A Literature Review on Serverless Computing

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Serverless computing is an emerging cloud computing paradigm. Moreover, it has become an attractive development option for cloud-based applications for software developers. The most significant advantage of serverless computing is to free software developers from the burden of complex underlying management tasks and allow them to focus on only the application logic implementation. Based on its benign characteristics and bright prospect, it has been an increasingly hot topic in various scenarios, such as machine learning, scientific computing, video processing, and the Internet of Things. However, none of the studies focuses on a comprehensive analysis of the current research state of the art of serverless computing from the research scope and depth. Such an analysis is a foundation for understanding an evolving research area. It can provide a global and detailed overview for researchers and practitioners and help them understand and propose promising strategies and best software practices for serverless application engineering.

To fill this knowledge gap, we present a comprehensive literature review to summarize the current research state of the art of serverless computing. This review is based on selected 164 research papers to answer three key aspects, i.e., research directions (What), existing solutions (How), and platforms and venues (Where). Specifically, first, we construct a taxonomy linked to research directions about the serverless computing literature. Our taxonomy has 18 research categories covering performance optimization, programming framework, application migration, multi-cloud development, cost, testing, debugging, etc. Second, we classify the related studies of each research direction and elaborate on existing solutions. Third, we investigate the distributions of experimental serverless platforms for existing techniques and publication venues for selected research papers. Finally, based on our analysis, we discuss some key challenges and envision promising opportunities for future research on the serverless platform side, serverless application side, and serverless computing community side. Our study’s summary can give a quick overview of the current state-of-the-art research on serverless computing for researchers and practitioners. Meanwhile, it will inspire researchers and practitioners to venture into new research topics, novel solutions, and best software practices and significantly contribute to serverless application engineering.

Additional Key Words and Phrases: serverless computing, literature review

1 INTRODUCTION

Cloud computing has attracted more and more software developers to develop and execute their applications on cloud infrastructure [106, 119, 123]. Compared with purchasing new machines and managing numerous operational tasks in traditional software development, software developers can directly benefit from resource availability and scalability provided by cloud computing. In cloud computing, with the promising growth of microservices architecture, a new and emerging cloud computing paradigm named serverless computing emerged and became an increasingly hot topic in industry [1, 3, 12, 18, 28] and academia [111, 112, 114, 184, 215]. According to a report [2], the serverless market size will reach nearly $22 thousand million in 2025 from $3 thousand million in 2017.

In serverless computing, it offers an additional abstraction layer into the traditional cloud computing, and this layer abstracts away complex and error-prone underlying management tasks from software developers. Therefore, software developers can focus on only the application logic. The reduction in underlying cloud management is undoubtedly exciting news for software developers without a background in hardware infrastructure. Moreover, in serverless computing, software developers pay for only the resources actually consumed or allocated by their applications at a fine-grained pattern. This point is different from traditional cloud computing, where software developers always rent and retain resources regardless of whether the application is running. On the other hand, serverless computing also makes
cloud providers manage resources in a unified manner, improving resource utilization and reducing resource waste. Based on these benign characteristics and its bright prospect, many major cloud providers have rolled out their serverless platforms, such as AWS Lambda [12], Microsoft Azure Functions [18], and Google Cloud Functions [28]. Moreover, there are also some available open-source serverless implementations, e.g., OpenWhisk [38] and OpenFaaS [36].

However, this emerging paradigm and its development way significantly differ from traditional cloud computing and traditional software development. Thus, it may face numerous issues or challenges in terms of technique and operation. Related issues or challenges have been concluded and identified [120, 215, 218, 219], such as cold start performance, programming framework, and testing and debugging. Some studies like empirical analysis, survey, literature view, evaluation measurement, etc., have discussed different aspects of serverless computing, including serverless architecture design [138, 210], development features and limitations [63, 107, 215], technology aspects [232], performance properties of serverless platforms [142, 219, 220], characteristics of serverless applications [93, 204], developers’ challenges [134, 218], etc. For instance, Li et al. [138] detailed the serverless architecture by introducing the related concepts, pros, and cons and provided some architecture implications. Yussupov et al. [232] presented a comprehensive technology review to analyze and compare the ten most prominent serverless platforms from development, event source, observability, access management, etc. A measurement study on commodity serverless platforms [220] was conducted to compare performance differences to help software developers choose the appropriate one. Eismann et al. [93] collected 89 serverless applications from various sources to characterize them from 16 aspects. To facilitate software developers’ practices on serverless applications, Wen et al. [218] uncovered 36 specific challenges that software developers encounter in developing serverless applications. In addition to the above studies, there have also been efforts to focus on analyzing research work for specific aspects, such as cold start problem and scheduling policy [137], and resource management [153]. These studies cannot provide a global overview of the current state-of-the-art in research, making the authors may give some wrong or already existing discussions and prospects for future work. Hassan et al. [110] presented a survey on serverless computing. However, this survey mainly summarized statistical information about research papers, such as the number of published papers per year, researcher distribution, and use cases. Overall, existing studies cannot provide a global and detailed overview of the current research state of the art of serverless computing.

Serverless computing is not only prevalent and important in industry, but a portion of its papers have been published in the software engineering (SE) research community. These papers focus on a wide range of topics about serverless computing, including serverless evolution [205], characteristic analysis of serverless applications [93, 94], developers’ challenges [218], application modelling [233], programming framework of specific applications [68, 237], multi-cloud development [183], stateful serverless applications [67], application migration [178], serverless economic [50], serverless dataset [98], technical debt conceptualization [135], testing and debugging [136], etc. However, to the best of our knowledge, neither the SE community nor any other community has a thorough analysis effort to investigate the current research state of the art of serverless computing from the research scope and depth. A comprehensive literature review is a foundation for understanding an evolving research area. In the absence of such a literature review, researchers and practitioners are hard to quickly know a global overview of research directions that the serverless computing field has been investigated, as well as specific solutions that have been carried out. Moreover, it may prevent best software practices for serverless application engineering and the long-term evolution of the serverless computing ecosystem.

In this paper, to fill this knowledge gap, we present a comprehensive literature review to explore the research scope and depth of the serverless computing literature. Our literature review is based on selected 164 research papers to analyze and answer three key aspects, i.e., research directions (What), existing solutions (How), and platforms and
venues (Where). Specifically, first, we aim to construct a taxonomy for research directions of serverless computing to provide a global literature overview. Our taxonomy contains 18 research categories covering performance optimization, programming framework, application migration, cost, testing, debugging, etc. Second, we aim to provide a depth analysis of existing solutions. We classify related studies of each research direction and elaborate on proposed solutions. Third, we investigate the distribution of experimental serverless platforms for existing solutions and the distribution of publication venues for selected research papers. Finally, we discuss key challenges and further envision promising opportunities for future research on the serverless platform side, serverless application side, and serverless computing community side.

Fig. 1 shows the content structure of this paper. In brief, Section 2 introduces the background of serverless computing. Section 3 presents our research questions and the selection strategy for research papers. Section 4 summarizes research directions of serverless computing. Section 5 classifies and elaborates on existing solutions for each research direction. Section 6 investigates the distributions of experimental platforms and publication venues. Section 7 explores key challenges and promising opportunities for future research, and Section 8 concludes this work.

![Fig. 1. Tree structure of the contents in this paper.](image-url)

2 BACKGROUND

In this section, we introduce the background of serverless computing, including its evolution, architecture, key characteristics, and mainstream serverless platforms. Moreover, we briefly summarize and compare the differences between serverless-based software development and traditional software development.

2.1 Evolution of Serverless Computing

Cloud computing provides the ability of computation services via the Internet. According to the NIST definition [156], traditional cloud computing has three service categories: “Infrastructure as a Service” (IaaS), “Platform as a Service” (PaaS), and “Software as a Service” (SaaS). Specifically, IaaS allows software developers to configure and use computation, storage, and network resources. For example, AWS provides the computation service like Elastic Compute Cloud (AWS EC2) [6] and the storage service like Simple Storage Service (AWS S3) [7]. However, IaaS does not hide the operation
complexity of the application; thus, developers are still responsible for resource provisioning, runtime configuration, application code management, etc. SaaS allows software developers to directly use the cloud provider’s applications, such as Gmail [30] and Docs [29] provided by Google. SaaS completely hides the underlying operation complexity, but use cases are limited. Moreover, developers completely lose control of the application. PaaS allows software developers to develop, run, and manage applications using the execution environment supported by the cloud provider. For example, Google provides the App Engine [27], while Azure offers App Service [16]. PaaS compromises the operation complexity between IaaS and SaaS, but software developers still are responsible for and manage some underlying tasks.

To ease the cloud management burden on software developers, cloud providers presented a new paradigm, i.e., serverless computing. Serverless computing is similar to PaaS; differently, it almost hides all complex underlying management tasks for developers, i.e., “server-less”, and it also allows developers to control their applications. Serverless computing-related applications (a.k.a., serverless applications) follow the microservice software style, which decomposes the application into a subset of independent tasks. However, the differences between serverless applications and microservice-based applications are as follows. First, the serverless application’s unit (a.k.a., serverless function) is a smaller granularity than the unit of the microservice-based application. Second, microservice-based applications still make developers face the additional effort of underlying tasks like scalability, fault tolerance, and load balancing. Third, serverless functions adopt the event-driven pattern while microservices are usually responsive to their interfaces. In addition, serverless computing is more suitable for short-lived and bursty applications because its platforms provide high and automatic scalability, while microservices are suited for long-running and stable applications.

2.2 Architecture of Serverless Computing

Serverless computing is an emerging and potential cloud computing paradigm, and its significant advantage is to free software developers from the burden of complex and error-prone server management tasks. Serverless computing provides “Backend as a Service” (BaaS) and “Function as a Service” (FaaS) [120], as shown in Fig. 2. Specifically, BaaS represents tailor-made cloud services provided by cloud providers, e.g., cloud storage and notification services. These services can service FaaS optionally to simplify the backend functionality development for software developers. FaaS represents that software developers can write stateless, event-driven serverless functions, making them focus on the logic of serverless applications. Generally, FaaS is the core of serverless computing, allowing developers to develop and control their applications.

![Fig. 2. The development diagram on the serverless platform.](image)

As shown in Fig. 2, serverless functions will be triggered by pre-defined events, e.g., HTTP requests, data updates of the cloud storage, and the arrival of a notification. These events represent the developers’ requirements, and developers
can define some rules to bind their serverless functions with the corresponding events. When serverless functions are triggered, the serverless platform automatically prepares required runtime environments, e.g., containers or virtual machines (VMs), to serve them. These runtime environments are called function instances, and their preparation process generally contains instance initialization, application transmission, application code loading, etc. After executions are complete, the platform will automatically recycle and release these function instances and the corresponding resources.

2.3 Key Characteristics of Serverless Computing

To better understand serverless computing, we introduce its key characteristics as follows.

- **Functionality and no operations (NoOps):** In serverless platforms, software developers can select their most appropriate and familiar languages (e.g., Python, JavaScript, and Java) to write the function-level code snippet to create serverless applications. Moreover, serverless platforms provide user-friendly integrated development environments (IDEs). For the deployment of serverless applications, software developers only need to upload their application code to the serverless platform without complex environment configuration. In addition, BaaS is the equivalent of off-the-shelf backend functionality. Its related services can be directly applied in the application by developers to replace similar backend functionalities. Therefore, developers do not have to redevelop these functionalities and deal with server configurations.

- **Auto-scaling:** Serverless platforms can automatically scale function instances horizontally and vertically according to the application workload dynamics. Horizontal scaling is to launch (i.e., scale-in) new function instances or recycle (i.e., scale-out) running ones, while vertical scaling is to add (i.e., scale-up) or remove (i.e., scale-down) the amount of computation and other resources from running function instances. After completing requests, the corresponding function instances and allocated resources will retain in memory for a short time to prepare to be reused by subsequent requests of the same function. If there are no subsequent requests, these instances and resources will be automatically recycled by the serverless platform, i.e., scaling to zero. However, scaling to zero makes incoming new requests face the cold start problem, which takes a long time to prepare required runtime environments from scratch.

- **Utilization-based billing:** In serverless computing, software developers charge for the actually allocated or consumed resources of the serverless application in the fine-granular execution unit. For example, AWS Lambda’s pricing is related to the allocated memory, and Azure Functions considers the consumed memory. On the other hand, serverless functions are event-driven; thus, they will not run without being triggered, and developers do not pay any cost. This feature eliminates the concern of paying for idle resources. In summary, the billing pattern of serverless computing is relatively reasonable and inexpensive compared with traditional cloud computing, which requires always renting and paying resources in memory on standby.

- **Separation of computation and storage:** Serverless computing adopts the separation way of computation and storage, i.e., separately scaling and independently provisioning and pricing. Generally, computation refers to stateless serverless functions, while storage represents cloud storage services provided by cloud providers to store data from the serverless function. This separation way can ensure the auto-scaling ability of the serverless platform for bursty workloads.

- **Additional limitations:** Cloud providers set some additional limitations for serverless functions to keep the vital auto-scaling feature of serverless platforms. Generally, these limitations contain function execution timeout, deployment package size, local disk size, memory allocation maximum, etc. Moreover, different serverless
platforms have different demands regarding these additional limitations. The following section will list specific demands for some serverless platforms.

The above key characteristics show the unique advantages of serverless computing. In addition, some features and limitations will also essentially influence the development of cloud-based applications.

2.4 Serverless Platforms

Major cloud providers have rolled out their commercial serverless platforms, such as AWS Lambda [12], Microsoft Azure Functions [18], and Google Cloud Functions [28]. However, these commercial serverless platforms hide the platform’s underlying details and have a vendor lock-in problem for software developers. To address these restrictions, the serverless computing community has presented some open-source serverless implementations, such as OpenWhisk [38] and OpenFaaS [36]. Their recognition and popularity are also due in part to the popularity of container orchestration like Kubernetes [33]. The serverless computing community is actively maintaining these open-source implementations. Commercial serverless platforms and open-source serverless implementations are designed based on serverless computing characteristics. Therefore, in our study, they are uniformly called serverless platforms. Next, we will introduce some mainstream serverless platforms.

**AWS Lambda**: AWS Lambda is the first widely mentioned serverless platform. After it was released in November 2014, serverless computing started to gain increasing attention, and other major cloud providers followed this trend to present their serverless platforms. AWS Lambda offers different interaction ways for developers, including the command-line interface (CLI), HTTP-based application programming interface (API), and graphical user interface (GUI). Moreover, software developers can use the related plugins for IDEs (e.g., Visual Studio and Visual Studio Code [44]) to access the platform through language-specific client libraries. The pricing of AWS Lambda is related to function execution time (in increments of 1 millisecond [13]), allocated memory size, and the number of invocations. The function execution timeout limitation of AWS Lambda is 900 seconds. For the deployment package size, AWS Lambda supports up to 250 MB uncompressed size and 50 MB compressed size. For the memory allocation configuration, AWS Lambda can allocate the memory of the function instance as 128 MB to 10,240 MB in the increment of 1 MB. For the observability of AWS Lambda, Amazon provides AWS CloudWatch [5] and AWS CloudTrail [9] to monitor and log serverless functions. In addition, AWS Lambda provides a serverless marketplace called AWS Serverless Application Repository (AWS SAR) [14] for application development purposes. This marketplace contains some serverless functions or applications contributed by third-party teams.

**Microsoft Azure Functions**: Microsoft released its serverless platform Azure Functions in 2016. Azure Functions offers various interaction ways like CLI, API, and GUI and uses related plugins for Visual Studio and Visual Studio Code [44] to access the platform. The pricing model of Azure Functions is similar to AWS Lambda, but it relies on the consumed memory of serverless functions. Moreover, the minimum execution time of billing is in increments of 100 milliseconds [19]. The function execution timeout limitation of Azure Functions is 600 seconds. In Azure Functions, it uses the function app as the execution and management unit, which is still composed of several functions. Azure Functions has no deployment package limit and uses a flexible memory allocation, supporting 1,536 MB at most. Microsoft uses Azure Application Insights [17] to provide the observability of Azure Functions. In addition, Azure Functions adopts three hosting plans: consumption, premium, and dedicated plans for serverless applications. For the marketplace, Microsoft provides a general-purpose Azure Marketplace [21] to include serverless applications.
**Google Cloud Functions**: In 2017, Google released its serverless platform, i.e., Google Cloud Functions. Like AWS Lambda and Azure Functions, Google Cloud Functions supports various interaction ways like CLI, API, and GUI. However, Google Cloud Functions seems to have no related plugins for IDEs to access the platform. The pricing model of Google Cloud Functions is related to provisioned memory and CPU. The function execution timeout limitation is 540 seconds. The deployment package size of Google Cloud Functions has a 250 MB uncompressed size limit and a 100 MB compressed size limit. Google Cloud Functions can assign memory values like 128 MB, 256 MB, 512 MB, 1,024 MB, 2,048 MB, 4,096 MB. In addition, Google does not provide a marketplace of serverless applications, but it has some code samples to guide the development process.

**OpenWhisk**: Apache OpenWhisk is an open-source serverless implementation developed and maintained by IBM and Apache. It was released in 2016. In OpenWhisk, it combines several key technologies, e.g., Nginx [35], CouchDB [22], Kafka [32], and Docker [25]. Function invocations can be transformed as HTTP requests and imported into the Nginx server that supports web protocol. The Nginx server pushes the request to the controller, which collaborates with the CouchDB that stores the application’s data. The controller and underlying worker nodes rely on Kafka, a publish-subscribe messaging system, to communicate. Kafka can receive messages from the controller to confirm the invoked worker node. For the programming model of OpenWhisk, actions, triggers, and rules are primary concepts. Specifically, actions represent functions to be executed, triggers are predefined events, and rules refer to the binding description between actions and triggers. In addition, OpenWhisk offers CLI and API interactions and supports local development and cloud environment development. Developers can leverage IDEs like Visual Studio Code [44] and Xcode [48] to connect OpenWhisk. In OpenWhisk, there is no marketplace for serverless applications.

**OpenFaaS**: OpenFaaS is a project developed by Alex Ellis in 2016. The underlying system of OpenFaaS is based on Docker [25] and Kubernetes [33]. OpenFaaS can be deployed in public or private clouds, even in edge devices, due to its lightweight. In OpenFaaS, developers can use CLI, API, and GUI to implement interaction operations, but no related development IDEs. Generally, developers utilize CLI to communicate with the OpenFaaS gateway. This gateway connects a function monitor tool called Prometheus [40], which records values of function-related metrics. In addition, OpenFaaS also supports workflow orchestration with synchronous and asynchronous function chains, parallelism, and branch. In OpenFaaS, it has an OpenFaaS Function Store [37] as its marketplace.

In these serverless platforms, CLI and API are common interface types to establish programmatic access. Except for Google Cloud Functions, other platforms support the development and deployment of the custom container image. This deployment way allows developers to use any programming language and heavy third-party library to avoid potential language and deployment package size limits. However, it also increases the additional burden of container management efforts, such as interface requirements and container interaction. For commercial serverless platforms, the corresponding cloud providers offer tailor-made monitoring and logging services to observe serverless functions. However, open-source serverless platforms generally integrate external tools to achieve the observability of serverless functions. In addition, commercial serverless platforms natively offer access management for authentication and resource, while open-source serverless platforms rely on only the hosting environment to implement the related access management.

### 2.5 Comparison with Traditional Software Development

Serverless-based software development and traditional software development are different in many aspects. In this section, we summarize some primary differences in Table 1 to further understand the software development paradigm of serverless computing.
Server management: In serverless computing, software developers do not manage complex server tasks, focusing only on application development. Therefore, the serverless application will require fewer engineers related to operation, maintenance, and resource management. However, in traditional software development, developers need to coordinate various components and implement all server-side functionalities. Moreover, developers endure a high failure rate for physical servers. In addition, server resources are not guaranteed to be optimally utilized.

Functionality implementation: Serverless functions are implemented as event-triggered functionalities. Moreover, these functions are short-lived and stateless; thus, runtime data cannot be stored in their function instances, making communication with other functions hard. An external storage service may be required to save data of serverless functions to solve the communication problem. Moreover, services contained in BaaS can be optionally used in applications to simplify the development of backend functionalities. However, in traditional software development, developers first pick a technology stack and development framework and then configure the local development environment based on the selected programming language. Moreover, developers need to implement complex backend functionalities themselves. Due to the local development, functions are stateful; thus, they can directly communicate.

Invocation pattern: Serverless applications are composed of multiple event-driven serverless functions. Therefore, invocations rely on the developer’s pre-defined events, and the invocation process may be automatic. However, invocations in traditional software development are dependent on client-side calls from the software developer.

Execution limitations: Serverless functions have inherent execution limitations, including function execution timeout, confined memory size, restricted local disk size of instances, etc. In traditional software development, the execution limitations have a high degree of uncertainty because they depend on the capacity of the leased servers.

Execution place: Serverless applications can be executed in function instances from the cloud with enough resource provision, while traditional software applications are executed in the limited local environment of developers.

Performance: The cloud provider of serverless computing manages runtime environments required for serverless functions. The advantage of unified resource management is that the serverless platform can respond to any bursty workload. These runtime environments are activated only if serverless functions are triggered. When required environments are not active, serverless functions may face the cold start problem, which introduces a long preparation time. There have been a lot of efforts to alleviate this problem [54, 74, 86, 164, 214, 243]. For traditional software development, runtime environments are always in the active condition to respond to application requests immediately. However, this will waste too many resources when there are no requests. Moreover, the local environment may not be able to handle workloads with variable requirements.

Cost: In serverless computing, software developers pay for only actually resources allocated or consumed by the serverless function. Moreover, using serverless computing saves a lot of application development time, and the application can be released to the market faster. However, in traditional software development, developers pay for everything, such as physical server purchase and installation, as well as the cost of maintenance-related engineers and electricity. Moreover, non-uniform architecture and low product maturity make application development time longer and market release time slower. In addition, once the application is deployed successfully to the server, the server will be “always-on”, and developers have to pay for it.

Tool maturity: Existing serverless platforms lack rich support tools, such as testing and debugging. The reason is that the event-driven, distributed, and platform detail masking features make the application architecture more complex and the execution flow harder to reproduce. For traditional software development, testing and debugging can be freely designed and evaluated based on the local environment. Furthermore, the relevant tools are already well-grounded in the software engineering research community.
Table 1. Comparison between serverless-based software development and traditional software development.

| Features             | Serverless-based software development | Traditional software development |
|----------------------|--------------------------------------|----------------------------------|
|                      | No management tasks                  | All management tasks             |
| Functionality        | Directly write event-driven and stateless code | Pick technology stack            |
| implementation       | Use BaaS to simplify development     | Pick development framework       |
|                      |                                      | Configure development environment|
|                      |                                      | Implement all functionalities from scratch |
| Invocation pattern   | Event triggers                       | Client-side calls                |
| Execution limitations| Fixed inherent limitations, e.g., execution timeout, confined memory size | Uncertain limitations, depending on server capacity |
| Execution place      | Cloud                                | Local                            |
| Performance          | Activate only if triggered           | Always activate                  |
|                      | Cold starts                          | No cold starts                   |
|                      | Flexibility                          | No flexibility                   |
| Cost                 | Pay for actually allocated/assumed resources | Pay for everything               |
|                      | Less application development time    | More application development time |
|                      | Less market release time             | More market release time         |
| Tool maturity        | Low                                  | High                             |

3 METHODOLOGY

In this section, we present our research questions and introduce the selection strategy of related research papers.

3.1 Research Questions

To better understand the research scope and depth of the current research state of the art for the serverless computing field, we aim to focus on the following three research questions.

- **RQ1 (What - Research directions):** *What have research directions been investigated in the serverless computing literature?* This research question aims to investigate the research goal of existing studies and provide a global overview of research directions about serverless computing.

- **RQ2 (How - Existing solutions):** *How do existing studies tackle specific problems for each research direction?* This research question aims to understand how to tackle the research problem for each research direction. We classify the related studies of each research direction and dissect the solutions to problems associated with each research direction.

- **RQ3 (Where - Platforms and venues):** *Where are the existing solutions implemented/evaluated and published?* This research question aims to investigate which serverless computing platforms existing techniques are implemented or evaluated on, and where existing serverless computing-related papers are published.

3.2 Data Selection Strategy

To answer these research questions, we select the relevant published research papers about serverless computing. In this section, we explain our data selection strategy. In brief, we search the related research papers by defining some keywords on the widely adopted engines and databases. Then, we make the corresponding selection rules to select the final research papers of literature review for analysis.
3.2.1 Literature sources. In our study, seven standard online engines or databases [110, 143, 194, 216, 232] are selected as literature sources. These sources contain (1) ACM Digital Library, (2) IEEE Xplore, (3) Google Scholar, (4) Elsevier ScienceDirect, (5) Scopus, (6) SpringerLink, and (7) DBLP Computer Science Bibliography.

3.2.2 Search string. To determine the research papers related to serverless computing, we follow the previous work [110, 143] to define extensive search string and then apply it to literature sources. The search string used in a survey of serverless computing [110] is (serverless OR FaaS OR function as a service OR function-as-a-service) AND (computing OR paradigm OR architecture OR model OR application OR service OR platform OR programming). Similarly, this search string is also applied in our study to crawl research papers from our defined literature sources on 2022.01.01. In this process, we obtain 398 research papers in total.

3.2.3 Inclusion and exclusion criteria. We formulate the inclusion and exclusion criteria to effectively filter and select relevant research papers of serverless computing.

**Inclusion criteria:** (1) Publications that belong to serverless computing; (2) Publications that address and present the corresponding design solutions, algorithms, optimization approaches, or general ideas in terms of specific aspects of serverless computing; (3) Publications that are written in English.

**Exclusion criteria:** (1) Publications that are the benchmark suite; (2) Secondary or tertiary studies, e.g., empirical studies, literature reviews, and surveys; (3) Publications that are not available or full text because they cannot provide complete information; (4) Publications that are bachelor, master, or doctoral dissertations; (5) Pre-printed studies that are submitted in the arXiv website.

After the paper screening, exclusion, and duplicate removal, we end up with 118 initial relevant research papers.

3.2.4 Snowballing. Based on the initial papers, we apply the commonly used backward snowballing process [110, 216] to increase the set of relevant research papers. The main idea of backward snowballing is to search for other relevant papers in the “Related Work” section of each selected paper. In addition, in our study, the newly added papers also adopt the same snowballing strategy to continue to search for other new papers. In this phase, we add 46 research papers to our paper list. As a result, we obtain 164 research papers in total for our literature review.

4 RQ1 (RESEARCH DIRECTIONS)

To answer the research question of which research directions have been investigated, we label all selected research papers to determine the research goal by viewing their Abstract, Introduction, Related Work, and Conclusion sections.

As shown in Fig. 3, we construct a taxonomy linked to research directions of serverless computing for selected research papers. Note that a research paper may belong to two or multiple research directions. For example, the work presented by Cordingly et al. [82] addressed the prediction problem of both application performance and cost because the cost is closely associated with the performance of the serverless application. Therefore, this work is assigned to the “Performance Prediction” research direction and “Cost Prediction” research direction. In our taxonomy, its total number of papers (174) is larger than the original number of selected research papers (164).

Our taxonomy includes 12 root categories of research directions represented in the black box, such as “Resource Management (22)” and “Performance (67)”. The number in parentheses indicates the number of papers that investigate the corresponding research direction. For example, 22 papers address resource management. In addition, the boxes with colors (e.g., blue, orange, and grey) represented sub-research directions under a particular research direction scope. For instance, the research direction “Performance” contains two sub-research directions represented in the blue box:
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“Performance Prediction” and “Performance Optimization”. The sub-research direction “Performance Optimization” includes two smaller research directions represented in the orange box: “Cold Start Performance” and “Runtime Performance”. Furthermore, “Runtime Performance” is still divided into two smaller research directions that cannot be subdivided and represented as the grey box, i.e., “Function Execution” and “Function Communication”. In total, there are 18 non-divisible research directions in this taxonomy.

![Fig. 3. A taxonomy of research directions in the serverless computing literature.](image)

Next, we explain our taxonomy in detail. First, studies related to “Performance” are the most, accounting for 38.51% (67/174) of all papers in this taxonomy. These studies contain 10.45% (7/67) “Prediction” and 89.55% (60/67) “Performance Optimization”. Specifically, the performance of serverless platforms or applications affects resource utilization or developers’ experience, respectively. Moreover, performance variance affects cost. Therefore, some studies have targeted the performance prediction of platforms or applications. However, most performance efforts are made on performance optimization, including 56.67% (34/60) “Cold Start Performance” optimization and 43.34% (26/60) “Runtime Performance” optimization. For the cold start performance, it refers to the overhead generated by the cold start process. When there are incoming requests, serverless platforms will automatically prepare the runtime environment from scratch to serve serverless functions, i.e., cold starts. This process needs to prepare instance initialization, application runtime, application code preparation, etc., and thus introduce undesired latency for requests and affect the user experience. For the runtime performance, it refers to the execution overhead of serverless functions (i.e., “Function Execution”, 30.77% (8/26)) and communication overhead between serverless functions (i.e., “Function Communication”, 69.23% (18/26)). The function execution overhead represents the time of executing the actual functionality of serverless functions, not the end-to-end response time of a request. For the function communication overhead, it is due to the stateless feature of serverless functions. Current serverless platforms do not provide a mature point-to-point communication mechanism between serverless functions via the network. Generally, developers leverage cloud storage services like AWS S3 [7] to save data of serverless functions for intermediary state management. In this situation, serverless functions need to keep fetching the required data in external services to accomplish the collaboration of functions, thus producing a high-latency communication overhead.

Second, in our taxonomy, the second-largest research direction in proportion is “Programming Framework” (18.39% (32/174)). Serverless computing is an emerging cloud computing paradigm, and thus it may not fully support applications with unique type requirements (i.e., “Specific Applications”, 59.38% (19/32)) or no type requirements (i.e., “General Applications”, 40.63% (13/32)). Therefore, related researchers have designed specific or generic programming frameworks to adapt to the corresponding requirement.

Third, our taxonomy shows that studies related to “Resource Management” account for the third-largest percentage, i.e., 12.64% (22/174). In serverless computing, resource management aims to manage the resource requirements of...
serverless applications and ensure the resource efficiency of serverless platforms. Better resource management will more easily make serverless platforms and applications achieve service-level agreements.

In addition, our taxonomy contains nine other research directions: “Stateful FaaS” (4.60% (8/174)), “Application Modelling” (4.02% (7/174)), “Application Migration” (5.75% (10/174)), “Cost” (8.05% (14/174)), “Multi-Cloud Development” (1.72% (3/174)), “Accelerator Support” (2.30% (4/174)), “Security” (2.87% (5/174)), “Testing” (0.57% (1/174)), and “Debugging” (0.57% (1/174)). The specific illustration is as follows.

- **“Stateful FaaS”**: Serverless functions are developed in a stateless way. However, supporting the stateful feature in serverless applications can fulfill a broader range of workloads. Therefore, some efforts have aimed to design stateful serverless computing.
- **“Application Modelling”**: Serverless applications follow a new development paradigm. Therefore, it may be limited in the expression of the serverless application. Some studies have addressed the application modelling problem to clearly show the specific representation and dependency for serverless applications.
- **“Application Migration”**: The prevalence and popularity of serverless computing make more and more legacy applications migrate to the serverless platform to enjoy its advantages like low cost and high scalability. This migration process corresponds to the application migration research direction of the serverless computing literature.
- **“Cost”**: Major serverless platforms adopt a unique cost pattern, i.e., utilization-based billing. The cost is closely related to the execution time of the serverless function, allocated or consumed memory size, and the number of invocations. Some researchers have explored how to predict and optimize the cost of serverless functions or applications based on these factors and possible impact factors.
- **“Multi-Cloud Development”**: Generally, software developers select a fixed serverless platform to develop their applications. However, different cloud providers offer various features for their serverless platforms. Using multiple clouds will allow application development and execution to enjoy more benefits. Therefore, some studies have made efforts toward the multi-cloud development of serverless computing.
- **“Accelerator Support”**: Serverless platforms mainly provide the CPU resource-dominated runtime environment. Therefore, software developers’ applications cannot use other accelerators like Graphics Processing Unit (GPU) and Field Programmable Gate Arrays (FPGA) hardware resources. However, more and more tasks like machine learning and deep learning require leveraging such hardware resources to accelerate their performance. In this situation, how to design accelerator-enabled serverless computing is essential to facilitate a wide application availability.
- **“Security”**: When using serverless computing, the serverless platform and application details are agnostic to each other. This situation also leads software developers and cloud providers to distrust each other. Some security problems have been investigated in the serverless computing literature.
- **“Testing”**: Similar to traditional software applications, serverless-related developers are also required to test their serverless applications. Testing plays a vital role in the software quality assurance of serverless applications. However, the distributed and event-driven natures of execution on the cloud make it challenging to test serverless applications.
- **“Debugging”**: Serverless computing hides the underlying system implementation for software developers. Moreover, serverless functions contained in applications are independent and event-driven. These features make the application debugging hard so that developers cannot determine the application’s correctness. However, debugging serverless applications is essential to facilitate serverless application engineering, although few attempts have been made in the current research effort.
5 RQ2 (EXISTING SOLUTIONS)

To answer the research question of how existing studies tackle specific problems for each research direction, we read the entire content of the research paper. Then, we classify related studies of each research direction and elaborate on the solutions to problems associated with each research direction.

5.1 Resource Management

In serverless computing, resource management is responsible for allocating the proper resource provision for serverless functions and scheduling serverless functions on appropriate function instances. This process guarantees software developers’ and cloud providers’ quality of service (QoS) requirements. The QoS goal of software developers is related to the serverless application’s performance, cost, security, etc. In contrast, the QoS goal of cloud providers is associated with the serverless platform’s resource utilization, load balancing, throughput, etc. Existing studies have tried to improve resource management from four kinds of solutions, including platform QoS requirement, dynamic resource adjustment, application characteristic, and architecture design.

- **Platform QoS requirement:** From the cloud provider’s perspective, achieving efficient resource utilization is critical in reducing resource waste. Therefore, some studies have considered managing the resource by measuring the QoS of the serverless platform. A QoS-aware resource manager can satisfy the QoS enforcement while maximizing the overall resource utilization of the serverless platform. HoseinyFarahabady et al. [112, 113] leveraged the model predictive controller to present the QoS-aware controller with feedback to guarantee the well-utilization of computation resources, the response time of processing events, and the QoS demand level for serverless functions. However, their studies have not considered the effect of the number saturation of the working thread. To address this problem, they presented a controller that can adjust the number of working threads for each QoS class [128]. This controller used a QoS violation index to determine the required resources, not the prediction module of the previous work [112, 113].

  Tariq et al. [208] first conducted a measurement study to uncover existing serverless platforms’ problems. They found inconsistent and incorrect concurrency limits, difficulty supporting bursty workloads, and inefficient resource allocation. To alleviate these problems, they introduced an effective QoS scheduler called Sequoia to realize a variety of flexible policies. Yuvaraj et al. [234] also presented a hierarchical resource allocation framework to address inconsistent and runtime limitations. This framework can enhance scalability and job parallelism degree. Schuler et al. [187] found the impact of concurrency levels on application performance; thus, they got the idea of adjusting the concurrency level for workloads. Specifically, they presented the reinforcement learning-based model, where the agent is responsible for evaluating the current system state in each iteration and making decisions for the concurrency level.

  Dynamic resource adjustment: Efficient and flexible resource management can handle various serverless workloads with different resources and latency requirements. Moreover, it can minimize cloud providers’ costs. Some studies have considered how to dynamically adjust resources like CPU in the serverless platform. For example, Kim et al. [127] presented a fine-grained CPU cap controller to dynamically adjust CPU usage limit according to the performance requirement similarity of serverless applications. This adjustment can minimize resource contention, improve the robustness of the controller, and thus reduce performance degradation. Similarly, function-level schedulers [202, 203] were presented to analyze the resource consumption and lifetime of serverless functions and then classify and schedule serverless functions. Meanwhile, these schedulers can dynamically adjust CPU-shares resources of containers for serverless functions. Furthermore, FnSched [202] used a greedy algorithm, which can allocate fewer function instances to respond to requests. However, these studies above on dynamic resource adjustment have not considered developers’
requirements (e.g., application deadline) in the load balancing policy. It may limit optimal resource usage and cannot generate efficient resource management. Therefore, Mampage et al. [152] designed a deadline-sensitive heuristic algorithm to manage the resource and minimize the cloud provider’s cost. Moreover, they dynamically adjust CPU resources during executions to meet the developer’s application deadline.

However, some applications may be complex since their consumed resources could vary with workload demands. Stronger resource management is essential for applications like big data analytics. Leveraging real-time, precise resource monitoring and feedback may be a possible solution. Enes et al. [97] presented such a real-time approach. This approach relied on the operating-system-level virtualization to dynamically change provided resources via cgroups and kernel-backed accounting features. In addition, Yu et al. [228] presented a new serverless resource manager to make full use of idle resources. This manager used an experience-driven algorithm to estimate the resource saturation point for the serverless function and then dynamically decided to harvest or offer resources for this serverless function.

**Application characteristic:** Some studies have considered application characteristics to design the corresponding resource management strategies. An efficient resource management system named Emars [181] analyzed the function execution history to predict the right memory consumption for the serverless function, enhancing memory resource utilization. Skedulix [84] was a greedy algorithm that used predictive models about the function execution time and network latency for each function to determine the function placement.

A serverless application can be viewed as a workflow. Existing serverless platforms may launch multiple containers to serve multiple serverless functions contained in the workflow, causing resource over-provisioning. In this situation, Bhasi et al. [70] presented a resource management framework called Kraken, which captured the workflow characteristic and invocation probability to estimate the number of containers provided and ensure the application performance. An application workflow may also have a workflow execution deadline. A scheduling algorithm should consider this factor and meet the constraint cost. Therefore, serverless deadline-budget workflow scheduling algorithms [123, 151, 167] were presented. These algorithms used a set of heuristic rules to process the workflow graph and assign the corresponding resources. Palma et al. [166] was a novel scheduling idea. It provided a declarative language for developers to describe the application requirements, such as expected scheduling policy and performance goals. The underlying scheduler can understand these requirements to select the appropriate instances.

The above studies have mainly maximized resource utilization. However, considering the billing model of serverless functions, resource management should also evaluate the task execution cost related to aggregated runtimes. Inter-task scheduling requires minimizing both cost and task completion time. It is hard to trade-off between cost and completion time since a short completion time means large allocated memory that causes a high pricing unit. A fine-grained task-level scheduler, Caerus [236], was presented to address this problem by on-demand invoking functions. Caerus used a step dependency model to model and schedule pipeline-able and non-pipeline-able dependencies across tasks.

**Architecture design:** Existing scheduling policies have been basically coarse-grained and may not suitably satisfy the bursty, stateless, and short-lived applications. In this situation, Kaffes et al. [121] presented a new scheduling architecture with a centralized core-granular scheduler. Core granular can directly assign functions to individual cores, guaranteeing performance stability. Centralized design can maintain a global view of the cluster to manage cores and resources and eliminate the migration of heavy functions. However, this scheduling architecture design considered only the CPU resource allocation.

Generally, serverless platforms adopt the strategy of over-provision resources for serverless applications to guarantee the application QoS. However, developers still pay for only resources that their applications actually consume. This kind of resource provision way is not friendly for cloud providers of serverless computing. In this situation, a new
architecture may be required to maximize the cloud provider’s benefits. Zhang et al. [240] leveraged Harvest VMs to design a new architecture. Harvest VMs is a faster, cheaper alternative than VMs. The authors leveraged a series of measurement results to illustrate the suitability of Harvest VMs in serverless computing. Meanwhile, these results also guided the architecture design with Harvest VMs.

5.2 Performance Prediction

For studies related to performance prediction, regression model-based prediction and statistical learning-based prediction are two common solutions. A summary of studies on performance prediction is shown in Table 2.

- **Regression model prediction:** Some studies have tried to train the regression model about performance by considering several affected factors. Cordingly et al. [82] thought about the performance prediction problem from the perspective of system resource usage. They generated the regression model for each serverless function to predict its runtime performance (e.g., CPU user mode time, CPU kernel mode time). This model considered the CPU heterogeneity of the serverless platform and memory settings. However, this approach trained the corresponding model for each serverless function; thus, this process may take a long time. Therefore, Eismann et al. [90] presented an approach called Sizeless that did not require dedicated performance learning. Sizeless designed an offline phase, which monitored some synthetic functions and collected the resource consumption data (e.g., system CPU time, bytes received) for all memory sizes. Based on the collected data, Sizeless trained the multi-target regression model to predict the execution latency in all memory sizes for a real function. However, these approaches above targeted only independent serverless functions, not the serverless application with multiple serverless functions and complex structures. Moreover, obtained performance models did not consider function features such as task type and input parameter size.

- **Statistical learning prediction:** Another kind of approach is to consider statistical learning to predict the performance of serverless platforms, functions, or applications. Some studies [105, 148, 149] aimed to predict the performance of serverless platforms. Some prediction models were presented to create performance-driven and predictive serverless platforms. These models considered some key parameters, such as the cold start rate, cold start latency, arrival rate of warm instances, and instance expiration rate, to the original system with the Markovian arrival process. Obtained platforms can decrease resource waste and guarantee the QoS of serverless applications.

Other studies aimed to predict the response time of serverless functions or applications. Akhtar et al. [52] presented a framework called COSE to learn a performance model of the serverless function from execution logs. This model used the Bayesian Optimization strategy to learn the gap between configuration and runtime statistically, and it predicted the optimal configuration that provided the satisfying user-specified performance. Lin and Khazaei [139] modeled the application performance into a probabilistic graph considering the structure transformation as well as the runtime response time of each serverless function. However, these approaches leveraged the collected history runtime information to predict the function or application performance. It is impossible to know the historical performance situation for new serverless functions or applications.

5.3 Performance Optimization

Studies on performance optimization are related to optimizing the cold start performance and runtime performance.

5.3.1 **Cold Start Performance.** To address the cold start problem, serverless platforms like AWS Lambda adopt the fixed “keep-alive” policy to keep resources in memory for a few minutes, i.e., becoming warm instances, when serverless functions finish their executions. Subsequent requests can reuse warm instances with required resources to reduce the
number of cold starts. However, this policy cannot capture the actual invocation frequency of serverless functions, leading to resource waste in no requests. Therefore, many researchers have continued to tackle the cold start problem. The main solutions contain instance prewarm preparation, data cache-based optimization, function scheduling, snapshot-based optimization, and architecture design.

- **Instance prewarm preparation**: Instance prewarm preparation is to launch some required function instances in advance to serve the incoming requests. This kind of solution prevents the serverless application from going through the cold start process. Some studies [86, 243] have focused on the cold start problem of serverless applications with the chain structure. The first serverless function contained in the chain-type serverless application is invoked, meaning that the following serverless functions will also be invoked in a cold start manner. Moreover, Daw et al. [86] found that the cold start latency increase with the application chain length. Therefore, some studies [86, 243] have leveraged this knowledge to design the corresponding approaches. These approaches can predict and prepare the runtime execution environment in advance for subsequent serverless functions contained in a chain-type serverless application. However, if the prediction fails, these approaches will introduce additional resource waste.

In order to alleviate the cold start problem, some other studies have used a prewarm pool to process requests quickly. Ling et al. [140] introduced an oversubscribed prewarm container pool, where containers had different resource configurations. This pool was based on a static setting and combined all resource sizes, e.g., 1-CPU, 2-CPU, and 4-CPU. However, such a pool led to low resource utilization and the risk of resource fragmentation. Suo et al. [201] maintained an adaptive live container pool to service incoming requests. This pool can be adjusted according to the container runtime history over time. However, these approaches may not quickly deal with burst requests and avoid resource waste. To further address these problems, Horovitz et al. [111] learned the seasonal invocation pattern of incoming functions through history invocation timestamps and then launched required instances for serverless functions in time. Similarly, Xu et al. [226] presented an adaptive strategy called AWU to predict when the serverless function will be invoked and then warm up the runtime execution environment in advance. AWU was based on time series prediction,
which considered the invocation number of the serverless function over time and the moments between serverless functions being called. In addition, Shahrad et al. [188] also presented a flexible and practical resource management policy. This policy can dynamically manage the prewarm time window size for each serverless function through the time series prediction. Unlike the time series prediction of the study [226], this policy [188] was based on each serverless function’s invocation frequency and pattern to dynamically adjust the prewarm time and keep alive time.

- **Data cache-based optimization:** The traditional runtime environment of serverless computing is VMs, which have strong isolation and flexibility. However, VMs lack the advantage of low start latency for applications, and this latency is usually greater than 1000 ms. In this situation, serverless computing uses another common runtime environment, containers, which can achieve low start latency (usually 50 ms - 500 ms) than VMs. Moreover, containers typically include binaries and libraries. Pre-importing necessary or commonly used data on such a runtime environment can speed up the cold start process.

The representative studies based on data cache-based optimization are SOCK [164] and SAND [54]. Specifically, SOCK [164] and its previous implementation, Pipsqueak [163], cached per-warmed interpreters and commonly used libraries in containers, and they provided the lightweight isolation mechanism for serverless functions. Following this caching idea, Nuka [176] was a generic serverless engine with millisecond initialization. This engine designed a local package caching to import required software packages. Moreover, it provided an isolation pool to reduce the latency of pulling container images. SAND [54] applied the application-level sandbox runtime sharing to reduce the number of containers and thus container preparation latency. SAND also provided the isolation mechanism for serverless functions to allocate or deallocate resources quickly. Similar to SAND, Dukic et al. [89] thought that current strict isolation is not necessary for safe concurrent requests of the same serverless function. Sharing the runtime may be a possible solution to alleviate the cold start problem for concurrent requests. Therefore, they presented an ultralightweight execution context named Photons, which can co-locate multiple function instances of the same serverless function in the same runtime via workload parallelism. However, the above studies on data cache-based optimization may be impractical since caching all required libraries or functions in memory will increase resource overhead, and cache policies are not easy to capture in the real workload.

Some related studies have designed other data cache approaches considering different objects, e.g., networking resources, image data, and containers. For example, Mohan et al. [157] found that the major overhead during container startup for concurrency invocations is the creation and initialization of network namespaces. Therefore, they cached networking resources in some pre-created containers to reduce the network overhead of container startup. Hermes [227] was a two-level caching mechanism including memory caching and local disk caching to support on-demand loading of image data and repeated fetching elimination. Such a mechanism can alleviate the transmission latency in cold starts. WLEC [195] was a container-based caching policy, which used cold, warm, and template queues to place required containers according to runtime information. These containers were managed and selected by a Container Management Service to respond to requests.

Except for considering different cache objects, Fuerst et al. [103] mapped keep serverless computing alive to caching study, where keeping instances warm is viewed to cache an object, and the warm start is a cache hit. They designed FaasCache containing a set of caching-based keep-alive policies to reduce cold start overhead.

In most cases, using the data cache can effectively alleviate the cold start problem. However, this kind of approach will introduce high resource overhead and imbalanced resource consumption, leading to performance interference from the system environment. Moreover, cache policies may be hard to be determined in the real world.
• **Function scheduling:** Generally, the function scheduling solution is to distribute incoming requests to warm instances to serve them. Warm instances have the prepared runtime execution resources, and thus they can serve requests faster than cold starts. Related studies have aimed to improve the existing schedulers or compensate for the insufficiency of scheduling strategies in reusing warm containers. First, existing schedulers may be agnostic of container lifecycle, i.e., creation, use, pause, or eviction of containers, and thus they are ineffective in reducing cold starts. In this situation, Wu et al. [224] proposed a container lifecycle-aware scheduler called CAS to distribute requests. This scheduler leveraged an affinitive worker to maintain and manage the states of containers. Second, existing schedulers showed erratic performance behavior in application workloads with multi-tenant and high concurrency. Therefore, Kim et al. [124] designed a novel scheduling algorithm called FPCSch, allowing serverless platforms to schedule available containers into requests to obtain stable performance while reducing cold starts.

Other researchers have considered the application structure [69, 132] or dependency relationships [190] among serverless functions to schedule serverless functions. If independent serverless functions can be fused or composed into a serverless function, the scheduler assigns these independent serverless functions to be executed on the same function instance. In this situation, the number of cold starts will directly decrease. Leveraging this knowledge to reduce the number of cold starts, Bembach et al. [69] orchestrated all serverless functions into a lightweight choreography middleware, and Lee et al. designed a function fusion solution [132] based on graph representation. In addition, Shen et al. [190] leveraged frequent pattern mining and invocation history to mine dependencies between serverless functions. These dependencies can guide the scheduler to schedule the connected functions on the same instance, thus diminishing the occurrences of cold starts.

Considering that some studies like SOCK [164] and SAND [54] used data cache techniques to alleviate the cold start problem, the scheduler or load balancing may significantly affect the cache-hit ratio, thus influencing the performance of cold start and overall application. Based on it, some scheduling algorithms like PASch [61], GRAF [133], and others [49] have been presented to distribute incoming requests into container instances with pre-loaded cache to improve the cache hit rate and thus the performance of serverless applications.

• **Snapshot-based optimization:** The industry and academia have used the snapshot way, a promising solution, to alleviate the high latency of cold starts. Specifically, this way captures the complete state (called snapshot) of the current function execution and stores the state in local storage (e.g., SSD) or in a disaggregated storage service. When the same function is invoked again, the serverless platform can quickly initialize the function instance according to the corresponding snapshot to immediately process this request. Snapshot-based optimization becomes attractive since it does not require main memory during functional inactivity and can reduce the high latency of cold starts.

Cadden et al. [74] presented SEUSS to capture the function state (containing function logic, language interpreter, and libraries) at an arbitrary point during executions. Moreover, SEUSS saved the state as an in-memory snapshot. New invocations of the same function can be rapidly started from its snapshot. A similar idea to SEUSS, Replayable Execution [214] was to use process-level checkpointing to save and restore the state. Moreover, the state was allowed to share between different containers. Du et al. [88] found that sandboxes have a high application initialization latency, which dominated the overhead of cold start latency. To reduce this part of overhead, they designed Catalyzer based on Google’s gVisor [31] to set checkpoints and restore application and sandbox runtime. Catalyzer minimized the critical path processing time of VM loading through the snapshot way. Following the same design principles as Catalyzer, a runtime environment called Firecracker [51] was presented by AWS. Its Firecracker VM was loaded from a snapshot, which contained the state of the virtual machine monitor and the emulated devices. Moreover, Firecracker customized the virtual machine manager (e.g., hypervisor) to create microVMs to isolate multiple tenants with affordable overhead.
However, Ustiugov et al. [209] characterized the snapshot-based serverless infrastructure Catalyzer [88] and found that a function executed from the snapshot took 95% longer to execute than if the same function was executed from a resident in memory, on average. Due to the state constantly being written to the page, the page frequently generates faults, thus causing high latency. Fortunately, they found the same stable working set of pages among different invocations of the same function. Therefore, they leveraged this insight to present REAP. REAP can obtain the function’s stable working set of guest memory pages and pre-load into memory to speed up the performance. However, REAP also posed shortcomings. For example, generating a stable working set is not enough when the input data payload is significantly different among invocations. In this situation, the runtime environment waited until all data was loaded to start, leading to a slower execution latency.

- **Architecture design:** Some studies have used novel design principles or underlying environments to present the new serverless platform, which will fundamentally alleviate the cold start problem. We briefly summarize the related studies as shown in Table 3. Specifically, Boucher et al. [71] presented a novel serverless platform based on language-based isolation. Using language-based isolation is faster than using process-level isolation for microsecond-scale serverless functions. In language-based isolation, a single-threaded worker process is hosted in each worker core, and it can directly execute serverless functions, one at a time. Moreover, the presented serverless platform used task preemption, supported by commodity CPUs at a microsecond scale. Other studies have applied the lightweight runtime. Hall and Ramachandran [109] and Long et al. [144] used the lightweight and fast WebAssembly runtime [46] to replace the container to remedy the performance overhead of cold starts. In contrast to VMs and containers, WebAssembly is a high-level language VM runtime and shows a binary format with inherent memory and execution safety guarantees.

Unikernel [43] is an emerging fine-grained, lightweight sandbox that uses libraryOS with essential dependency libraries. Security of the Unikernel is higher than containers, the image size is also small, and notably, the start latency is within 10 ms. USETL [99] was a Unikernel-based design to be specific to the cold start performance of serverless extract, transform, load (ETL) workloads. USETL leveraged strong language preference and maintained a pool of Unikernels with initialized runtime. Following the Unikernel idea, Tian et al. [206] also used the Unikernel design to make serverless functions run in the Unikernel, offering extremely low cold start latency to execute functions. Moreover, this design leveraged a hardware technique named VMFUNC [45] to achieve communication among serverless functions in different Unikernels.

Table 3. A summary of architecture design studies on cold start performance optimization.

| Study              | Architecture design | Description                                               | Security |
|-------------------|---------------------|-----------------------------------------------------------|----------|
| Boucher et al. [71]| Language-based isolation (Rust) | It is faster than traditional process-level isolation | High     |
| Hall and Ramachandran [109] Long et al. [144] | WebAssembly | It is a lightweight high-level language VM runtime | High     |
| Fingler et al. [99] Tian et al. [206] | Unikerel | It is a lightweight sandbox with libraryOS and has strong flexibility | High     |

5.3.2 **Runtime Performance**. Studies on runtime performance optimization are about performance optimizations of function execution and function communication.

1. **Function Execution**
In the related studies on performance optimization of function execution, memory configuration, function scheduling, and architecture design are common solutions.

- **Memory configuration**: Generally, the response time of the serverless function is affected by the allocated memory [220, 230]. However, when the allocated memory size is large enough, the response time of the serverless function becomes insensitive to the memory [139]. Therefore, changing the size of the allocated memory may be an opportunity for performance optimization. Lin and Khazaei [139] used their performance model with a heuristic algorithm to find a memory configuration. This configuration can achieve the minimum average response time of the serverless application under budget constraints.

- **Function scheduling**: Designing an appropriate scheduling strategy can reduce resource competition for CPU and network among function instances, thus improving the execution performance of serverless applications. Current serverless platforms are agnostic to the application type or invocation frequency during the request processing. It may make certain serverless functions be located on the same VM node, influencing their execution performance. Mahmoudi et al. [150] considered the application type (e.g., CPU, memory, and I/O) to design an adaptive function placement algorithm. This algorithm used statistical machine learning to analyze resource utilization and the application’s profile. Then, it arranged the runtime environment with the best performance for functions. Przybylski et al. [172] considered the collected information, including the invocation frequency and function duration time, to propose a data-driven function scheduling to minimize the response time.

When there are bursty or real-time workloads, a real-time serverless prototype is required to execute them at a guaranteed invocation rate and minimal performance effect. Such a prototype can be achieved through predictive container management and admission control [162]. However, the Alibaba Cloud Function Compute team found that the deployment way to use custom container images needs to pull large container images (larger than 1.3 GB) from the backend store. When bursty workloads are to pull the same large container image, it will cause a severe performance problem of network bandwidth. Therefore, they presented a rapid container provisioning FaaSNet [212] to accelerate container provisioning to serve bursty requests. FaaSNet organized VMs as function-based tree structures and used a tree balancing algorithm to dynamically adapt the tree topology to adjust VM joining and leaving.

- **Architecture design**: Some new architectures have been designed to optimize the function execution performance. Atoll [193] was a scalable, low-latency serverless platform where the control and data planes of its architecture were redesigned via decoupling sandbox allocation from scheduling, introducing deadline-aware scheduling, and co-designing the load balancing and scheduling layers. Atoll can handle short-lived serverless functions with unpredictable arrival patterns and maximize the request processing with the user-specified deadline. In addition, instead of using traditional pre-compiled libraries, Chadha et al. [78] used a Just-in-Time compiler, which is based on LLVM [34] for Python, to optimize the performance of compute-intensive serverless functions. In addition, Carreira et al. [75] tried to utilize runtime knowledge to optimize the executed function code. First, they demonstrated the significant impact of runtime optimizations. Moreover, the code to execute multiple times (i.e., in hot starts) was optimized code, which is executed at the maximum performance. Then, they presented a holistic system named Ignite to share code optimization information across runtimes for the same function to reduce profiling and compilation overheads.

### 2. Function Communication

Since serverless functions are stateless and are executed in different function instances, they generally rely on external storage to communicate with each other to accomplish complex tasks. However, such communication collaboration introduces additional overhead for application execution. Some studies have aimed to alleviate this overhead through different strategies: memory sharing, cache-based design, storage optimization, and network optimization.
• **Memory sharing:** When serverless functions are co-located on the same machine, using memory sharing can avoid the overhead of data movement. Generally, memory sharing-based approaches [83, 117, 130, 180, 192] refer to designing and managing shared memory to achieve low-latency communication between serverless functions. Specifically, Shillaker and Pietzuch [192] presented a runtime called Faasm, which contained a WebAssembly-based isolation abstraction to isolate the memory of running functions and allow memory to be shared among functions in the same address space. However, Faasm was based on specific assumptions about the language-based isolation and application programming interface. Jia et al. [117] presented a runtime named Nightcore to address the overhead imposed by interactive serverless functions. Nightcore supported arbitrary invocation patterns to execute multiple invocation requests of the same function in the same container. Moreover, it optimized I/O between requests via efficient threading. Overall, the internal function call of Faasm [192] and Nightcore [117] had the same functionality. Differently, Faasm made serverless functions execute within the same process leveraging WebAssembly-based isolation. Nightcore directly co-located multiple requests on the same container and used shared memory to achieve efficient function communication. However, Faasm and Nightcore were both to modify the serverless application. In this situation, the lightweight Faastlane [130] was presented to minimize the latency between function interactions, supporting unmodified applications. Its data sharing leveraged simple load/store instructions, and Faastlane made serverless functions contained in a workflow execute as threads within a shared virtual address space.

• **Cache-based design:** Some approaches have used caches to improve state consistency guarantees and runtime performance of serverless applications. Lambdata [207] was a novel serverless system that allowed developers to declare the data read and write intents of their serverless functions. To speed up the communication performance, Lambdata leveraged the additional object caching layer of the computation node to save the same data for multiple function invocations and scheduled the related functions to the same computation node to reuse data. Linking the caching layer to the computation node was also adopted by Wu et al. [223]. They presented HydroCache to optimize network traffics. HydroCache chose an autoscaling key-value storage engine, Anna [8], to provide low-latency data access and transactional causal consistency. However, the worker of HydroCache established multiple times with the storage to obtain the latest version, leading to the tail latency of function execution. To address this problem, Lykhenko et al. [145] proposed a solution called FaaSTCC, combining a multi-site cache with the storage layer. The key idea was to leverage a small amount of metadata that is passed from function to function to capture the difference between versions.

Similar to HydroCache, Sreekanti et al. [199] introduced a stateful serverless platform named Cloudburst, which also used Anna and imported a local storage cache to execute multiple serverless functions. However, HydroCache and Cloudburst introduced specific assumptions, such as consistency semantics and protocols, since they relied on Anna. Moreover, the work of Cloudburst did not discuss the specific caching configuration. A work designed at the same time as Cloudburst was OFC [159]. OFC designed an opportunistic RAM-based caching system to dynamically predict caching efficiency and memory usage through machine learning. OFC had stronger consistency and persistence guarantees than Cloudburst, and it supported more widely workload types. However, these approaches have not considered another critical factor, i.e., scaling, which may mitigate the data access impact. Therefore, Romero et al. [179] presented FaaT, which was serverless and bundled in the serverless application as an in-memory caching layer. In FaaT, different cache replacement and persistence policies were designed to achieve auto-scaling and transparency.

• **Storage optimization:** Since the data of serverless functions are generally stored in external storage, characteristics (e.g., data correctness, scalability, and efficiency) of the storage are essential to cooperate serverless functions. Some studies have aimed at storage optimization to present new storage systems. Sanity [160] was a storage system to tackle the limitation of duplicated data. Data de-duplication operation was performed close to the event sources to reduce
the function redundancy activation. To use an elastic and distributed data storage, Klimovic et al. [129] presented a novel storage system named Pocket to access data and automatically scale with the serverless application under desired performance and cost. Pocket can dynamically adjust resources and provide low latency, high throughput, scalable resources, and smart data placement across multi-tier storage, such as DRAM, Flash, and disk. Locus [173] used a mixture of fast but expensive storage and slow but cheap storage to balance the communication performance and cost. Overall, Pocket and Locus were both to implement the multi-tier storage solution to improve the performance and cost-efficiency of serverless workloads. A data-driven middleware Zion [184] for object storage was presented to improve data locality and reduce communication latency. Zion incorporated computation into the data pipeline and executed it in a scalable way to address the storage’s scalability and resource contention problems. Besides incorporating computation into the data pipeline, embedding small storage functions into the storage was also noticed by Zhang et al. [238]. They presented low-latency cloud storage, Shredder, for serverless function chains. Developers can embed some small storage functions in the storage to directly interact with the required data. These storage functions can mitigate the network overhead between the serverless application and data.

Mahgoub et al. [147] compared different data passing methods, including VM-Storage, Direct-Passing, and state-of-the-art Remote-Storage. The results showed that these methods performed poorly in all serverless scenarios. Therefore, they presented a management layer called SONIC to deploy a hybrid approach about three data passing methods to improve the application performance. A unified API was exposed to developers, allowing them to select the optimal data passing method according to application-specific factors, such as input payloads. SONIC also can leverage the optimized storage like Pocket [129] and Locus [238] in its selection methods.

Network optimization: In practice, current serverless functions cannot directly communicate with each other via the network. To address this problem, Wawrzoniak et al. [217] presented a system called Boxer to support direct function-to-function communication in the existing serverless platform. Boxer used the TCP hole-punching technique of P2P to bypass the network constraints in conventional TCP/IP network stack. Such a system can directly achieve direct data exchange to benefit serverless computing.

5.4 Stateful FaaS

In the research direction of stateful FaaS, some studies have tried to address it by considering application model design, log-based mechanism, and architecture design.

Application model design: Mainstream cloud providers have rolled out their serverless orchestration services. In fact, these services play a kind of glue to compose serverless functions together. For example, AWS Step Functions [15] uses the state machine to combine multiple serverless functions in different patterns (e.g., sequential or parallel executions) and provides the state store in this serverless orchestration service. Microsoft Azure used durable functions [47] as the extension of serverless functions to allow developers to add the state and establish communication. In academia, Akhter et al. [53] presented a high-level application model to help developers develop and deploy their stateful applications. This model can transfer serverless functions and the required data as a stateful dataflow graph, and the data can be shared automatically to achieve scalability and low latency. Another high-level application model with an extension stateful function language and a compiler [73] was developed to help software developers generate cloud infrastructure supporting the state access of the serverless application.

Log-based mechanism: To build serverless stateful functions on existing serverless platforms, Zhang et al. [235] was inspired by the log-based fault tolerance protocol to propose Beldi. Beldi introduced new refinements to the existing log-based fault tolerance approach in terms of data structure and specific algorithms. These refinements can record
the application state and logs. Moreover, Beldi periodically re-executed functions that have not yet finished executing, guaranteeing the at-least-once execution semantics to prevent duplicated operation execution. In addition, Beldi’s design motivated Boki’s shared log approach [116] for stateful serverless computing. Boki exported the shared log API to serverless functions to store the state. Moreover, read and write paths were separated and individually optimized. However, developers need to adapt the way of Boki with shared logs to write their applications since Boki-based development is different from the original development of serverless applications.

- **Architecture design:** Some studies have designed new architectures for serverless computing to support stateful applications. Cloudburst [199] was a specified architecture for incorporating states into serverless functions. In Cloudburst, it used Anna storage with flexible auto-scaling, which is a good fit for serverless computing. Crucial [66, 67] was also a new design for providing fine-grained state management. The invocation of a serverless function was mapped to a thread, and a distributed shared object layer was built on the in-memory data store. This way can guarantee strong state consistency and simplify the global state semantics across threads. Since the Beldi solution [235] offered the at-least-once execution semantics for failed function attempts, it may expose fractional writes. Therefore, Sreekanti et al. presented AFT [198] with stronger fault tolerance. AFT demanded servers to interpose and coordinate all database accesses and introduced a fault-tolerant shim layer for stateful serverless functions. Moreover, it used built-in atomicity and idempotence guarantees to provide exact-once semantics with safety and liveness in failures. However, AFT modified the server running so that it was limited to other platforms.

5.5 Application Modelling

This research direction refers to modeling the serverless application to deepen the understanding of software application design and reflect the changes in high-level abstraction or low-level implementation. There are two kinds of solutions: specification-based analysis and configuration-based analysis.

- **Specification-based analysis:** It is helpful for application modelling to leverage certain specifications [131, 174, 191, 225]. For example, F(X)-MAN [174] was a model considering services and connectors as entities. Different connectors (e.g., composition connectors, adaptation connectors, and parallel connectors) are composed of atomic or composite services. Considering the event-driven feature of serverless computing, Wurster et al. [225] used the standard topology and orchestration specification for cloud applications (TOSCA) to design an event-driven deployment modelling approach. TOSCA can capture the lifecycle of application provision and management. However, TOSCA was incomplete since it did not contain the platform’s requirement representation and could not support all application lifecycle aspects, such as deployment, requirement, and metric ones. Overall, there is no specification language to model the serverless application in a platform/cloud-independent manner. To address this problem, Kritikos et al. [131] proposed the extension of the cloud modelling language named CAMEL to specify serverless functions in an independent manner. CAMEL was a multi-domain-specific language that could cover all application lifecycle aspects. Furthermore, Yussupov et al. [233] relied on TOSCA and business process model and notation (BPMN) to present a vendor-and technology-agnostic modelling method. BPMN captured the control flow composed of multiple activities, and this flow can be represented as a semantically-transparent graphical notation.

- **Configuration-based analysis:** In serverless computing, the configuration operation is essential for serverless applications since it represents some developers’ requirements. However, the event-driven feature complicates serverless application modeling compared to traditional applications. Considering that some configuration information may be written in a configuration file like “.yml” [42], Obetz et al. [165] analyzed events associated with serverless functions in this configuration file to construct a new type of call graph for the serverless application. The call graph modeled the
relationships between serverless functions, events, and used services. On the other hand, configuration changes may reflect the low-level implementation of the serverless application. To simplify the low-level implementation, Samea et al. [182] introduced a model-driven approach to automatically transform the source model of applications into the low-level implementation by analyzing the configuration.

5.6 Programming Framework

Some limitations of serverless computing urge researchers to present new programming frameworks to serve specific applications and general applications. Fig. 4 shows the type distribution of programming frameworks presented by existing studies. We find that designing frameworks for general applications is the most common, accounting for 40.63% of all frameworks. In frameworks of specific applications, the Internet of Things (IoT) scenario is most widely investigated, accounting for 21.88% of all frameworks. Next, we introduce specific frameworks and general frameworks.

5.6.1 Specific Applications. Serverless computing has been applied to various specific scenarios, including numerical computing, video processing, Internet of Things, file processing, big data analytics, and machine/deep learning. However, different scenarios may pose new challenges that need to be solved in the serverless computing paradigm or have some problems that leverage serverless computing to overcome.

- **Numerical computing**: Traditional numerical computing tasks need scientists to manage infrastructure and maintain scalability in order to handle the varied resource parallelism. Serverless computing can free scientists from these burdens. Moreover, serverless computing shows a disaggregated data center pattern. In fact, this disaggregation makes linear algebra workloads with large dynamic memory and computation requirements obtain benefits. However, the computation time of such workloads is the dominant overhead. In this situation, a serverless linear algebra framework named NumPyWren [189] was presented to address this problem. NumPyWren analyzed the data dependencies in the serverless application to extract the task graph that had potential parallel executions. Parallel functions can use an intermediate state in a distributed object store to speed up the processing latency. In practice, NumPyWren was implemented based on PyWren [119], which was a queue-based master-worker approach and processed serverless functions in parallel when possible.

- **Video processing**: Video processing workloads would invoke thousands of threads of execution in a few seconds. However, fine-grained parallelism did not support video encoders. In this demand, ExCamera [102] and Sprocket [60]...
were developed for serverless video processing. ExCamera achieved a high-parallel video encoder to handle chunks of video. Furthermore, ExCamera used a state machine for tasks to support fine-grained control and overcome the communication challenge. Sprocket was a scalable video processing framework to enable much more sophisticated video processing applications. Sproket transformed a single video input according to a user-specified program. Moreover, it supported dynamic task creation during processing through dynamic levels of parallelism.

- **Internet of Things:** The development paradigm of serverless computing could be beneficial for IoT applications. In the industry, AWS presented AWS IoT Greengrass service [11] to process data on edge. Azure designed Azure IoT edge service [20] to connect edge devices and serverless functions. In academia, some researchers also have focused on IoT frameworks. A summary is shown in Table 4. Specifically, the event-driven programming pattern and the separation of computation and storage make IoT applications inefficient. To address the supportability for data-intensive or dataflow IoT applications, Cheng et al. [80] proposed a functional programming model to allow the movement between code and data. Moreover, they designed a context-driven orchestration system to optimize deployment and resource utilization. However, considering that resources are constrained on edge nodes, Pfandzelter and Bermbach [171] designed a lightweight serverless framework, tinyFaaS, to adapt the edge feature. Specifically, tinyFaaS provided a specified endpoint with alternative messaging protocols for the communication of low-power devices. Moreover, their team also presented another approach called AuctionWhisk [68]. AuctionWhisk used the auction-inspired mechanism to control and arrange function locations across geo-distributed sites. In addition, some cloud platforms may provide specified hardware resources such as GPU to speed up the application performance. A serverless teleoperable hybrid cloud system called STOIC [237] was presented to cooperate with edge clouds and public clouds. In STOIC, dynamic feedback control mechanism and hardware resource acceleration were considered. Dyninka [100] was designed to define and compose multiple serverless functions leveraging the multi-tier programming paradigm and compiler.

To simplify the deployment operation of IoT applications, a new IoT programming model, CSPOT [222], was designed to host services at device scale, edge scale, and cloud scale. CSPOT integrated various features, including multi-tier processing, robustness, compatibility, security guarantee, and record-and-replay debugging. To consider the platform heterogeneity, Jindal et al. [118] introduced an extension framework of FaaS to address the data access behavior over heterogeneous clusters via Function Delivery Network (FDN). FDN can deliver the function to the appropriate cluster according to the required computation and data.

| Study            | Objective of the problem to be solved                          |
|------------------|----------------------------------------------------------------|
| Cheng et al. [80] | Supportability of data moving for data-intensive IoT applications |
| Bermbach et al. [68, 171] | Resource constraint and function placement issues on edge nodes |
| Zhang et al. [237] | Function composition and communication                         |
| Fortier et al. [100] | Deployment operations simplification                           |
| Wolski et al. [222] | Data access over heterogeneous clusters                        |
| Jindal et al. [118] | Data access over heterogeneous clusters                        |

- **File processing:** Serverless computing allows developers to upload their files to the serverless platform. Triggered serverless functions handle them and return the processed output. However, early serverless platforms were limited to support all programming languages. Therefore, Pérez et al. [169, 170] introduced a highly-parallel event-driven programming model, which combined a middleware that can simplify the development and deployment process. Moreover, it used customized runtime environments, i.e., container image, to bypass the language limitation. However,
at the time our paper was written, serverless platforms had provided the deployment way of the container image to support serverless applications written in any language. Compared with simply providing the source code to the serverless platform, using a custom container image has to follow specific interface requirements, introducing additional management efforts for software developers.

- **Big data analytics**: MapReduce is one of the most widely used programming models for big data applications. Giménez-Alventosa et al. [106] investigated the suitability that serverless computing was applied in MapReduce tasks. Moreover, they presented a new framework with high performance for MapReduce tasks. This framework automated the partitioning of input data according to the allocated memory. Similarly, for MapReduce jobs, Enes et al. [97] relied on operating-system-level virtualization technology to design a novel scalable framework to provide resources dynamically.

- **Machine/deep learning**: Serverless computing can provide flexible resource provisioning and easy-to-use deployment opportunity for machine learning (ML) applications. Moreover, the billing advantage of serverless computing is attractive to developers of machine learning. SIREN [213], a serverless programming framework for distributed machine learning, was presented to process data via serverless functions. SIREN leveraged deep reinforcement learning to design a novel serverless scheduler. This scheduler can dynamically adjust the assignment of function instances and memory sizes in each ML training epoch, reducing the training cost.

  ML tasks generally generate and save the trained models in order to be used for the subsequent inference. However, some models may be larger than the deployment size limit of serverless computing, showing the infeasibility issue. To fill this gap, researchers presented Gillis [229] and AMPS-Inf [115] frameworks. They used the automatic model partitioning idea for the large model in the serverless computing environment. Gillis [229] leveraged the coarse-grained partitioning to transfer multiple consecutive layers as a layer group, and multiple layer groups were parallelized across multiple serverless functions. AMPS-Inf [115] considered model partitioning dimension and resource provisioning, which was formulated as a Mixed-Integer Quadratic Programming problem to minimize cost and maintain performance.

  Serverless computing is suitable for ML inference tasks due to the short-lived execution feature. Batching is a crucial factor in improving the execution performance in ML inference tasks. However, serverless computing is stateless, which may not support batching and its associated setting parameters (batch size and timeout). Ali et al. [57] demonstrated that ML inference tasks could not benefit from serverless computing without batching. Therefore, they presented the BATCH framework to support batching for ML tasks in serverless computing using a dispatching buffer. Moreover, BATCH can provide automated adaptive batching and setting parameters to guarantee the performance and cost.

5.6.2 **General Applications**. Many general programming frameworks have been designed to make serverless computing popular and less restrictive and facilitate the practice of broader applications. These frameworks have been based on various improvement points, including orchestration model design, function scheduling, runtime mechanism, abstract-based design, and architecture design.

- **Orchestration model design**: Major cloud providers of serverless computing have presented the corresponding orchestration services of serverless functions, such as AWS Step Functions [15] and Azure Durable Functions [47]. These services allow software developers to construct complex applications with more serverless functions and various structures via a central orchestrator or workflow engine. This way is similar to the service composition approach [141], integrating multiple services with different types to obtain new benefits.

  Except for orchestration services from industry, some studies in academia have also proposed new orchestration models. Baldini et al. [65] presented a robust programming model to express and build the orchestration of existing software function blocks. Moreover, they provided the foundation for implementing function orchestration leveraging
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OpenWhisk reactive core. Considering that the type of input arguments and intermediate results should be checked on their compatibility during the function orchestration, Gerasimov [104] designed an orchestration-specific domain language called Anzer to check the compatibility between serverless functions. GlobalFlow [241] was a new orchestration model considering the cross-region scenario of serverless functions. There were two strategies, including copy-based strategy and connector-based strategy. In the copy-based strategy, all serverless functions were copied to execute in one region. This strategy is suitable for tasks without any data usage or data communication. In the connector-based strategy, serverless functions were grouped according to regions, and functions with the same region were integrated into a sub-workflow. Then, a lightweight connector was used to establish the communication of sub-workflows. This strategy can achieve data locality and reduce the data communication overhead. In addition, Maslov and Petrasenko [154] used a control-flow graph and the finite automaton to arrange the function orchestration according to developers’ demands. First, it accepted the workload, wrote to storage, and added to the task queue. Then, it used the graph to represent the state and connection among serverless functions.

**Function scheduling:** Researchers have considered designing efficient schedulers in new programming frameworks. WUKONG [76, 77] was presented as a serverless-oriented and decentralized framework. It adopted a decentralized scheduler that incorporated static scheduling and dynamic scheduling. Specifically, first, it partitioned the global task graph into multiple local subgraphs before and during executions. Then, each WUKONG’s executor scheduled and executed the functions contained in the subgraph, improving the data locality. Moreover, the data reading and writing problem was addressed by task clustering and delayed I/O. WUKONG can greatly improve application performance and resource utilization. However, WUKONG may introduce additional security risks due to its weak isolation.

**Runtime mechanism:** For some presented general frameworks, researchers have modified their runtime mechanisms to obtain a stronger processing ability. Specifically, to allow software developers to develop general-purpose parallel applications in serverless platforms, functionality partition challenges need to be solved to satisfy the execution constraint of serverless functions. A programming framework called Kappa [239] was designed to address these challenges. Kappa ran the serverless application code on the original serverless platforms like AWS Lambda. Then, it used checkpoints to check the timeout issue of serverless functions and provided concurrency mechanisms for general-purpose parallel applications. Instead of checking the application code, Al-Ali et al. [55] designed the new application primitive that provided the process, not the function, to execute a broad class of applications in serverless architecture. In addition, gg [101] was presented. In gg, a unique intermediation representation layer was designed to manage various applications by abstracting the computation and storage. Additionally, gg leveraged common services like dependency management, straggler mitigation, and scheduling to support widely used applications, e.g., software compilation, unit tests, and video encoding.

**Abstract-based design:** Some studies have considered different abstract representations to design general programming frameworks. 𝜆 [114] was an operational semantics to keep low-level behaviors of serverless platforms, including concurrence, function retry, failure, and instance usage. In addition, retro-𝜆 [155] was a concept specified for serverless applications. It extended the event sources to obtain the application persistence, allowing the application logic decomposition to support the retroactive programming capability of serverless platforms.

**Architecture design:** Serverless platforms restrict the function execution time and storage space of function instances, making some applications unable to run in the platform. Therefore, Mujezinović and Ljubović [158] proposed a novel architecture, which combined AWS Lambda with AWS Fargate technology [10] to bypass these limitations. Moreover, the architecture used the famous producer-consumer architectural pattern to handle applications with high-frequency data. In addition, to address the shuffle operation problem that needs to exchange data across all
instances, Sánchez-Artigas et al. [185] presented the design of Primula, which had the shuffle operator ability by employing object storage for serverless functions. Moreover, Primula also provided automatic parallelism and data detection to guarantee executions.

5.7 Application Migration

In studies related to application migration, manual and automated conversion approaches have been presented.

- **Manual conversion:** For manual conversion approaches, researchers of related studies have illustrated step-by-step how to transform applications in a manual way. However, major studies have been specific to a certain class of applications. For example, a partial migration method [64] was proposed to handle web applications. In this method, some scalable and resource-intensive components were implemented as microservices, while components with short-lived functionality were transformed as serverless functions. Christidis et al. [81] and Chahal et al. [79] processed AI-related applications by considering some restricted factors, such as the code size, model storage, training and inference difference, and performance tuning. Elordi et al. [96] aimed at deep neural network inference tasks. They provided a specific decomposition methodology, where original applications can be transformed into an application pattern that can execute on AWS Lambda.

   Except for specific applications, Stafford et al. [200] designed multiple refactoring iterations for general applications to analyze memory usage and execution time before and after the refactoring. Then, they determined the best practices, such as function type, dependency relationship, and request type.

- **Automated conversion:** For automated conversion approaches, the application conversion process is done automatically. However, in this process, applications need to be assessed for their portability on a specific serverless platform before migration. SEAPORT [231] was an automated assessment method that used a canonical serverless application model and assessment metrics (e.g., service and component similarity). TheArchitect [168] was a rule-based system to automatically generate high-level serverless architecture design diagrams, simplifying the conversion process. However, how to automate conversions is still a critical question. ToLambda [122] targeted Java applications to serverless applications. It automatically parsed the original code, transferred it as the event-driven functions, and changed service requests as the function call. With a strategy similar to ToLambda, Node2FAAS [87] converted Node.js monolithic applications into serverless applications. However, Node2FAAS cannot process or access any external functions or libraries. Therefore, complex applications still have to be reconstructed manually, leading to an impractical effort. Ristov et al. [178] also targeted Node.js applications and resolved the problem of Node2FAAS. They presented the Dependency-Aware FaaSifier (DAF) to automatically transform source code and dependency libraries to equivalent serverless functions via specific annotations. However, DAF was limited to processing nested functions and recursive calls of the same function, as well as chained functions.

5.8 Cost

Regarding the cost aspect of serverless computing, related researchers have addressed problems about cost prediction and cost optimization of serverless applications.

5.8.1 Cost Prediction. Cost prediction studies mainly have two common solutions, including regression model prediction and statistical learning prediction.

- **Regression model prediction:** Some cloud providers of serverless computing have provided pricing calculators on their websites, but these calculators do not generate the corresponding cost for average runtime and memory size.
Therefore, Cordingly et al. [82] referenced the platform’s pricing policy to estimate the cost for the predicted runtime performance. The runtime performance was obtained from the regression model that considered different CPUs and memory settings. Differently, Eismann and Grohmann [92] found that the execution latency of the function was related to the function’s input parameters. Based on this insight, they presented a prediction approach, which applied the monitoring data from this function to mixture density networks to predict distributions of execution latency and output parameters of the serverless function. Then, runtime performance information was combined into a workflow model to estimate the cost via the Monte-Carlo simulation.

- **Statistical learning prediction:** Another kind of approach is to consider statistical learning. Considering that the cost is affected by the allocated memory, Akhtar et al. [52] proposed a framework called COSE. COSE used Bayesian Optimization to learn the relationship between cost and unseen configurations of a serverless function from trace logs. COSE can predict the cost under different configurations. Lin and Khazaei [139] treated the serverless application as the directed acyclic graph. Then, they introduced a probability-based cost graph that can get the average cost of the serverless application. This graph considered the consumed memory and execution time of each serverless function, as well as transition probability between serverless functions.

### 5.8.2 Cost Optimization

In studies related to cost optimization, there are three solutions, including function scheduling, underlying combination, and resource adjustment.

- **Function scheduling:** Generally, the serverless application is composed of one or more serverless functions. The transition from one function to another will increase the number of invocations. However, the price is related to the number of invocations. In this situation, a possible solution is to fuse multiple functions as a function and then schedule this function to an appropriate instance for executions. Based on it, Elgamal [95] discussed the problems of function fusion and function placement and then presented the corresponding cost graph. The cost optimization was concluded as the constrained shortest path problem about this cost graph to find the best structure. In addition, developers may use a hybrid public-private cloud to develop and execute their applications. In such an infrastructure environment, the scheduling strategy of functions is critical in minimizing the cost of public cloud usage while meeting the specified performance deadline. A hybrid cloud scheduling strategy called Skedulix [84] was presented to solve this problem. Moreover, Skedulix used a greedy algorithm to determine the function placement dynamically.

- **Underlying combination:** Specific applications executed in serverless platforms may be costly since serverless computing is currently good at short-lived and stateless tasks. The combination of serverless computing and VM rentals may make applications cost more cost-effective. Some studies [108, 111, 146] have presented scalable and hybrid approaches to analyze and choose the optimal cost in the environment of serverless computing and VM rentals, while ensuring the performance constraint.

- **Resource adjustment:** The cost of the serverless function is affected by the pre-allocated memory size. Therefore, some studies [52, 72, 139, 242] have presented optimization algorithms to provide an optimal configuration setting (e.g., memory) that can achieve the minimum cost under performance constraints. In addition to finding the optimal memory configuration, Spillner [197] measured the memory consumption situation of the serverless function within a particular time and then created trace profiles in advance to automatically update memory.

### 5.9 Multi-Cloud Development

To support the multi-cloud development of serverless computing, researchers have mainly designed new serverless computing architectures or frameworks. Soltani [196] was a Peer to Peer architecture that used container cluster manager
technology to allow developers to enjoy the respective strengths of multiple clouds. The multi-cloud development architecture presented by Vasconcelos [211] contained three key components, i.e., FaaS Cluster, FaaS Proxy, and Multi-Cloud Resource Allocator. Specifically, FaaS Cluster represented a cluster that contained multiple instances from geographically different cloud infrastructures, while FaaS Proxy provided the request interface like a gateway. Multi-Cloud Resource Allocator can control resources in any of the clouds. In addition, Sampé et al. [183] presented an extensible multi-cloud framework to execute regular Python code in any serverless platform transparently. The architecture design of this framework was motivated by Python’s multiprocessing and dynamism features.

5.10 Accelerator Support

Generally, the runtime environment of serverless platforms is mainly based on CPU resources. However, more and more tasks like video processing and deep learning require leveraging other hardware resources to accelerate. In the related studies, researchers have tried to support GPU and FPGA accelerators in serverless platforms.

5.10.1 GPU Support. To address the GPU supportability, Kim et al. [125] presented a new serverless framework, which integrated NVIDIA-Docker into the open-source serverless framework. Moreover, this new framework can support the deployment of GPU-supported containers. However, the biggest disadvantage of this approach is that each GPU cannot serve multiple function invocations simultaneously.

Different from using GPU-support containers, Naranjo et al. [161] used GPU virtualization. They tried several virtualized access methods to GPUs, including remote access to GPU devices via the rCUDA framework [41], as well as direct access to GPU devices via PCI passthrough [39]. The results showed that using GPU virtualization is an efficient and accelerated way in serverless computing, achieving the sharing of GPUs among functions.

5.10.2 FPGA Support. To make the serverless platform support FPGAs, Ringlein et al. [177] designed a platform architecture with disaggregated FPGAs for serverless computing. In addition, BlastFunction [62] was a distributed FPGA sharing platform, which contained multiple device managers to monitor and time-share FPGAs. Moreover, BlastFunction can achieve multi-tenancy for FPGAs.

5.11 Security

In the security aspect of serverless computing, there are mainly two kinds of solutions, including SGX-based design and information flow tracking.

- **SGX-based design:** Serverless applications follow the event-driven paradigm, and they generally are triggered by HTTP requests; thus, the API gateway is a crucial component. However, this component often suffers from malicious attacks. To alleviate this situation, Qiang et al. [175] leveraged Intel Software Guard Extensions (SGX) and WebAssembly sandboxed environment to design Se-Lambda to protect the API gateway. Particularly, SGX can create a trusted execution environment where sensitive data can be stored and used normally, preventing malicious attackers from stealing sensitive data from the serverless application. Moreover, Alder et al. [56] used SGX with the trustworthy resource measurement mechanism in the serverless platform to guarantee security and accountability.

- **Information flow tracking:** Since serverless applications are composed of multiple serverless functions, using information flow control (IFC) methods may be suitable and beneficial for information security in serverless computing. Trapeze [58] was implemented as a dynamic IFC model to track and monitor the global information flow. Trapeze achieved the security guarantee through static program labeling with dynamic data labeling. However, on one hand, Trapeze left the burden for developers on the definition of information flow policies and the implementation of
declassification functions. In contrast, Valve [85] did not require declassification. Valve was a transparent function-level information flow model, allowing developers to use fine-grained controls in their serverless applications and write proper policy configurations. On the other hand, Trapeze’s implementation also relied on the programming language of serverless functions and pre-defined key-value store functions. Based on these limitations of Trapeze, a transparent approach named will.iam [186] was presented, which was agnostic to serverless functions and underlying platforms. will.iam can automatically check access control policies and make a decision for requests in advance. Valve and will.iam were complementary, where Valve was to understand the data flow information of their serverless applications and write reasonable policies for will.iam.

5.12 Testing

In the distribution environment of serverless computing, serverless functions interact with other functions or cloud services. It makes serverless application testing hard [136]. Winzinger and Wirtz [221] implemented a data flow testing framework to obtain the function coverage. This framework used additional instrumentations in the source code to detect data flows between functions and services, between return values, and between functions and functions.

5.13 Debugging

Debugging the serverless application is an essential step in facilitating serverless computing [134, 205, 218]. However, few efforts are made, and the current solution is to use the record and replay approach. Watchtower [59] was presented to observe the application changes through instrumenting libraries. Watchtower can be structured as a serverless application to scale at the same rate. Then, developers can analyze output logs to detect the violations affecting the correctness of serverless applications. If a violation was found, a record-and-replay debugger contained in Watchtower can be used to recreate and re-execute the application from a specific state on the developer’s local machine.

6 RQ3 (PLATFORMS AND VENUES)

To answer the research question of which platforms existing techniques are implemented/evaluated on and where research papers are published, we view the Implementation and Evaluation sections and other parts that may be mentioned in each research paper to determine the experimental or evaluated serverless platforms for the presented solution. Meanwhile, we search the Internet to determine each research paper’s publication venue, e.g., a specific publication conference or journal. The results are shown in Fig. 5 and Fig. 6.

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**Fig. 5.** The distribution of experimental or evaluated serverless platforms for existing solutions.
Fig. 5 shows the distribution of experimental or evaluated serverless platforms for existing solutions. The distribution shows that a wide variety of serverless platforms are available for implementing or evaluating proposed solutions. These serverless platforms include AWS Lambda, custom systems related to serverless computing, OpenWhisk, OpenFaaS, OpenLambda, Google Cloud Functions, IBM Cloud Functions, Azure Functions, and other serverless platforms like Alibaba Cloud Function Compute, Knative, etc.

From the percentage of serverless platforms in Fig. 5, we can summarize the following four points. First, AWS Lambda is the most widely used serverless platform in the serverless computing literature, accounting for 32.00% of all serverless platforms. Moreover, AWS Lambda is used far more than other commercial serverless platforms like Google Cloud Functions and Azure Functions. It illustrates that AWS Lambda is more mature regarding serverless features and infrastructure to help researchers design or present their solutions. For instance, Pocket [129] was a novel storage system for optimizing the communication problem between serverless functions. Pocket placed the original storage and collaborated with AWS Lambda to scale with the serverless functions automatically. Second, 28.57% of serverless platforms are custom systems, the second-largest percentage. To address problems of a certain serverless aspect, some researchers [54, 74, 88, 121, 127, 208] have designed new serverless platforms to implement or host their solutions. For example, SAND [54] was a novel, high-performance serverless platform, which designed some custom components to improve the cold start performance. Kaffes et al. [121] designed a new serverless system to execute highly bursty, stateless, and short-lived applications. This platform highlighted a centralized core-granular scheduler, which is more fine-grained than traditional serverless schedulers. The new requirement of the scheduler forced researchers to present the new underlying design of serverless platforms; thus, their solution was implemented in a custom system. Third, the most commonly used open-source serverless platform is OpenWhisk, which accounts for 14.29% of all serverless platforms. OpenWhisk is an open-source implementation with serverless features. Specific details can see in Section 2. Researchers can modify the underlying architecture of OpenWhisk to add or redesign components to achieve their goals. For instance, Zhang et al. [240] presented a new insight into using Harvest VMs, whose resource management differed from traditional underlying resource management for VMs and containers. Considering the characteristics of Harvest VMs, they redesigned a load balancer on OpenWhisk. Finally, the “Others” category in Fig. 5 refers to serverless platforms with low usage, containing Alibaba Cloud Function Compute, Knative, Fission, Kubeless, and Huawei’s FaaS Framework. These serverless platforms account for only 4.57% of the total platforms, illustrating that these platforms have not been widely used in the serverless computing literature. For example, the Alibaba Cloud Function Compute team [4] presented a rapid container provisioning approach, FaaSNet [212], to improve its own platform’s container provisioning speed to serve bursty requests.

Fig. 6 shows the distribution of publication venues for research papers addressing specific aspects. Due to the long name of the publication venue, we use abbreviations to represent them, and the corresponding full names are shown in Fig. 6. For example, “SoCC” represents ACM Symposium on Cloud Computing, while “CLOUD” represents IEEE International Conference on Cloud Computing. The “Others” category represents a collection of publication venues publishing only one paper related to serverless computing. For example, the work presented by Barcelona-Pons et al. [67] was published in “TOSEM”, which refers to ACM Transactions on Software Engineering and Methodology.

From Fig. 6, we can summarize three key points. First, we find that research papers related to serverless computing are published in a wide range of conferences or journals. There were 24 categories of publication venues publishing more than two or more papers related to serverless computing. Moreover, in the “Others” category, there are 58 publication venues, where one paper related to serverless computing is published in each publication venue. In total, there are 82 publication venues in the serverless computing literature. Second, the top three publication venues are “SoCC”,
“CLOUD” and “USENIX ATC”, accounting for 16, 9, and 9 of the 164 papers, respectively. Serverless computing is the next generation of a promising cloud computing paradigm. Therefore, it is reasonable that more research papers are published in cloud computing-related conferences like “SoCC” and “CLOUD”. Third, current publication venues contain two kinds of communities, i.e., the Software Engineering community and the System community. Specifically, some studies have been published in software engineering-related journals, such as "SPE" (5), "IEEE Software" (4), "TOSEM" (1), etc. These studies have addressed problems with application modelling [233], programming framework of specific applications [68, 237], stateful applications [67], multi-cloud development [183], application migration [178], etc. Other researchers have presented their approaches in system-related conferences or journals, such as “TPDS” (4), “EuroSys” (4), “ASPLOS” (4), and “SOSP” (2). These approaches mainly resolved problems with resource management [236, 240], cold start issues [88, 103, 209], function communication [129, 173], etc. Overall, this key point illustrates that current serverless computing has difficult unresolved issues on the software application side and serverless platform side. In practice, the biggest beneficiaries of serverless computing are software developers. Existing difficult issues will prevent software developers from enjoying the advantages of easy development and fast application execution. Therefore, addressing issues on the software application side and serverless platform side is to better facilitate software developers’ application development practices on serverless platforms.

7 CHALLENGES AND OPEN OPPORTUNITIES

In this section, we aim to discuss key challenges compared to the efforts already made and envision promising opportunities on the serverless platform side, serverless application side, and serverless computing community side.
7.1 For Serverless Platform Side

**Security and efficient direct communication between serverless functions.** To alleviate the function communication problem, researchers have adopted various optimization solutions, such as memory sharing [117, 130], cache-based design [207, 223], and storage optimization [129, 173]. However, these strategies have still been built on the idea of temporary data stored in a specific place like memory and external storage for function communication. On the one hand, this idea may expose security issues, especially for sensitive data. Even if data can be encrypted during function communication, data shared in memory or cached in containers may still be maliciously attacked or stolen by other tenants. Therefore, providing a secure serverless platform remains challenging but also an opportunity. On the other hand, this idea of temporary data stored in a specific place cannot avoid the additional overhead of saving and fetching or managing data. Boxer [217] supported the direct communication between serverless functions. It leveraged a modified network, which used TCP hole-punching techniques of P2P to solve the limitation of the conventional network. However, for large-scale communication-intensive applications, Boxer may not provide high-throughput and low-latency networks for functions. Therefore, it will elicit a promising research opportunity, i.e., how to design efficient direct network communication for serverless functions.

**Effectiveness of the pricing model.** Existing studies about cost prediction and optimization [95, 146, 197, 242] have been based on the billing model that pays for actually consumed computation resources. Such a billing model is effective and economical for computation-intensive workloads. However, when developers execute I/O-intensive or disk-intensive workloads, the current billing model may be expensive, and allocated computation resources are also not efficiently utilized. In this situation, the challenge that cloud providers of serverless computing face is to further consider a more suitable billing pattern for various resource types, e.g., CPU, memory, networking, and storage. Moreover, exiting solutions of cost prediction and optimization studies relied solely on the consumption of computation resources. A dynamic pricing prediction and optimization scheme may be an opportunity in the future.

**Fine-grained resource configuration.** Generally, software developers configure a small set of parameters (e.g., function timeout, memory size, and cloud providers) for their applications, and these parameters are simple. This development way frees developers from underlying resource management. However, some experienced developers may be willing to configure the fine-grained resource policies to effectively improve the overall quality of service of applications [52]. Therefore, this situation also motivates an opportunity for performance improvement. The serverless platform can optionally support some fine-grained configuration options about the underlying runtime information. For example, developers can configure network conditions, function placement, I/O bandwidth, and so on.

**Heterogeneous accelerator support.** Besides existing studies about GPU support [125, 161] and FPGA support [62, 177], other accelerators like Tensor Processing Unit (TPU) also should be noticed for cloud providers of serverless computing. However, supporting new accelerators may be very challenging in serverless platforms because it may require designing a new scheduler, resource allocation pattern, or billing model. Moreover, accelerators generally have some internal restrictions, e.g., I/O bandwidth and energy efficiency, and thus they are difficult to implement in the serverless platform. On the other hand, supporting more accelerators may not be economically viable for certain scenarios. However, providing heterogeneous accelerator support creates a new research dimension of significant importance for scenarios that use function instances with a mix of CPU, GPU, FPGA, and TPU.

**Monitoring tools.** The monitoring capability may not be enough in current serverless platforms. Some third-party monitoring tools, such as Epsagon [26] and Datadog [23], may also be applied to trace the serverless application. However, they still do not contain resource consumption and infrastructure-related metrics, e.g., CPU utilization,
network condition, and infrastructure performance, to further understand the serverless application and platform. Therefore, in the serverless platform, providing comprehensive observability of both serverless applications and platforms is a complex undertaking, but it is also an opportunity for future research on serverless computing.

7.2 For Serverless Application Side

Generalizability of application conversion approaches. Based on the benign characteristics of serverless computing, various applications are migrated to the serverless platform for executions. As reported in the characterization study about serverless applications [93], applications are diverse and not limited to any specific types. However, existing application conversion approaches have targeted only a few specific applications, such as AI applications [79, 81, 96], Web applications [64], and Java applications [87, 122]. There are not yet genetic conversion tools for any application. Though Stafford et al. [200] presented a multiple-refactoring iteration approach, this approach just changed the runtime results of different states. Then, it determined which change was beneficial to the application. Moreover, this approach did not provide specific conversion steps. Providing a generic application conversion approach is challenging, which requires addressing a series of problems, e.g., application type, vendor lock-in, function granularity identification, event-driven code transformation, cloud service selection, and state communication.

Cold start performance. Although the state-of-the-art solutions for cold start performance optimization (e.g., data cache-based optimization [54, 164] and snapshot-based optimization [74, 214]) can effectively improve the cold start performance, they mainly target the acceleration of container creation or runtime initiation. However, containers generally lack isolation or flexibility due to their inherent nature. Therefore, providing isolation or flexibility for current common sandboxes like containers is a tricky problem. On the other hand, even if there is a short time for container acceleration, cold start performance still faces another overhead, i.e., application initialization overhead, which may take up a large portion of the cold start time in the future. In this situation, it also reveals a new opportunity, i.e., how to optimize the overhead of application initialization in the case of faster runtime initialization already available.

Variability factor of performance prediction. In related studies of performance prediction for serverless functions, most solutions have been based on the collected runtime information of a serverless function in a period to predict the performance value of a constant [52, 82, 90]. However, the auto-scaling feature of serverless computing makes function performance variable and resource allocation dynamic. It is not enough to rely on factors considered constant value to predict dynamic performance. Eismann et al. [91] discussed the performance variability of serverless computing and determined serverless-specific changes, such as uncertainty in cold and warm starts, load intensity, and short-term and long-term performance fluctuations. Therefore, it is essential that the performance prediction problem of serverless computing take into account the dynamic feature or distributions. Unfortunately, most serverless platforms are untouchable to software developers and expose little to no information about the underlying environment. Therefore, considering performance variability in performance prediction is difficult, but it also hints at a future research opportunity.

Data privacy of IoT applications. In the related studies of the programming framework, IoT-specified serverless frameworks are the most widely studied in specific application scenarios, accounting for 36.84% (7/19) of all specific frameworks. Presented frameworks have addressed the movement problem of data and code [80], resource constraint problem of edge devices [171, 237], deployment operation problem [222], heterogeneous cluster access problem [118], etc. However, these studies did not focus on the data privacy challenge for IoT applications. Edge devices are placed in different geographical locations and may collect data not wanted to be made public. Moreover, they communicate with each other. In this situation, edge devices have no unified cloud management like serverless functions; thus, they are vulnerable to attacks. Data privacy preservation is critical for IoT applications. With respect to data confidentiality,
developers can encrypt the data before storing it in external cloud storage when writing IoT functions. However, when another IoT function queries the required data from the storage, query operation may encounter obstacles in the absence of decryption. In future work, a possible solution is to design a novel “index”, which uses encryption techniques that can support the execution of operations or query evaluation.

**Testing tools.** AWS Lambda can use GUI to invoke serverless functions, indirectly implementing the intent of the function testing. In practice, there is still a lack of mature testing tools for serverless applications. Although Winzinger and Wirtz [221] implemented a data flow testing framework, tested applications still need to be deployed in the serverless platform after modifying the corresponding source code. The most challenging part of implementing testing tools may be to mock the real serverless environment in the local environment [136]. This is unlike monolithic applications and microservice applications, where the environment can be tested directly locally. In serverless computing, software developers do not know which containers will be used in underlying platforms during deployment; thus, it shows an open challenge for serverless application testing. Moreover, the serverless application is composed of multiple dependent serverless functions. Integration testing may be necessary to ensure the correctness of the serverless application. Therefore, providing a serverless-specific testing tool will be a promising opportunity for serverless applications.

### 7.3 For Serverless Computing Community Side

**Representativeness and completeness of benchmark dataset.** Studies related to serverless computing have used some benchmark datasets to verify the efficiency of their solutions [54, 92, 116, 240] or characterization and measurement results [93, 142, 219, 220]. However, we find that these studies have not used a standard benchmark dataset. For example, SAND [54] used image processing applications, while Boki used the real applications from DeathStarBench microservices [24]. Moreover, the measurement work [240] used multiple Python serverless functions from FunctionBench [126]. To characterize serverless applications, the authors [93] collected different applications from open-source projects, academic literature, industrial literature, and domain-specific feedback. This situation of the used benchmark dataset indicates that the serverless computing community has not a uniform and representative dataset, which may be a challenge for the serverless computing field. On the other hand, the completeness of the benchmark dataset (i.e., containing diverse application types) is also critical for evaluating generic techniques or frameworks. A complete dataset can validate the key insights and find potential weaknesses.

Serverless computing is an emerging concept, and its related techniques will continue to be updated and adapted in the future. In our study, we aim to provide a snapshot of the current research state of the art of serverless computing at the time of writing. Moreover, we will make the list of collected research papers and summarized data publicly available to allow other researchers to update the taxonomy of research directions, supplement other solutions, and refresh the distributions of experimental platforms and publication venues for solutions.

### 8 CONCLUSION

In this paper, we presented a comprehensive literature review to summarize the current research state of the arts of serverless computing. Specifically, first, we analyzed 164 research papers to construct a taxonomy containing 18 non-divisible categories linked to research directions of the serverless computing literature. Second, we classified the related studies of each research direction and elaborated on existing solutions. Third, we investigated the distributions of experimental serverless platforms for existing solutions and publication venues for selected research papers. Finally, we discussed key challenges and envisioned promising opportunities for future research on the serverless platform side, serverless application side, and serverless computing community side. Our analysis of available research work on
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serverless computing can significantly decrease ambiguity and the entry barrier for novice researchers and practitioners. Moreover, summarized taxonomy, solutions, distributions, and analyses will be of great value for (1) future researchers to pursue promising research topics and insightful ideas for solutions and (2) future practitioners to conduct best software practices of serverless application engineering.

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