Offline Mining of Microservice-based Architectures

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Abstract: Designing, implementing, and operating microservices is known to be complex and costly, mainly due to the multitude of heterogeneous software services forming a microservice-based application. Such tasks can be simpler if a specification of the microservice-based architecture (MSA) of an application is available. At the same time, due to the number of services and service interactions in a MSA, manually generating a specification of such MSA is complex and costly. For this reason, in this paper we present a novel technique for automatically mining the specification of a MSA from its Kubernetes deployment. The obtained MSA specification is in μTOSCA, a microservice-oriented profile of the human- and machine-readable OASIS standard TOSCA. We also present a prototype implementation of our technique, which we use to assess it by means of case studies based on third-party applications.

1 INTRODUCTION

Microservice-based architectures (MSAs) are known to enable realising so-called *cloud-native* applications, viz., applications architected to fully exploit the potentials of cloud computing platforms (Kratzke and Quint, 2017). This resulted in MSAs becoming commonplace. For instance, Amazon, Netflix, or Twitter are already exploiting MSAs to deliver their businesses (Soldani et al., 2018).

MSAs are essentially service-oriented architectures satisfying some additional key design principles, e.g., ensuring services' independent deployability and horizontal scalability, or isolating failures (Zimmermann, 2017). It is hence crucial to determine whether a service-based application adheres to the key design principles of MSAs, and understanding how to refactor an application to resolve possible violations of such key design principles (Soldani et al., 2021).

μTOSCA and μFRESHENER (Brogi et al., 2020) enable modelling, analysing, and refactoring the architecture of a service-based application, to enhance its adherence to the key design principles of MSAs. μTOSCA is a model enabling to specify MSAs with the human- and machine-readable OASIS standard TOSCA (OASIS, 2020). MSAs are represented by typed directed graphs, called *topology graphs*, where nodes model the services, integration components (e.g., load balancers or message queues), and databases forming a MSA. Oriented arcs represent the interactions among such components.

μFRESHENER (Brogi et al., 2020) enables visualising the μTOSCA specification of an MSA, and automatically analysing the specified MSA to check whether the application includes some known architectural smells, viz., possible symptoms of violations of the key design principles of MSAs. μFRESHENER also enables reasoning on how to refactor an application to resolve identified architectural smells, based on applying practitioner-shared refactorings known to resolve their occurrence (Neri et al., 2020).

On the other hand, MSAs can often include hundreds of interacting services (Forti et al., 2022). This makes manually specifying MSAs in μTOSCA a complex, time-consuming, and error-prone process (Soldani et al., 2021). To this end, μMINER (Muntoni et al., 2021) was proposed to automatically mine the μTOSCA specification of the MSA of an application, given the latter's Kubernetes deployment. μMINER first elicits the services, integration components, and databases in an MSA from the deployment specification in Kubernetes. It then runs the application deployment on a devoted cluster, and it loads the deployed application. μMINER also sniffs the packets exchanged among the deployed application components to mine the occurring interactions. This requires μMINER to run with root privileges on the cluster, and the application to not encrypt any of the messages ex-

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changed among deployed components, which can of course happen only in a testing environment. The deployed application must also be loaded to stress all possible service interactions, to allow μMINER to monitor them. In short, μMINER requires to run the target microservice-based application in a suitably configured testing environment.

In this paper, we propose a different technique for mining the μTOSCA specification of the MSA of an application, which can work with any existing application deployment, rather than requiring a suitably configured testing environment. Our technique starts from the Kubernetes deployment of an application, configured to also exploit Istio[1] and Kiali[2], two Kubernetes-native tools for proxying deployed services and monitor their interactions. It then processes, *offline*, the Kubernetes manifest files specifying the application deployment and the Istio-based proxying of its services, as well as a graph generated by Kiali in any former run of the application, e.g., its production run. The Kiali graph models the deployed software components (as nodes) and their monitored interactions (as oriented arcs). Given such inputs, our technique can automatically mine the MSA of an application in two steps. It first elicits the software components and their interactions, producing a first draft of the MSA of an application. The draft is then refined by distinguishing services from integration components and databases, and by characterising the mined interactions, e.g., determining whether circuit breakers or timeouts are used therein. The refined architecture is finally marshalled to μTOSCA, obtaining a specification which can be processed by μFRESHENER.

To illustrate the feasibility of the proposed mining technique, we present an open source prototype implementation, called μTOM (μTOSCA *Offline Miner*). We also show how we used μTOM to run case studies based on two existing, third-party applications, viz., *Robot Shop* (Instana, 2021) and *Online Boutique* (Google Cloud, 2021). The case studies show that μTOM effectively mines the MSAs of the considered applications, and that it also captures more details if compared with μMINER.

The paper is organised as follows. Section 2 provides the necessary background on μTOSCA, Kubernetes, Istio, and Kiali. Section 3 presents our technique for mining MSAs offline, while Section 4 introduces its open source prototype implementation. Section 5 illustrates the case studies assessing our technique. Finally, Sections 6 and 7 discuss related work and draw some concluding remarks, respectively.

[1]https://istio.io.

[2]https://kiali.io.

2 BACKGROUND

We hereafter provide the necessary background on μTOSCA (Section 2.1), Kubernetes (Section 2.2), and Istio and Kiali (Section 2.3).

2.1 μTOSCA

The μTOSCA type system (Figure 1) allows specifying MSAs as typed topology graphs in TOSCA, the *Topology and Orchestration Specification for Cloud Applications* (OASIS, 2020). Topology nodes model the services, communication patterns, or databases in an MSA. A Service runs some business logic, e.g., a service managing users' orders in an e-commerce application. A CommunicationPattern implements message-based integration pattern (Hohpe and Woolf, 2003), viz., MessageRouter and MessageBroker, which decouples the communication among two or more components. MessageBrokers are also distinguished based on whether they implement message brokering asynchronously (AsynchronousMessageBroker) or synchronously (SynchronousMessageBroker). Finally, a Database is a component storing the data pertaining to a certain domain, e.g., a database of orders in an e-commerce application.

Topology arcs instead model the interactions among the components in an MSA, throughout InteractsWith relationships. Such relationships can be further characterized by setting three boolean properties, viz., circuit_breaker, timeout, and dynamic_discovery. circuit_breaker, timeout allows specifying whether the source node is interacting with the target node via a circuit breaker or by setting proper timeouts. dynamic_discovery instead allows to specify whether the endpoint of the target of the interaction is dynamically discovered (e.g., by exploiting a discovery service).

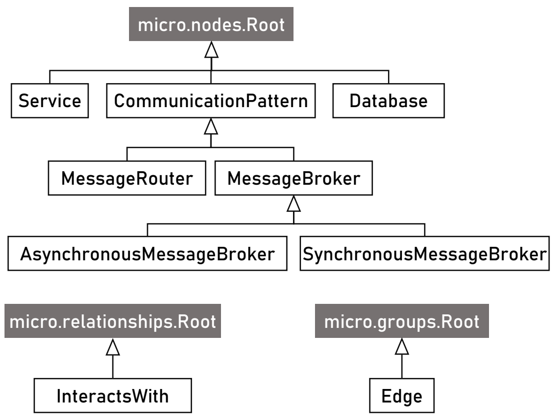


Figure 1: The node types, relationship types, and group types defining μTOSCA. The corresponding definitions in TOSCA are publicly available on GitHub at https://di-unipi-socc.github.io/microTOSCA/microTOSCA.yml.

Finally, nodes can be added to an Edge group. The latter specifies the application components that are publicly accessible from outside of the application, namely those components that can be directly accessed by external clients.

Example. Figure 2 displays an example of μTOSCA topology modelling the MSA of a toy e-commerce application. The application includes four services, i.e., frontend (accessible by external clients), orders, payment, and shipping. It is then completed by two integration components, i.e., router and queue, and two databases, i.e., catalogDb and ordersDb. The frontend allows browsing the catalogue of available products, by interacting with catalog. The actual instance of catalog used to access the catalogDb is dynamically discovered by a message router implementing server-side service discovery. The frontend also allows to place orders, by interacting with orders. The latter allows to upload new product orders, which are stored in ordersDb, and which are also enqueued in the asynchronous message broker implementing the queue of orders to be shipped. The latter is consumed by the service shipping, which pulls orders from the queue and proceeds with their shipping.

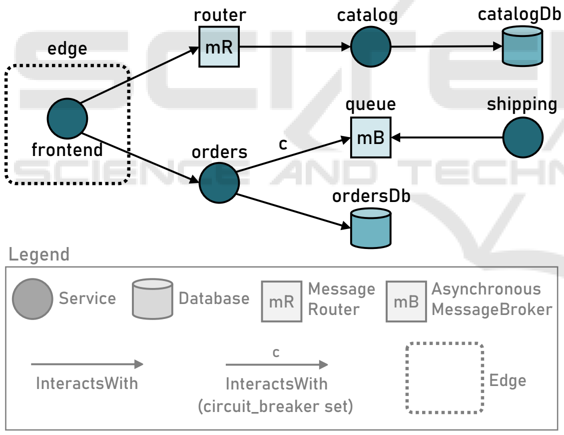


Figure 2: An example of μTOSCA topology modelling the architecture of an application.

2.2 Kubernetes

Kubernetes allows deploying and managing multi-service applications in distributed clusters. Such a deployment and management is realised by orchestrating *pods*, which constitute Kubernetes' deployment units. A pod is a deployable instance of an application service, which is shipped within a single container or in several tightly coupled containers. A pod can actually encapsulate multiple Docker containers that need to share the same resources, e.g., when a containerised service is accompanied by "sidecar" containers monitoring it or proxying its communications.

Pod instances are deployed and managed with Kubernetes *controller*s. The latter allow to spawn and manage pod instances from pod templates, which are included in *workload* resource specifications, e.g., *Deployment*s, *StatefulSet*s, and *ReplicaSet*s. The latter specify the Docker containers running in a pod, their target state, as well as the number of replicas of the pod that must be deployed. Kubernetes controllers then ensure that the specified number of replicas of a pod continue to run on a cluster, with each pod instance reaching and maintaining its target state.

Replicated pods can be accessed through Kubernetes *service*s, which define their load balancing policies. A Kubernetes service indeed implements a message routing component, which receives requests and balances them among the pods it manages according to the specified balancing policy. Kubernetes services can be of multiple types, depending on whether they should be accessible only within the Kubernetes cluster (viz., *ClusterIP* services), or whether they should be exposed to external clients (viz., *NodePort* or *LoadBalancer* services).

2.3 Istio and Kiali

Istio and Kiali are two Kubernetes-native tools for controlling and monitoring service interactions. Istio includes so-called *envoy* proxies in a Kubernetes deployment. Envoy proxies are deployed as sidecar proxies alongside application services to control how they interact with each other. This is done by specifying *VirtualService*s or *DestinationRule*s, which allow defining how to route a message to its destination. This includes, e.g., indicating whether timeouts or circuit breakers are used to avoid the sender to continue waiting for an answer when the receiver has failed.

Kiali is an observability console, which comes natively integrated with Istio. It exploits Istio envoy proxies to store the interactions they proxy, so as to trace the interactions among deployed services. Each interaction is stored together with its metadata, including the source and target Kubernetes workloads or services, and whether the interaction successfully completed. Kiali then exploits such interactions to build different types of graphs, which enable visualising them at different abstraction levels in the Kiali dashboard, and which can be exported to JSON graph data files. In the rest of this paper, we consider Kiali graph modelling monitored service interactions, viz., *service* graphs.[3]

[3]https://kiali.io/docs/features/topology

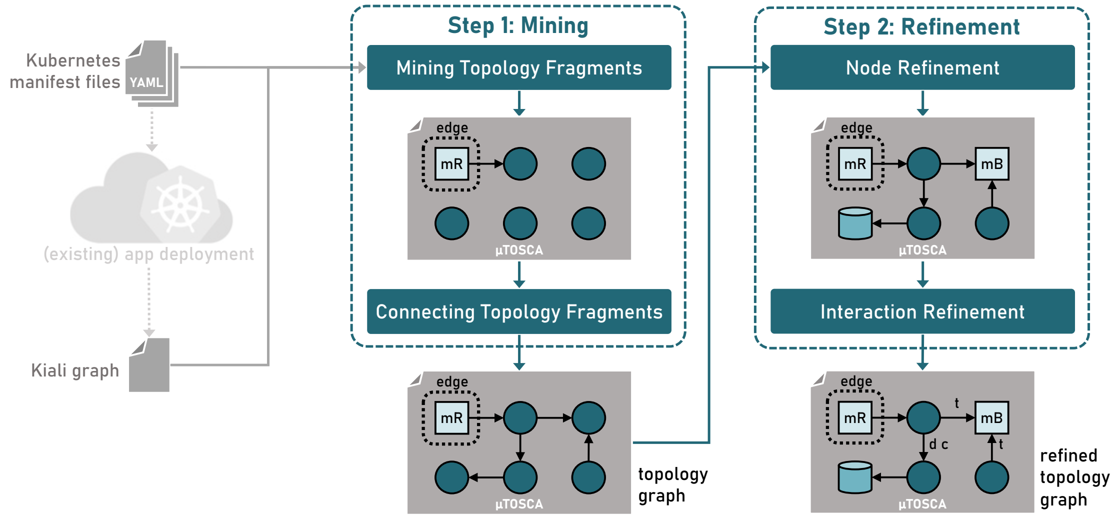


Figure 3: Our two-steps technique for mining MSAs from their Kubernetes deployment.

3 MINING MSAs

Our technique for mining MSAs consists of a pipeline of two steps (Figure 3), which processes the Kubernetes manifest files specifying the application deployment and a JSON graph data file specifying the graph generated by Kiali while monitoring an existing application deployment. Such inputs are first processed by the *mining* step, which elicits the nodes and interactions forming the target MSAs, and which produces a first corresponding μTOSCA topology graph. The graph is then passed to the *refinement* step, which distinguishes the types of the nodes therein, and which characterises the mined relationships by indicating whether dynamic discovery, circuit breakers, or timeouts are used in the corresponding interactions.

3.1 Step 1: Mining

The mining step processes the available inputs to determine the nodes and interactions forming the target MSA. Firstly, μTOSCA topology fragments are mined from the Kubernetes manifest files, by essentially mapping Kubernetes entities to μTOSCA nodes. The topology graph is then completed by connecting mined topology fragments based on the runtime interactions contained in the Kiali graph.

Mining Topology Fragments. Topology fragments are extracted from the Kubernetes manifest files by first mapping the workloads and services specified therein to μTOSCA nodes. Each Kubernetes workload specifies the pod configuration for a component of the target MSA, by indicating the Docker container

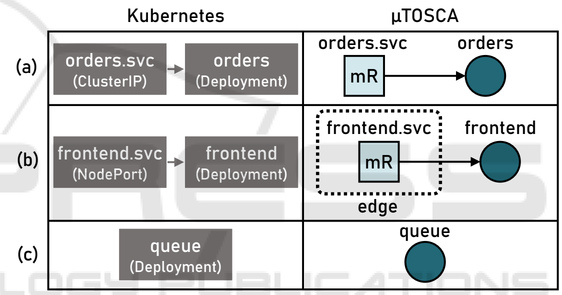


Figure 4: Three examples of μTOSCA topology fragments mined from Kubernetes services and workloads.

from which it runs and its target configuration (Section 2.2). Therefore, each Kubernetes workload is mapped to a μTOSCA node of type Service. The type may change in the refinement step, if the workload is used to deploy an integration component or database.

A Kubernetes service instead implements a message routing component balancing the traffic sent to the replicas of the pod they manage, specified by a Kubernetes workload (Section 2.2). They are hence mapped to μTOSCA nodes of types MessageRouter, which are directly specified to InteractsWith the Service node corresponding to the workload they manage. In addition, if a Kubernetes service is specified to be a *NodePort* or *LoadBalancer*, its corresponding MessageRouter node is placed within the Edge group. This reflects the fact that *NodePort* or *LoadBalancer* services that can be invoked by external clients.

Figure 4 illustrates three examples of application of our topology fragment mining. In case (a), a Kubernetes *ClusterIP* service orders.svc manages the

Deployment workload running the service orders. By applying our node mining technique, we obtain a MessageRouter node modelling the Kubernetes service, which InteractsWith the Service node modelling the workload. Case (b) is similar, with the only difference that the MessageRouter node is placed in the Edge group, since Kubernetes *NodePort* services are exposed to external clients, while the same does not hold for *ClusterIP* services. Finally, case (c) considers a *Deployment* workload used to deploy a message queue, without any Kubernetes service balacing its load. In this case, we obtain a singleton Service node. Case (c) also provides an example of μTOSCA node that may be typed as Service only temporarily: the type of queue might be changed to AsynchronousMessageBroker, if it actually implements an asynchronous message broker (Section 3.2).

Connecting Topology Fragments. The topology fragments obtained by parsing the Kubernetes manifest files are interconnected to model the runtime interactions occurring among the components they model. This is done by parsing the Kiali graph, which explicitly models the component interactions that were monitored in a former deployment of the application, e.g., in its production deployment.

A monitored interaction is represented as an *edge* in the Kiali graph, which connects the node corresponding to the the Kubernetes workload that started the interaction to the Kubernetes service that was invoked.[4] Each *edge* is hence mapped to InteractsWith relationships connecting the Service node modelling the starting workload to the MessageRouter node modelling the target Kubernetes service. In addition, the mined InteractsWith relationship are directly set to enact dynamic_discovery, given that Kubernetes prescribes to invoke services based on their name and to rely on Kubernetes' native DNS to resolve the address of the actual host to contact.

Figure 5 illustrates an examples of mined InteractsWith relationship, which connects two of the topology fragments in Figure 4. The Kiali graph specifies that the Kubernetes workload running the frontend service interacted with the Kubernetes service managing the replicated orders service. This is modelled by including an InteractsWith relationship connecting the corresponding μTOSCA nodes, viz., the Service frontend and the MessageRouter orders.svc.

[4]Kiali unifies a Kubernetes service with the Kubernetes worklaod it manages, assuming that Kubernetes services are used to enact server-side service discovery, as recommended by Kubernetes documentation (https://kubernetes.io/docs/concepts/services-networking/service).

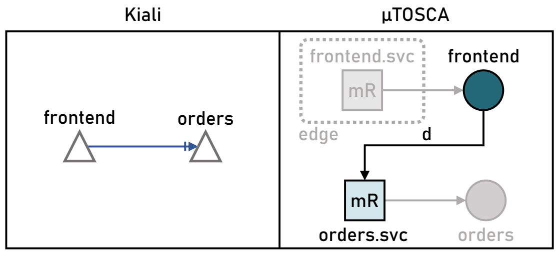


Figure 5: Examples of μTOSCA InteractsWith relationship mined from the Kiali graph.

3.2 Step 2: Refinement

The *mining* step produces a "draft" of the μTOSCA topology modelling the target MSA, in which all nodes and interactions are recognised, but associated with default types and properties.

Node Refinement. After the *mining* step, nodes are associated with either one of two types: MessageRouter or Service. Whilst nodes types as MessageRouter are truly routing messages in the Kubernetes deployment of an MSA (being them obtained from Kubernetes services), Service is used as the default type for all other nodes. Nodes initially typed as Services may however implement other components than those running some business logic, namely databases or asynchronous message brokers. The objective of the *node refinement* substep is hence to identify such nodes and assign them with the corresponding μTOSCA type, viz., Database and AsynchronousMessageBroker.

Database and message brokers can be seen as "passive" components: despite they reply when being invoked by other components, they are not proactively invoking other components (Soldani et al., 2021). They hence appear as "sink nodes" in the mined μTOSCA topology graph, meaning that they are targeted by InteractsWith relationships, whilst no such relationship outgoes from them. The *node refinement* substep hence focuses on the Service nodes being sink nodes, and determines whether they should be rather typed as Database or AsynchronousMessageBroker. This is essentially done by looking at the Docker image running in the corresponding Kubernetes workload: if such image is one of the official Docker images for databases or message brokers (Table 1), then the node's type is changed to Database or AsynchronousMessageBroker, respectively. Otherwise, the node continues to be a Service.

As a result, there might be nodes typed as Services, despite they are implementing some databases or message brokers by means of unofficial Docker images. If this is the case, the application developer can refine the generated μTOSCA representation of the target MSA by suitably changing their types. To support this, the implementation of our technique (which we describe in Section 4) not only features the fully *automated* mode described above, but also an *interactive* mode prompting developers when a sink node may implement something different from a Service. This enables them to explicitly indicate whether such node should be typed as Service, Database, or AsynchronousMessageBroker.

Interaction Refinement. The *interaction refinement* substep is intended to characterise mined interactions by associating them with other properties than the default dynamic_discovery property included during the *mining* step. More precisely, it associates each mined InteractsWith relationship with properties circuit_breaker and timeout, if a circuit breaker or a timeout is used during the corresponding interactions. This is done by inspecting the Istio traffic management rules defined for the service targeted by each mined InteractsWith relationship.

Istio traffic management rules are defined in *VirtualService*s and *DestinationRule*s (Section 2.3). *VirtualService*s allow explicitly setting a `timeout` field to indicate the maximum amount of time after which the interaction with the target service is considered to have failed (Figure 6a). *DestinationRule*s instead feature a field `outlierDetection` that allows defining circuit breaking policies, by setting the maximum number of tolerated consecutive errors before the circuit breaker trips, as well as the amount of time it remains tripped (Figure 6b).

The *interaction refinement* substep hence checks whether *VirtualService*s or *DestinationRule*s are defined for the target of each interaction. To avoid unnecessarily browsing the input Kubernetes manifest files, it relies on the metadata included in the Kiali graph. Kiali indeed already determines whether the target of an interaction is reached through a *VirtualService* or through a *DestinationRule* defining some circuit breaking policy. If this is the case, Kiali associates the service targeted by a monitored interaction with properties `hasVS` or `hasCB`, respectively. Therefore, if the property `hasVS` is set for a service in the Kiali graph corresponding to the target of a mined InteractsWith relationship, the *interaction refinement* substep looks for the corresponding *VirtualService* in the Kubernetes manifest files. It then checks whether such *VirtualService* sets some `timeout` (similarly to Figure 6a). If this is the case, timeout is set on the corresponding *interactsWith* relationship, to model that a timeout is used therein.

Similarly, if the service in the Kiali graph corresponding to the target of a mined InteractsWith relationships has the property `hasCB` set, the *interaction refinement* substep looks for the corresponding *DestinationRule* in the Kubernetes manifest files. The *interaction refinement* substep then checks whether such *DestinationRule* sets a circuit breaking policy through the `outlierDetection` field (similarly to Figure 6b). If this is the case, circuit_breaker is set on the corresponding InteractsWith relationship, to model that a circuit breaker is used therein.

Instead, if none of the above applies, e.g., since no Istio traffic management rule is applied to the component targeted by a relationship, the latter remains with the only dynamic_discovery property set.

```
kind: VirtualService
spec:
  hosts:
    - orders
  http:
    - route:
        - destination:
            host: orders
      timeout: 0.5s
```

(a)

```
kind: DestinationRule
spec:
  host: catalog
  trafficPolicy:
    conectionPool:
      tcp: {maxConnections: 1}
      http:
        http1MaxPendingRequests: 1
        maxRequestsPerConnection: 1
    outlierDetection:
      consecutive5xxErrors: 1
      interval: 1
      baseEjectionTime: 3m
      maxEjectionPercent: 100
```

(b)

Figure 6: Examples of how (a) timeouts and (b) circuit breakers can be defined with Istio traffic management rules.

Table 1: Official Docker images of software implementing a database or message broker.

Databases	Message Brokers
`cassandra`, `db2`, `iris`, `mariadb`, `mongo`, `mysql`, `neo4j`, `oracle`, `postgres`, `redis`, `sqlite`	`activemq`, `kafka`, `mosquito`, `nats`, `rabbitmq`

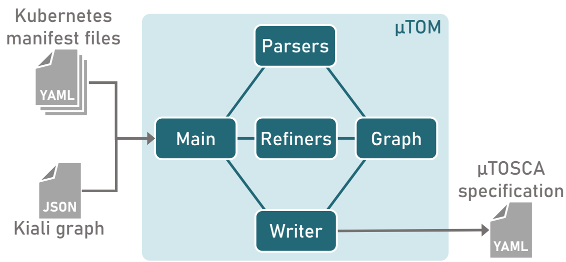


Figure 7: Architecture of μTOM.

4 PROTOTYPE

To assess the feasibility of our mining technique, we developed the μTOM (μTOSCA *Offline Miner*), an open source prototype tool implemented in Java.[5] μTOM provides a command-line interface that automatically generates the μTOSCA specification of an MSA, given the Kubernetes manifest files specifying the corresponding application deployment and a Kiali graph obtained from an existing deployment. It does so by featuring both the *automated* and *interactive* modes described in Section 3.2.

μTOM consists of the five components shown in Figure 7. Main implements the command-line interface offered by μTOM and coordinates the other components for enacting our two-steps mining technique. It first invokes Parsers, which resembles the Java classes implementing the logic for running the *mining* step (Section 3.1) by parsing the input Kubernetes manifest files and Kiali graph. The mined MSA is represented by istantiating Graph, and returned to Main. The latter then invokes Refiners, which resembles the Java classes implementing the logic of the refinement step (Section 3.2). This results in updating the Graph instance, which is refined by updating the types associated with mined nodes and by characterizing mined relationships. The refined Graph instance is returned to Main, which passes it to Writer. The latter implements the logic for marshalling the received Graph instance to a μTOSCA specification in YAML, which constitutes the output of μTOM.

μTOM can be run by issuing:

```
java -jar microTOM-1.0.jar WORKDIR [-i]
```

"`microTOM-1.0.jar`" is the executable file JAR file obtained from μTOM's sources. "`WORKDIR`" is instead the path to a directory containing the Kubernetes manifest files and the Kiali graph to be passed as input to μTOM, and where μTOM will also store the generated μTOSCA file. Finally, the option "`-i`" enables activating the *interactive* refinement mode, prompting the user with the nodes that remain assigned with type Service, even if their interactions are such that they may implement some different component. By default, μTOM however runs the fully *automated* refinement mode.

[5]https://github.com/di-unipi-socc/microTOM.

5 CASE STUDIES

To assess our approach, we exploited μTOM to mine the MSA of two open source, third-party applications, namely *Robot Shop* (Instana, 2021) and *Book Info* (Istio, 2021). We actually compared the MSA mined by μTOM (in its fully *automated* mode) with that declared in the online available documentation of the considered applications, as well as with that mined by μMINER, the state-of-the-art tool for mining the μTOSCA specification of an MSA. As a result, we observed that μTOM effectively mined the MSA of the considered applications (as per what declared in their documentation), and that it generated more informative μTOSCA specifications if compared with μMINER. For instance, μTOM identified the use of timeouts and circuit breakers in mined interactions, which were not instead detected by μMINER.

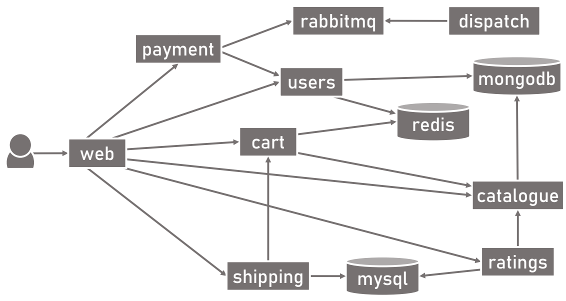
We hereafter report on the mining of the MSAs of *Robot Shop* (Section 5.1) and *Book Info* (Section 5.2). To enable repeating all our experiments, we anyhow published all the necessary inputs on GitHub.[6]

5.1 Robot Shop

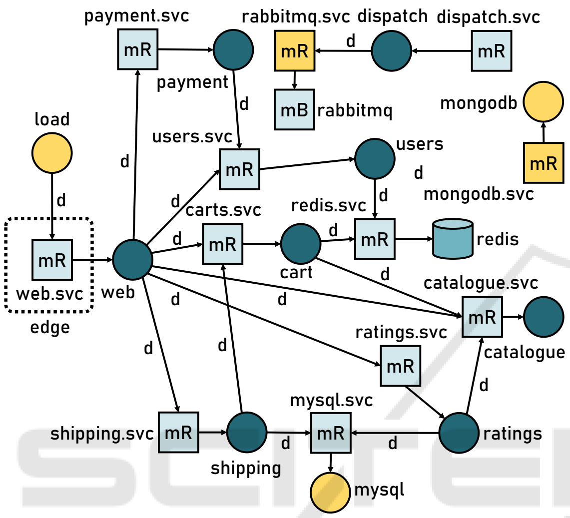
Robot Shop (Instana, 2021) is a microservice-based application simulating an e-commerce website selling robots. It does not include failure handling mechanisms like timeouts or circuit breakers, and its MSA is documented to be as shown in Figure 8a.

We run both μMINER and μTOM on the publicly available Kubernetes deployment of *Robot Shop* to automatically generate a μTOSCA representation of the MSA of *Robot Shop*. In both cases we exploited the *Robot Shop*'s load component to generate workload for the application and monitor the runtime interactions among its components. In the case of μMINER, we used the load directly in its dynamic mining step (Muntoni et al., 2021). In the case of μTOM, we instead deployed the application, used the load component to generate workload, and then downloaded the Kiali graph from the running deployment, which we then provided as input to μTOM

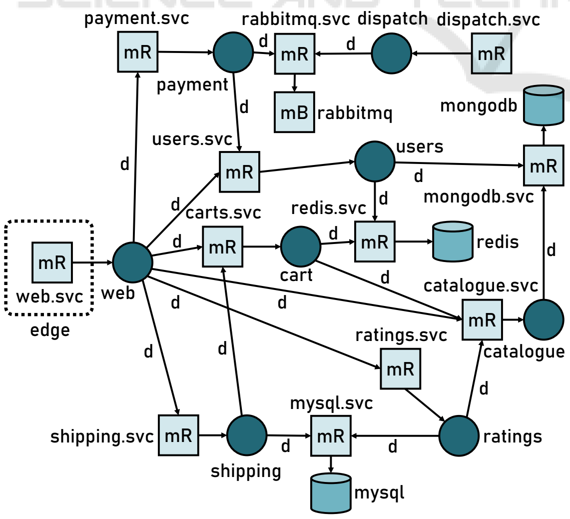
[6]https://github.com/di-unipi-socc/microTOM/tree/main/data/examples.



(a)



(b)



(c)

Figure 8: MSAs of *Robot Shop* (a) taken from its documentation and mined with (b) μMiner and (c) μTOM. Issues in the MSA mined by μMiner are highlighted in yellow.

itself. The μTOSCA representations generated by μMiner and μTOM are shown in Figure 8b and Figure 8c, respectively.

By looking at Figure 8, we can observe that both μMiner and μTOM successfully identified all components forming the MSA of *Robot Shop*. Given that they are deployed as Kubernetes workloads managed by Kubernetes services, each mined node is proxied by a MessageRouter node implementing the corresponding Kubernetes service. At the same time, we can observe that there are some issues in the nodes mined by μMiner, viz., (i) mongodb and mysql are not recognised to be Databases, but rather typed as Services, and (ii) the load component used to generated workload is included in the mined MSA, even if it is not truly part of the MSA of *Robot Shop*. The same does not hold for μTOM, which successfully identifies mongodb and mysql as Databases, and which does not include the load component in the mined MSA.

In addition, whilst both μMiner and μTOM effectively characterise the mined InteractsWith relationships, two relationships are missing in the MSA mined by μMiner. The latter does not include the interactions from payment and catalog to the Kubernetes services managing rabbitmq and mongodb, respectively. As a result, the portions including rabbitmq and mongodb results to be disconnected from the rest of the MSA in the μTOSCA topology mined by μMiner. The same does not hold for the μTOSCA topology mined by μTOM, which successfully identifies all the interactions in the MSA of *Robot Shop*.

5.2 Book Info

Book Info (Istio, 2021) is a microservice-based application developed to experiment Istio. It consists of the four services in Figure 9a. We instrumented its Kubernetes deployment by exploiting Istio to set a timeout in the interactions between productpage and details, and a circuit breaker in that between productpage and reviews. This enabled us to show that μTOM outperforms μMiner in determining whether timeouts or circuit breakers are used in interactions.

The above can be readily observed by looking at the μTOSCA representations of the MSA of *Book Info* generated by μMiner and μTOM, which are shown in Figure 9b and Figure 9c, respectively. Whilst both μMiner and μTOM effectively mined all components and interactions forming *Book Info*, only μTOM successfully detected the timeout and circuit breaker used in the InteractsWith relationships outgoing from productpage.

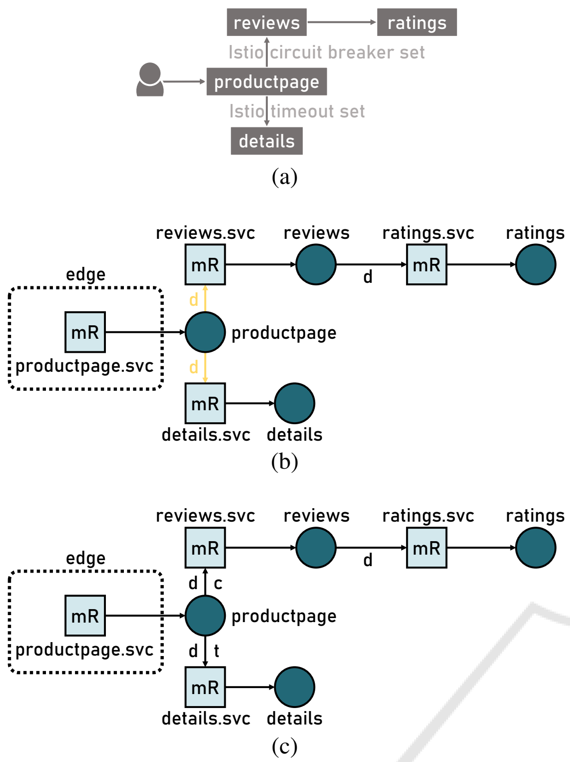


Figure 9: MSAs of *Book Info* (a) taken from its documentation and mined with (b) μMINER and (c) μTOM. Issues in the MSA mined by μMINER are highlighted in yellow.

5.3 Summary

Table 2 shows the success percentages of μMINER and μTOM in identifying and typing nodes in our case studies. The table also shows their success percentages in identifying the interactions occurring among such nodes, and in characterising such interactions by eliciting whether dynamic discovery, timeouts, or circuit breakers were used therein. In both cases, the success percentages are counted as the ratio of successfully identified/characterised nodes and interactions over all those appearing in the applications in our case studies. The numbers in Table 2 again show how μTOM outperformed μMINER in mining the MSAs of the two considered applications.

Table 2: Success percentages of μMINER and μTOM in identifying and characterising the nodes and interactions in the applications considered in our case studies.

	nodes		interactions	
	identified	***typed***	***identified***	***characterised***
μMINER	100%	87.5%	97.3%	91.9%
μTOM	100%	100%	100%	100%

6 RELATED WORK

Several solutions have been proposed for mining the MSAs of existing applications. The closest to ours is μMINER (Muntoni et al., 2021), which is the only existing solution mining a μTOSCA representation of an application's MSA from its Kubernetes deployment. As we already discussed in Section 1, μMINER requires to run in a Kubernetes cluster with root privileges. This limits the applicability of μMINER, e.g., not allowing it to consider an existing deployment of the application, like its production deployment. The same does not hold for our technique, which can work with existing Kubernetes application deployments, therein included their production deployment. We also compared μMINER and our technique in their mining capabilities, showing that our technique outperforms μMINER in the quality of the μTOSCA representation of mined MSAs (Section 5).

Other approaches worth mentioning are (Ma et al., 2018), (Rademacher et al., 2020), (Alshuqayran et al., 2018), (Granchelli et al., 2017b), and (Granchelli et al., 2017a). They introduce different techniques, which differ from ours in the mining approach and in the generated representation of mined MSAs. As for the latter, we generate a representation of the mined MSA where components are distinguished among services, integration components, and databases. This is intended to enable checking whether the mined MSA is affected by some architectural smells, by giving the mined MSA to smell detection tools like μFRESHENER (Brogi et al., 2020). The same is not supported by (Ma et al., 2018), (Rademacher et al., 2020), (Alshuqayran et al., 2018), (Granchelli et al., 2017b), and (Granchelli et al., 2017a), which do not distinguish the type of mined components.

As for the enacted mining approach, (Ma et al., 2018), (Rademacher et al., 2020), and (Alshuqayran et al., 2018) reconstruct the MSA of an application by statically analysing the source code of its components. They hence follow a "white-box" approach, assuming the availability of the source code of the components forming a MSA. Our mining technique instead works also in "black-box" scenarios, viz., when the source code of application components is not available. We indeed only require the manifest files specifying its deployment in Kubernetes and the runtime interactions monitored among its components. In addition, while our mining solution can be fully automated, both (Rademacher et al., 2020) and (Alshuqayran et al., 2018) require developers to manually intervene while mining a MSA.

Similar considerations apply to (Granchelli et al., 2017a) and (Granchelli et al., 2017b), which also employ a white-box, semi-automated technique to mine a MSA from the source code of its components. Such technique is semi-automated since it relies on developers to manually refine the obtained MSA by removing the infrastructure facilities (e.g., service discovery components) used to let application components interoperate. At the same time, (Granchelli et al., 2017a) and (Granchelli et al., 2017b) are a step closer to ours, given that they enrich the mined MSA by relying on runtime monitored interactions. Our technique hence differs from what proposed in (Granchelli et al., 2017a) and (Granchelli et al., 2017b), since it can fully automate the mining of a MSA, and since it can work in black-box scenarios, i.e., when the source code of some application components is not available.

Finally, it is worth relating our mining technique with existing system for monitoring Kubernetes-based application deployments. For instance, Kiali (Section 2.3), KubeView (Coleman, 2021), and WeaveScope (Weaveworks, 2021) are three open source tools for monitoring and visualising the structure of applications deployed with Kubernetes. They differ from our technique mainly because of their ultimate goal, which is to enable visualising the deployed Kubernetes objects (e.g., workloads and services) and their interactions. Our solution instead generates a machine-readable representation of a MSA, whose components are distinguished among services, integration components, and databases forming a MSA, and where component interactions are characterised by indicating whether client-side service discovery, timeouts, or circuit breakers are used therein.

Similar considerations apply to Instana (Instana, 2021), another tool for visualising applications deployed with Kubernetes. Instana (Instana, 2021) is however closer to our mining technique in the generated representation, given that it distinguishes the deployed component among services and databases. Our mining technique goes beyond this, by recognising whether deployed components are implementing message routing/brokering patterns, and whether service discovery, timeouts, or circuit breakers are used in component interactions. Additionally, whilst Instana (Instana, 2021) is a commercial and subscription-based tool, an open source implementation of our technique is publicly available on GitHub.

7 CONCLUSIONS

We presented a technique for mining MSAs from their Kubernetes deployment. Our technique also inputs the component interactions monitored in a former deployment with Kiali, and it process all such

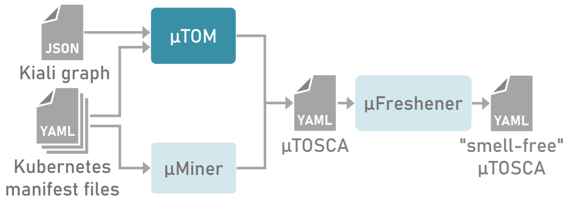


Figure 10: Updated μTOSCA toolchain. Existing tools are in light blue, whilst the newly introduced tool is darker.

inputs offline. As a result, it automatically generates a representation of the mined MSA in μTOSCA, a microservice-oriented profile of the TOSCA standard.

We have also presented μTOM, a prototype implementation of our mining technique. μTOM plugs into the μTOSCA toolchain (Soldani et al., 2021), as shown in Figure 10. It actually provides an offline alternative to μMINER (Muntoni et al., 2021) to generate μTOSCA representations of MSAs, which can still be processed by μFRESHENER (Neri et al., 2020) to identify and resolve the architectural smells therein. μTOM showed to outperform μMINER in generating more informative representations of mined MSAs, without requiring to run the target application in a suitably configured testing environment, but rather by processing the information monitored with Kubernetes-native monitoring in former application deployments, e.g., production deployments. If such information is not available, e.g., since Kubernetes-native monitoring is not enabled, one could anyhow still use μMINER to mine the MSA of an application.

We anyhow plan to further enhance the mining capabilities of μTOM and, more generally, of our mining technique. For instance, we plan to enhance the detection of the type of mined components, which currently detects message brokers or databases when they run from official Docker images of software distributions known to implement such components. The type of component run by a Docker image may be detected by exploiting machine learning techniques, e.g., similary to what done in (Guidotti et al., 2019) to predict the popularity of Docker images, or by inspecting them with approaches like that proposed in DockerFinder (Brogi et al., 2017).

We also plan to enable our technique to work with other technologies than Kubernetes, Istio, and Kiali. For instance, we plan to include support for manifest files specifying the deployment of a microservice-based application with Docker Compose/Swarm. We also plan to support processing the interactions monitored with other tracing tools, e.g., Jaeger (Jaeger, 2021) or Zipkin (OpenZipkin, 2021).

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