. For instance, RDMA holds the promise of low-latency access to remote memory in a cluster, thereby accelerating query processing and improving efficiency by sharing resources across nodes more easily.

Due to improvements in data center networking, the ratio of latency of I/O to remote storage or caching tiers vs. local SSDs has been reducing, thereby favoring architectures where compute and storage tiers are separated. However, if new hardware technologies such as NVRAM (which are significantly lower latency compared to SSDs) gain traction for use in databases, then this ratio might once again increase. Understanding the impact of such technology on cloud data services architecture is an open area of study.

3.6 Resource Estimation

Despite a large body of research work on resource estimation, adoption in practice has been limited, in part due to lack of robustness of the techniques. Cloud database providers can collect telemetry on resource usage of many databases and even individual queries. Developing robust models for resource estimation of queries and databases by leveraging such telemetry, particularly for ad-hoc queries and fast-changing or unseen datasets, will be crucial for effective resource management by cloud providers.

4 BIOGRAPHICAL SKETCHES

Vivek Narasayya is a Partner Research Manager in the Data Systems group at Microsoft Research. His areas of interest include infrastructure for cloud data services, physical database design, query optimization and data preparation. He is the recipient of a VLDB 10 year Best paper award. In collaboration with his colleagues at Microsoft Research, he has helped incorporate resource management technologies into Azure Data, and index tuning and data cleaning capabilities into Microsoft SQL Server. Vivek received his Ph.D. from the University of Washington in 2000.

Surajit Chaudhuri is a Distinguished Scientist at Microsoft Research and leads the Data Systems group. His current areas of interest are enterprise data analytics, data discovery, self-manageability and cloud database services. Working with his colleagues in Microsoft Research, he helped incorporate the Index Tuning Wizard (and subsequently Database Engine Tuning Advisor) and data cleaning technology into Microsoft SQL Server. Surajit is an ACM Fellow, a recipient of the ACM SIGMOD Edgar F. Codd Innovations Award, ACM SIGMOD Contributions Award, a VLDB 10 year Best Paper Award, and an IEEE Data Engineering Influential Paper Award. Surajit received his Ph.D. from Stanford University in 1992.

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