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Chapter 8: Automation, Orchestration, and Self-Optimizing Pipelines

8.1. Introduction

Automation uplifts the efficiency, speed, and quality of software development, operations, and maintenance. A plethora of techniques have materialized over the years, forming a diverse toolset from which practitioners choose the ideal combination for their application. Despite this abundance, several areas remain problematic or laborious. In particular, the orchestration of the various automation techniques within the organization, product, or project life cycle remains largely manual or low-level, which detracts from the achieved speed, efficiency, and reliability. Such shortcomings may be mitigated through the definition of self-optimizing automation pipelines.

The phenomenon of self-optimizing pipelines goes beyond mere automation or orchestration; it is a combination of both concepts taken to their logical conclusion. As such, it requires a more rigorous treatment than a list of examples. The analysis provides an overview of the relevant concepts in software development and operation: automation in software development, orchestration as workflow management, and self-optimizing pipelines. These concepts serve as the foundation for techniques that automate and orchestrate software development and operations. These in turn provide the basic building blocks for defining self-optimizing pipelines, with a focus on self-optimizing feedback loops, machine learning for optimization, and autonomous scheduling and resource allocation.

8.1.1. Background and Significance

Automation and orchestration meet self-optimizing pipelines with rigorous, evidence-based analysis and formal structure. Software development and foundational concepts address two key aspects of automation—delivery pipelines and orchestration as workflow management; the remaining analysis focuses on self-optimizing pipelines that

leverage feedback mechanisms or adaptive techniques to make operational decisions without operator intervention.

The growing complexity of software systems and their execution environments poses ever-increasing challenges for the definition, repeatability, and consistency of deployment processes. Continuous integration and continuous delivery pipelines automate and orchestrate these processes, improving software quality while enabling frequent updates as desired. Because these processes involve data movement and transformation, they can be modeled as dataflow pipelines independent of the control-flow paradigm more commonly used in scripting. However, the addition of observability and telemetry creates opportunities to exploit feedback loops for automated quality-of-service improvement. In particular, self-optimizing pipelines make operational decisions without operator intervention by applying techniques such as control theory, machine learning, or adaptive algorithms for scheduling and resource allocation. These concepts complement previous analysis of automation and orchestration in delivery pipelines.

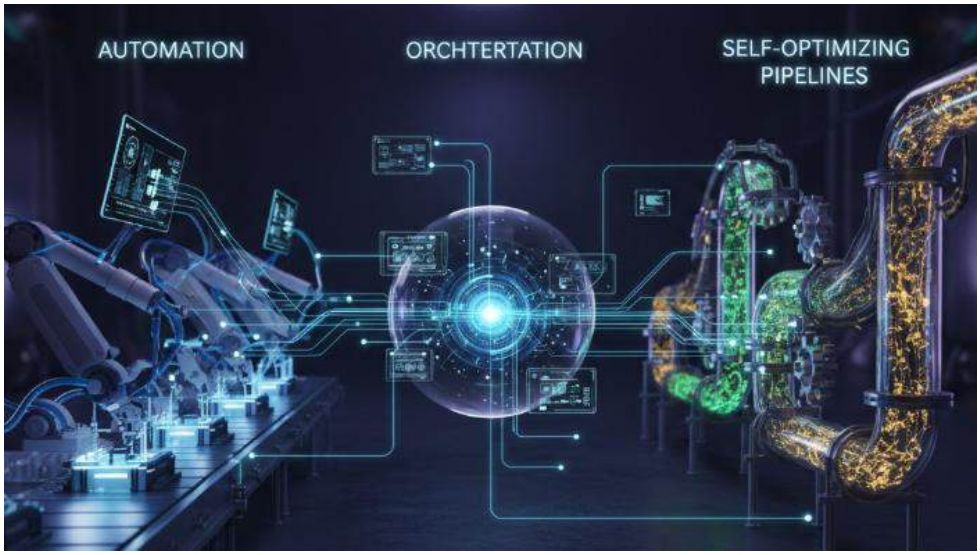

Fig 8.1: Automation, Orchestration, and Self-Optimizing Pipelines

8.1.2. Research design

Automation and orchestration meet self-optimizing pipelines with rigorous, evidence-based analysis and formal structure.

Building upon the ideas presented in the preceding section, research is synthesized by integrating different aspects of automation, orchestration, and self-optimizing pipelines into a coherent whole. Telemetry is discussed not only as a necessary enabler for self-

optimization, but as a fundamental ingredient in the orchestration of software development and deployment. These two, orthogonal dimensions of orchestration become evident; a layered view of software delivery fades away and the pipeline becomes the focus of attention. While pipelines have proven to be an effective mechanism for automation—a necessary condition in continuous delivery—the requirement for self-optimization has engendered techniques and concepts that seem as yet poorly integrated into the toolbox of general automation toolboxes. For all practical purposes, such a toolbox has become a prerequisite for delivering software projects rapidly and reliably.

The structured exploration of these ideas is positioned within the context of two key concepts in software development—automation and orchestration—and particularly with respect to four views of the effects that can be produced: declarative configuration; event-driven orchestration; continuous delivery pipelines; and self-optimizing pipelines. The foundations of automation have been laid down; the foundations of orchestration are established by investigating a second theme associated with the principles of self-optimizing pipelines. The analysis indicates that self-optimizing pipelines, like observability and telemetry, should be regarded as a property of the pipeline mechanism itself.

8.2. Foundational Concepts

Automating the design, development, deployment, and maintenance of software systems eases the burden on developers while ensuring that systems behave reliably and are maintained in a correct and consistent manner. Orchestration adds another layer, allowing the provisioning and operation of infrastructure and services while ensuring that all components are in the desired state. These layers can be extended to continuous integration and continuous delivery pipelines. Beyond simple automation and orchestration, pipelines can incorporate self-optimizing structures that adapt to changes in operating conditions.

Automation reduces the manual work that developers need to perform and ensures that systems are configured and maintained in a consistent manner. This in turn provides greater reliability, as systems are less likely to suffer from incorrect manual touches or drift caused by ad hoc changes made directly in production. Orchestration focuses on the desired state of infrastructure and services, automatically providing a service if one is required but not already available. Continuous integration, continuous delivery, and continuous deployment pipelines encapsulate the processes used to prepare, test, and release software changes. Self-optimizing pipelines incorporate feedback mechanisms to automatically adapt to changes in operating conditions, for instance by altering the schedule or resource allocations.

8.2.1. Automation in Software Development

Considerable research has been directed at automation in software development, typically in the form of development and deployment tools—such as static analysis, quality assurance, runtime monitoring, and test integration—that take over repetitive or error-prone tasks. However, the gap between human and machine capabilities remains substantial. The research in the area has examined how the automation gap in software development may be narrowed using recent advances. Among these are declarative configuration languages, which allow users to express what they want, leaving the how to be inferred by the tool; end-user programming languages that allow task automation through user-written scripts; and feedback controllers, feedback loops, and neural networks, which address both general automation and particular tasks, such as resource occupancy in cloud systems.

Automation can thus best be understood as a continuum, with a mix of general-purpose tools augmented by tools targeted to specific tasks. It has finally become important enough to warrant dedicated research efforts into its automation gap, whether in terms of formalizing the automation process and the hard-to-define transition between control-order automation and eventual goal-state automation or in terms of requirements and goals that predictive machine-learning can natively satisfy.

8.2.2. Orchestration and Workflow Management

Automation and orchestration are frequently conflated, yet they have essentially different functions. While automation can be defined as eliminating human involvement from operations, orchestration acts as a conductor in an orchestra, allocating roles without removing human agency. On larger scales, orchestration can operate across multiple domains and with disparate platforms, where a company services may exist on AWS and its Data Warehouse on GCP. Orchestration has become a necessity for organizations that use many different cloud and SAAS products, each with their own APIs and authentication methods; individually invoking each through custom scripting quickly becomes unmanageable.

Workflow engines enable orchestration for a set of tasks that, together, accomplish a goal. The focus can be on managing long-running scheduled tasks, or routing complex conditional workflows based on business events and the associated metadata. When the requirement is for a service level agreement of sub-minute response times, other paradigms such as event-driven architecture may be more appropriate. Workflow engines can also become an anti-pattern when the execution time of the controlled tasks is on the order of seconds; in such situations the automation of a single task, rather than orchestration of many, would yield a more performant system. However, whenever a

botched call or a sensitive operation requires an alert or log to be generated, orchestration through a workflow engine enables all bot operators to be kept informed rather than keeping this only for the developer or Ops team tracking the API and database logs.

8.2.3. Self-Optimizing Pipelines: Definitions and Rationale

A self-optimizing pipeline adapts its configuration and behavior to changing conditions while still fulfilling its functional and nonfunctional requirements. The motivation behind these systems is evident: a software pipeline often runs for extended periods and may change its environment during its lifecycle, leading to a performance drop over time. A self-optimizing system increases the probability that the functional and nonfunctional requirements are still fulfilled and removes the need for a human operator to adjust the parameters continually. Feedback loops, control theory, machine learning, and process mining play important roles in achieving this automation.

Self-optimizing pipelines are sometimes considered to be a capability of an orchestration engine, as many logically different optimization opportunities exist for each engine event; the main focus in these cases is the orchestration engine. However, the use of self-optimizing capabilities extends beyond orchestration engine optimization to numerous other pipeline-related decisions, such as resource allocation and scheduling for each technique.

8.3. Architectural Considerations

Architectural models for automation and orchestration must balance control and data flow, manage complex interactions, and provide observation, analysis, and telemetry to enable self-optimizing pipelines.

A layered control architecture is an effective way to achieve high-level automation and orchestration functions through suitable specialization of the individual layers. Control-flow-based orchestration platforms focus on high-level control of resource management or access to external systems. General-purpose event-driven or message-oriented platforms facilitate a loose coupling of different external systems and participants. Often, monitoring and alerting functions are built in to support low-cost, reactive, event-based automation, leaving higher-cost operations for the human operators or for scheduled business cycles. More-specialized workflow engines allow complex, long-running IT processes to be automated with high-level workflows while taking care of resource dependencies, human interactions, or error handling. These platform-specific orchestration capabilities address a different class of requirements and are often embedded directly into the systems.

The dataflow model represents a different special-case paradigm for long-running IT processes. While workflow engines build on a control-flow model, dataflow systems treat any data movement through the system as a process. There is thus no explicit notion of a user request to the underlying system. A publisher/subscriber model provides a loose coupling of data producers and consumers; the selection of operations is defined by data-processing pipelines that filter, join, enrich, or otherwise transform the ingested data records. The system takes care of horizontally scaling data processing. Within a business context, such systems support near-real-time analysis or monitoring of salient information, often with notification capabilities when complex events detected in the runtime data.

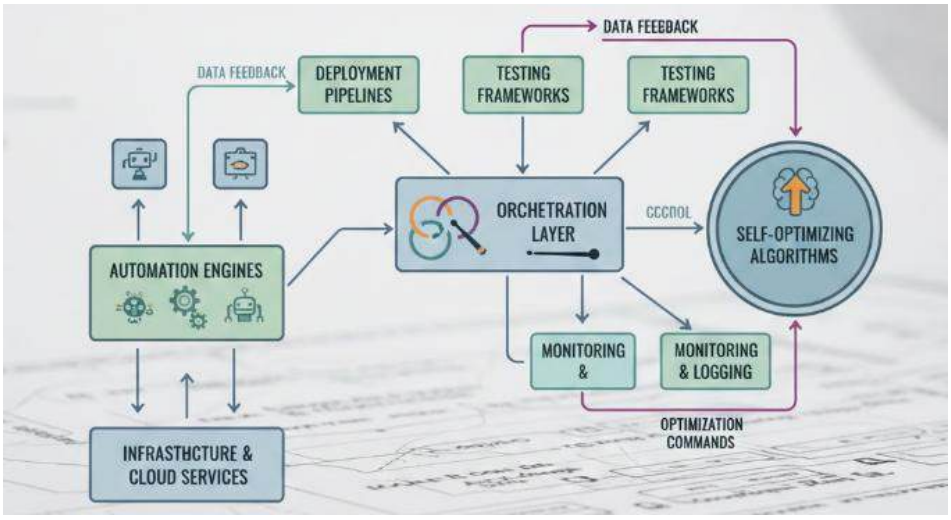

Fig 8.2: Architectural Considerations

8.3.1. Layered Architectural Models

The layered architectural model is a ubiquitous software system organization pattern. Each layer exposes a higher-level abstraction or functionality to the layer above and relies on the service offered by the layer below for its implementation. Furthermore, during their execution, higher layers are mainly concerned about the control flow of the execution, while more primitive layers are focused on processing data.

The dataflow and control-flow paradigm describe two common styles for control orchestration of software processes. In the dataflow paradigm, the control flow basically follows the data dependencies among processing units. The control flow is, instead, an explicit concern in control-flow-based architectures. In addition to these specific paradigms, there are also emerging layering patterns that deal with the orchestration within observability and pipeline testing. Monitoring data collections can also be

recursively aggregated through hierarchical structures facilitating observability. In-depth analysis of an executed pipeline with respect to nonsystemic aspects can also be performed by intermediary components called probes, that can be attached to a pipeline execution for debugging, quality assessment, and unit test.

8.3.2. Dataflow versus Control-Flow Paradigms

Self-optimizing pipelines with an internal dataflow are generally implemented using a control-flow model. These architectures converge data-centric and control-centric workflows through an internal control flow on distributed dataflow systems. Yet, they also admit deviations from this hybrid approach by integrating direct dataflow systems into the dataflow part to serve feedback or learning loops. Such codes usually put the self-optimization decisions into the hands of human operators.

Dedicated data-inspired model transform this layering into a more visible separation: the dataflow pipeline connects several high-level services expressed as dedicated data-transformation statements. The latter are compiled and scheduled into a control-flow architecture for execution on a distributed dataflow framework. The usage of a self-optimizing overlay is optional and left to the discretion of the operators. These performers process large amounts of constantly arriving data and wish to extract new information quickly. This implies a constant data-volume increase with pressure to reduce delivery time. Neither latency nor downtime can be afforded. Dependencies should hence be established automatically but hidden: the creation of a direct dependency should trigger immediate replication, while the loss of an indirect one should promote its suppression.

The pipeline connects the dedicated data-transformation requests with a fast machine-learning routine as used in specialized online-setup pipelines. Results from the latter are used in dedicated adaptive-scheduling applications to restrict or modify the execution orders in the control-flow framework. The same principle is applied to the adaptation of the feedback-management policy controlling the self-optimizing overlay. The internal monitoring is enriched with online-cycle throughput sampling to minimize the response time of a request.

8.3.3. Observability and Telemetry in Pipelines

Domain-agnostic pipelines and self-optimizing pipeline layers require observability mechanisms to deliver metrics for analysis, simulation, and optimizations. Observability, in addition to providing information about the performance of running applications to the operators, aims to offer all the information needed to refine self-

optimizing mechanisms. Defining a telemetry subsystem not only for production use but also for simulation and control can be a difficult task. Simulation requires a different set of metrics than production monitoring. Observability is essential in both cases, and the telemetry subsystem should allow for both goals.

Similarly, machine learning approaches for pipeline self-optimizing require a different set of metrics to build effective predictive models. A classification problem that identifies the best-performing configurations in historical logs exploits a different set of metrics than a regression problem that predicts the performance of a configuration based on other metrics. The appropriate classification and regression datasets should also be captured in production without incurring excessive overhead. Both production data and control theory can be valuable for building self-optimizing pipelines; therefore, the monitoring system should be thought of as the brain of the pipeline as a whole and for all its layers.

8.4. Techniques for Automation and Orchestration

Automation and orchestration in software development leverage several key techniques. Declarative configuration frameworks allow infrastructure, middleware, and application services to be expressed in a simple, human-readable form and make it possible to track configuration drift and synchronize back to a desired and known good state. Event-driven orchestration systems enable cross-component business logic that is neither embedded in application code nor implemented as cumbersome monitoring scripts. Continuous integration and continuous delivery (CI/CD) pipelines accelerate delivery by automating many of the repetitive steps of building, testing, and deploying changes to production.

Declarative configuration frameworks for IT infrastructure, middleware, and application systems simplify automation and orchestration in these domains. Declarative configuration for IT infrastructure applies to provisioning cloud resources, deploying on-premises virtualization, or implementing bare-metal services using tools like Terraform, CloudFormation, or Saltstack. Desired state management behaviors and semantics make it easy to track configuration drift and synchronize back to a desired and known good state. Its use in AWS CloudFormation or OpenStack Heat enables consistent provisioning, maintenance, and de-provisioning of infrastructure. Similar principles applied to the configuration of middleware and applications enable fully automated provisioning of the complete stack (including the application itself) with sufficient test coverage and monitoring in place to validate correct operation of the system.

At a higher level, business logic that spans multiple components can be implemented using event-driven orchestration to remove the risk of missing steps or extraneous human intervention. Cumulus Networks uses an event-driven model to automate the discovery, configuration, and monitoring of network switches.

8.4.1. Declarative Configuration and Desired State Management

Declarative techniques for configuration management have been developed to facilitate the automation of software management tasks such as provisioning, configuration of servers and runtime environments, and installation and configuration of software packages. These tasks can now be specified in a high-level DSL for declarative configuration and a logic-programming framework for modelling runtime configuration. Systems for automatic server and environment provisioning have also been developed and applied by a few large companies to overcome inconsistency problems.

In a declarative approach to configuration management, the configuration parameters are expressed as constraints on the desired state of the system. Therefore, the configuration management problem becomes one of exploring an explicit space of system states, rather than of executing a series of commands in a pre-defined order. The constraints can be expressed in a straightforward way, as when defining which subset of the variables of a service or an application should be set to the same value. However, these systems can also be used to impose finer level consistency constraints on a system, boosting therefore the traditional Sys Admin role toward a much more higher-level Engineer activity.

8.4.2. Event-Driven Orchestration

Event-driven orchestration enables automatic triggers for pipeline processes based on real-time updates. Such triggers are not limited to the initiation of a pipeline execution; various software artifacts are typically tracked—identified by events in plain-text format or as JSON objects. An example of such a trigger is the deployment of a new release, allowing a security team to trigger a new round of vulnerability scanning. Natural integrations exist among various pipeline constituents, with many suppliers providing ecosystem connectors that can be leveraged when assembling desired orchestrations. Workflow management systems, for instance, naturally integrate with source control repositories, enabling actions to be triggered by repository changes, such as commit pushes or pull request modifications.

Simplifying user-configured applications increases convenience and decreases error potential. Desirable telemetry is often pushed by systems instead of being pulled by monitoring management platforms. Externalized workflow management systems allow

users to define their workflows within the system without code changes, accessing an intuitive graphical user interface. Publishing and subscribing directly through message brokers bypass unnecessary points in a pipeline. As information becomes richer, additional concerns and requirements appear. Logical conditionals and Boolean flags within an organization guide decisions and responses to events. Executing robots and threads moves a step further toward all-pipeline deployment, creating a system that self-monitors and self-repairs based on accessibility, application load, potential security vulnerabilities, and user-defined system interaction paths.

8.4.3. Continuous Integration and Continuous Delivery Pipelines

Continuous Integration (CI) and Continuous Delivery (CD) pipelines automate software build, test, and deployment phases to support frequent updates of production services by developers. A CI/CD pipeline is typically orchestrated by a workflow management engine, and automated testing guarantees that code changes do not introduce regressions. Changes are delivered at a rate determined by the development team. Although CI/CD pipelines may be inefficient for rare and large updates, these can usually be postponed until the enabling conditions for such an update arise.

CI/CD pipelines rely on a declarative definition of the desired sequence of build and deployment steps, which is recorded in a repository. Such a definition improves developer productivity by minimizing the planning effort needed to apply code updates and ensures consistency of the pipeline implementation with the update requirements expressed by the team. Moreover, the operations are initiated automatically in response to events that occur in the repository, but in practice they are usually triggered manually to prevent roll-out of potentially faulty changes. A CI/CD pipeline implements only a subset of the principles of continuous testing; consequently, some stages of the pipeline may take longer than would be practical for a real continuous-testing approach.

8.5. Self-Optimization Mechanisms

Feedback loops, metering metrics, control theory methods, statistical analysis, and machine learning can all be used for self-optimization in pipelines. Telemetry enables accumulating historical data, and metrics allow observing the status from various angles. Feedback loops provide “ways of monitoring the effects of actions and deciding whether to switch between different approaches or make different choices” and “are an essential aspect of any adaptive system.” Quantitative feedback theory is used in adjustable autonomous systems, because “by generating simple quantitative state variables and finding means to control their time derivatives, it is frequently possible to obtain simple but severe yet predictable group performance bounds.” This approach is reminiscent of

feedforward control in product developments that employs statistical quality control expertise to monitor and reduce output variability by means of adjusting process input levels.

Machine learning techniques are increasingly being incorporated in software engineering domains including build pipelines. Actual build durations are predicted based on a set of features, and these predictions are used for dynamically adjusting the levels of parallelism in the pipeline. Support-vector regression was identified as the best-performing technique for prediction. A set of build-specific characteristics that affect build times in CI environments has been identified, along with a description of the influence of these characteristics on incremental builds. Self-tuning approaches can adjust build parallelism during runtime or in response to changing user demand for lower or higher build latency. Resource allocation for CI/CD pipelines is also dynamically adjusted.

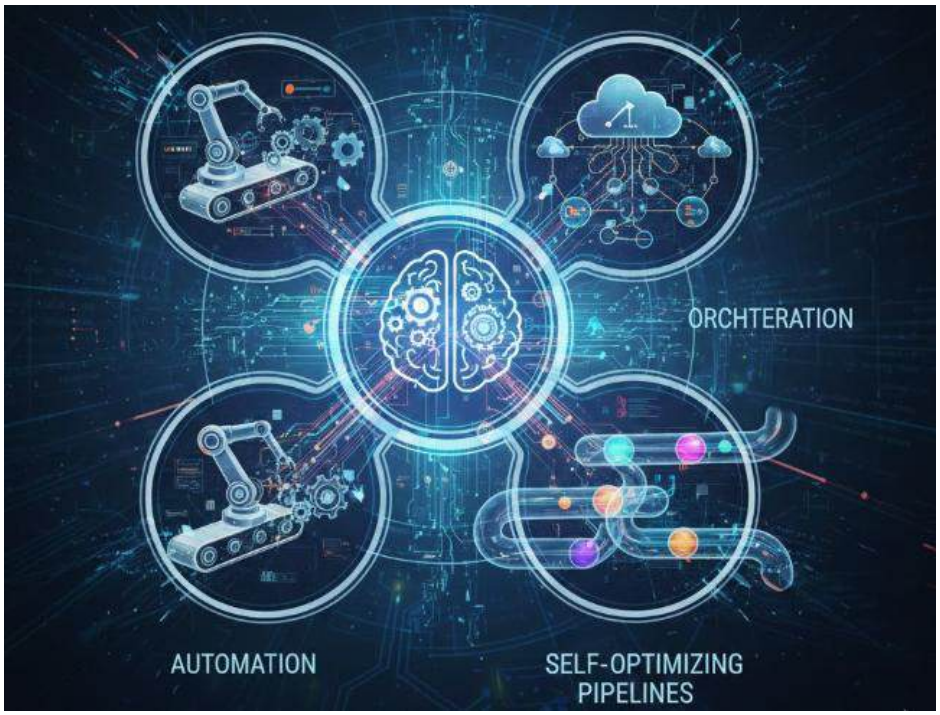

Fig 8.3: Self-Optimization Mechanisms

8.5.1. Metrics, Feedback Loops, and Control Theory

Control-theoretic principles provide insight into the self-optimization of pipelines for software systems. Guided control theory, originally developed for mechanical control systems, focuses on modifying the trajectory of operations so that a trajectory can be

achieved over time. Similarly, dynamic supervision, a branch of the theory of intelligent activities, emphasizes an understanding of the decision-making process and thus provides a basis for modelling the learning support for self-optimizing processes. Applying dynamic supervision to continuous software engineering shows that these concepts may provide an appropriate foundation for the monitoring, supervision, and learning/making process to enable the self-adapting control of continuous software-engineering processes and systems.

Successful application of reinforcement learning to continuous deployment suggests that other aspects of continuous software engineering more generally can also be formulated as a reinforcement learning problem. The application of neural architecture search provides evidence that there is sufficient data to learn the optimization. Consequently, it is possible to achieve self-optimizing pipelines for software systems. Further application of feedback loops and other optimization mechanisms is suggested by specification of a set of metrics that provide the basis for systemic monitoring of continuous software-engineering pipelines. Machine learning can assist with tasks more readily characterized as self-optimizing but require that sufficient data be acquired to support supervised or unsupervised learning.

8.5.2. Machine Learning for Pipeline Optimization

To extract knowledge from an ever-increasing volume of metrics and measurements describing the ongoing behavior of pipelines, an interesting approach consists of applying Machine Learning to manage the pipeline's operation. Typically, such an approach is called predictive maintenance; it applies supervised ML approaches to detect when a pipeline is likely to misbehave (failure prediction) and models the incipient failure in order to apply corrective maintenance strategies or procedures (remaining useful-life estimation). These two categories of predictive maintenance are of utmost importance. However, simply defining schedules for corrective interventions, based on foreseen resource depletions or recommissioning, is not sufficient; the cost of the intervention could easily surpass the work lost in a cluster node.

An alternative to predictive maintenance is trying to handle processes that are intrinsically tolerant to equipment failures. Multi-tenancy can be seen in this spirit, together with redundancy and disaster recovery strategies that enable business continuity; however, ML enables going beyond business continuity to predict when failures become probable and to adapt resources accordingly (for instance, to instantiate additional replicas of the expected failing equipment). ML-based decision support systems built for requirements adaptive game engines also fit this category.

8.5.3. Adaptive Scheduling and Resource Allocation

Pipelines can self-optimize by adapting scheduling policies and resource allocation to changing usage and workload patterns over time. A typical example of a self-optimizing pipeline is a cloud computing facility with associated Microservice-based applications, where resource allocation and scheduling of the underlying infrastructure is performed automatically using Platform as a Service (PaaS) capabilities.

In order to perform the self-optimization, a control-theory-feedback-loop structure is created using performance and deployment metrics that signal the need for actions such as the addition, removal or resizing of resources or the migration of applications. The control action is produced by a scheduler that typically implements the Auto-Scaling process of adding or removing resources of a system in response to real-time metrics and thresholds pre-defined by the administrator. Virtualization technologies ease this process by decoupling the providing of the resource from the actual deployment of the application.

8.6. Conclusion

Recent developments in the fields of automation and orchestration are enhancing the adaptability and responsiveness of software delivery pipelines, allowing them to act in this way. The discussion synthesizes the growing body of literature on automation and orchestration in software delivery, and on self-optimizing pipelines that implement this process. Pipelines play an important role in contemporary software delivery by bringing together the various elements of software delivery, publishing, and hosting into a coherent data flow. However, these flows are often static and require manual intervention to adapt to changes in environments, demand, and usage patterns. Automation and declarative specification reduce the need for such intervention, while telemetry and event-driven invocation improve responsiveness.

Automation and orchestration meet in self-optimizing pipelines that adapt automatically, with minimal or no human involvement, to changes in the state of the underlying system. Evidence of increasing interest in such pipelines appears in both academic research and practical applications, and important foundational concepts are already well understood. The growing literature in these areas is synthesized and structured rigorously. The concept of self-optimizing pipeline is defined formally, and key techniques for implementation are identified with recommended sources for further reading. Readers seeking in-depth examination of particular topics can follow the pointers to the relevant areas of the literature.

8.6.1. Future Trends

Automation and orchestration meet self-optimizing pipelines with rigorous, evidence-based analysis and formal structure. Future trends are considered.

Future trends in automation, orchestration, and self-optimizing pipelines are rooted in larger technology trends such as increasing digitization, faster delivery of digital services, and the growing need for responsibility, security, and support for environmental, social, and governance (ESG) initiatives. These trends expand the need for automation, reduce the need for custom orchestration, and increase pressure to self-optimize pipelines.

Many organizations have adopted a DevOps approach that combines development and operations, requires the close collaboration of developers and operators, and shortens the development and delivery cycle for digital services. DevOps is founded on CI/CD principles. A natural extension of DevOps is the practice of site reliability engineering (SRE), which takes a service-focused approach to automation and orchestration. In doing so, SRE also generates the operational data and, hence, operational telemetry required for self-optimizing pipelines.

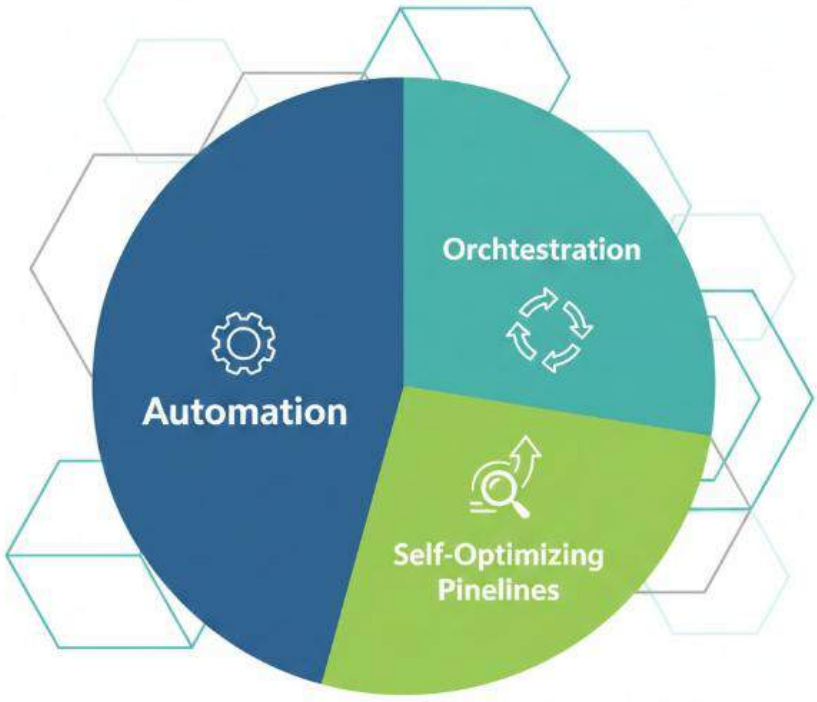

Fig 8.4: Automation, Orchestration, and Self-Optimizing Pipelines

The need for increased operational telemetry naturally heightens interest in artificial intelligence for IT operations (AIOps)—the application of machine learning to improve

the availability and performance of IT services. Machine-learning models are increasingly used to automate recurring operational tasks and detect anomalies in service performance, availability, and security that have Privacy, Security, Fraud and ESG implications. Rotating metrics into a dashboard as the observed signatures of abnormalities form the basis of self-optimizing pipelines..

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