



PerfSPEC Learning Phase

Aplicación proactiva de políticas de seguridad
basadas en perfiles de rendimiento
para contenedores

H. Kermabon-Bobinnec et al.,
"PerfSPEC: Performance Profiling-based Proactive Security Policy
Enforcement for Containers,"
in IEEE Transactions on Dependable and Secure Computing,
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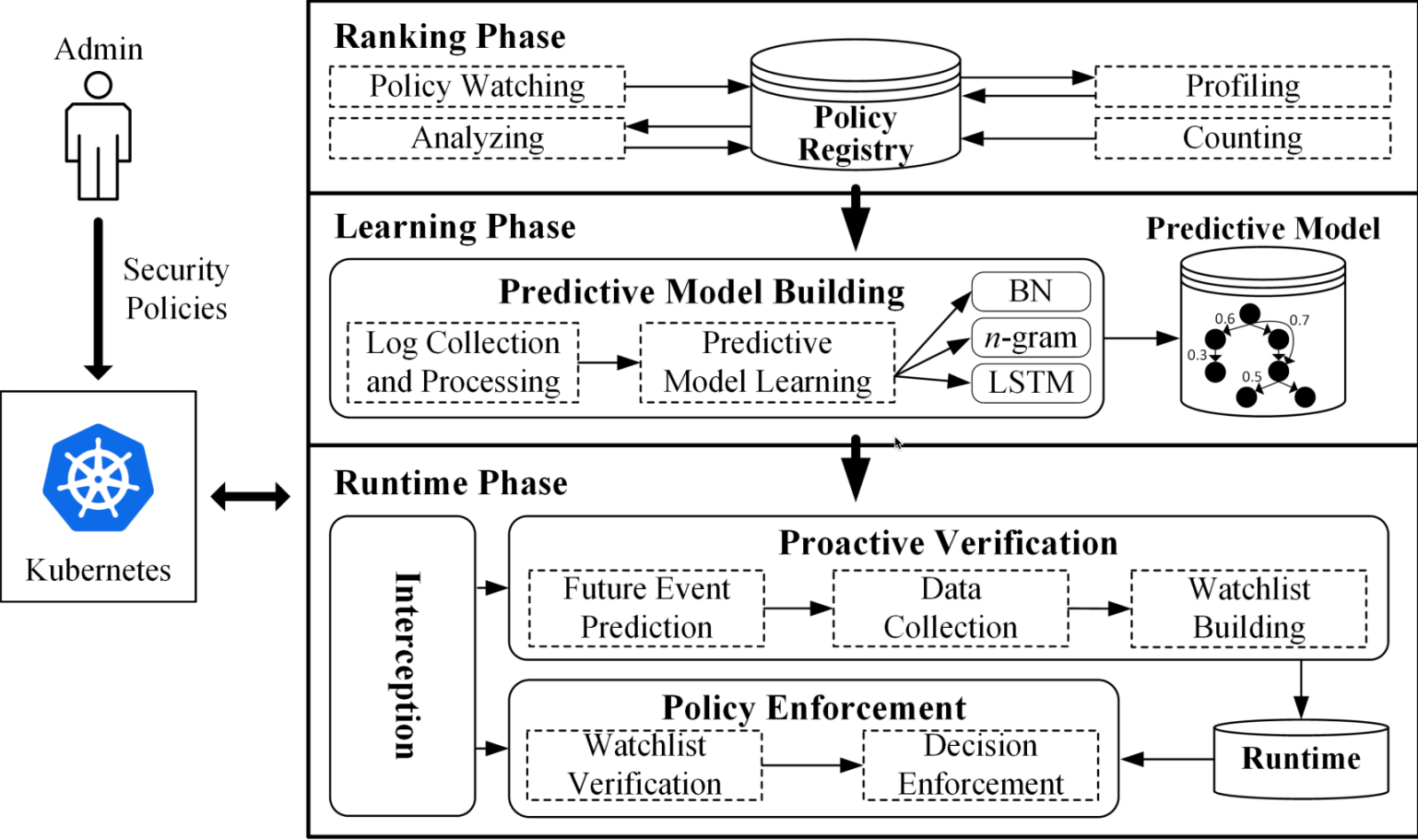
PerfSPEC

Aplicación proactiva de políticas de seguridad basadas en perfiles de rendimiento para contenedores

Performance Profiling-based Proactive Security Policy Enforcement
for Containers -- IEEE publication

Abstract—Container environments provide cloud native applications with scalability, flexibility, and portable support. As a popular container orchestrator, Kubernetes facilitates automatic deployment and maintenance of a large number of containerized applications. However, potential misconfigurations, vulnerabilities, or implementation flaws may empower attackers to exploit the Kubernetes cluster. Although existing solutions such as runtime security policy enforcement may prevent an attack, they can be inefficient in large scale container environments. In this paper, we propose a performance profiling-based proactive security policy enforcement solution, namely, **PerfSPEC**. First, we **accelerate the proactivization of policies** (which typically requires significant manual effort) **by proposing to profile and rank existing policies according to their induced overhead**. This allows us to better focus our efforts and greatly improve the overall response time (e.g., by 98% in contrast to less than 49%). Then, we address the performance limitations of existing solutions **by leveraging learning-based approaches to predict future events and compute their verification results in advance**. As a result, PerfSPEC achieves a viable response time (e.g., less than 10 ms in contrast to 600 ms with one of the most popular existing approaches) even for large container environments (up to 800 Pods).

PerfSPEC





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Proceso

■ Recolección logs

Recopilación de logs de eventos del entorno. Para ello, [PerfSPEC](#) primero requiere habilitar la función de **auditoría en logs** de **Kubernetes**

■ Procesado

- Se extraen los eventos de los datos históricos y se genera un log de auditoría realista y representativo.
- Se extraen los campos `objectRef[resource]` y métodos de los logs de eventos y se almacenan en un archivo
- Usando herramientas de análisis de datos, se procesa cada entrada tipificando los eventos, a los que se asigna al par (método, recurso) una cadena `metodo_recurso` (tipo de evento).

■ Modelo Aprendizaje Predictivo

Implementar una de las tres diferentes aproximaciones propuestas: *Bayesian network*, *n-gram* y *LSTM*.

Recolección logs

Metodología

- Para generar eventos, se adoptan los 60 **Helm** más populares disponibles en ArtifactHub que se implementan y eliminan a intervalos regulares para simular operaciones administrativas.
- Como estos paquetes de software son utilizados comúnmente por los usuarios para implementar aplicaciones y servicios en **Kubernetes**, se considera que las secuencias de operaciones realizadas para cada implementación y eliminación son **realistas y representativas**.
- Guardamos los eventos utilizando los logs de auditoría de **Kubernetes**

DataSet

- 60 paquetes
- 16.548 eventos

Procesado

Collecting and Processing Logs

1. Collecting raw logs

```
{ "kind": "Event", "user": "kubernetes",  
  "verb": "create", "requestURI": "/api/v1/  
pods", "sourceIP": "192.168.1.1",  
  "objectRef": { "resource": "pod" } }  
{ "kind": "Event", "user": "kubernetes",  
  "verb": "delete", "requestURI": "/api/v1/  
pods", "sourceIP": "192.168.1.1",  
  "objectRef": { "resource": "pod" } }  
{ "kind": "Event", "user": "kubernetes",  
  "verb": "create", "requestURI": "/api/v1/  
services", "sourceIP": "192.168.1.1",  
  "objectRef": { "resource": "service" } }  
...
```

2. Extracting events

- Create Pod
- Delete Pod
- Create Service
- Create Pod
- Create Pod
- Create Pod
- Create Service
- Patch Service
- Create Pod
- Patch Service

3. Remove repetitions

- Create Pod
- Delete Pod
- Create Service
- Create Pod
- ~~Create Pod~~
- Create Service
- Patch Service
- Create Pod
- Patch Service

4. Build sequences

- Create Pod, Delete Pod
- Delete Pod, Create Service
- Create Service, Create Pod
- Create Pod, Create Service
- Create Service, Patch Service
- Patch Service, Create Pod
- Create Pod, Patch Service
- Patch Service

Aprendizaje Predictivo

Approach	Size of Window	Accuracy	Offline Learning Time	Runtime Inference Time
Bayesian Network	<i>N.A.</i>	79.7%	4.29 s	1e-4 s
LSTM	1	92.3%	24.01 s	0.06 s
	2	97.6%	32.75 s	0.07 s
<i>n</i> -grams	1	88.2%	0.01 s	1e-4 s
	2	97.3%	0.07 s	2e-4 s

LSTM

Long Short Term Memory



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CONDA Conda package manager





pandas Pandas Data Analysis

marimo Python notebooks

jupyter Python notebooks

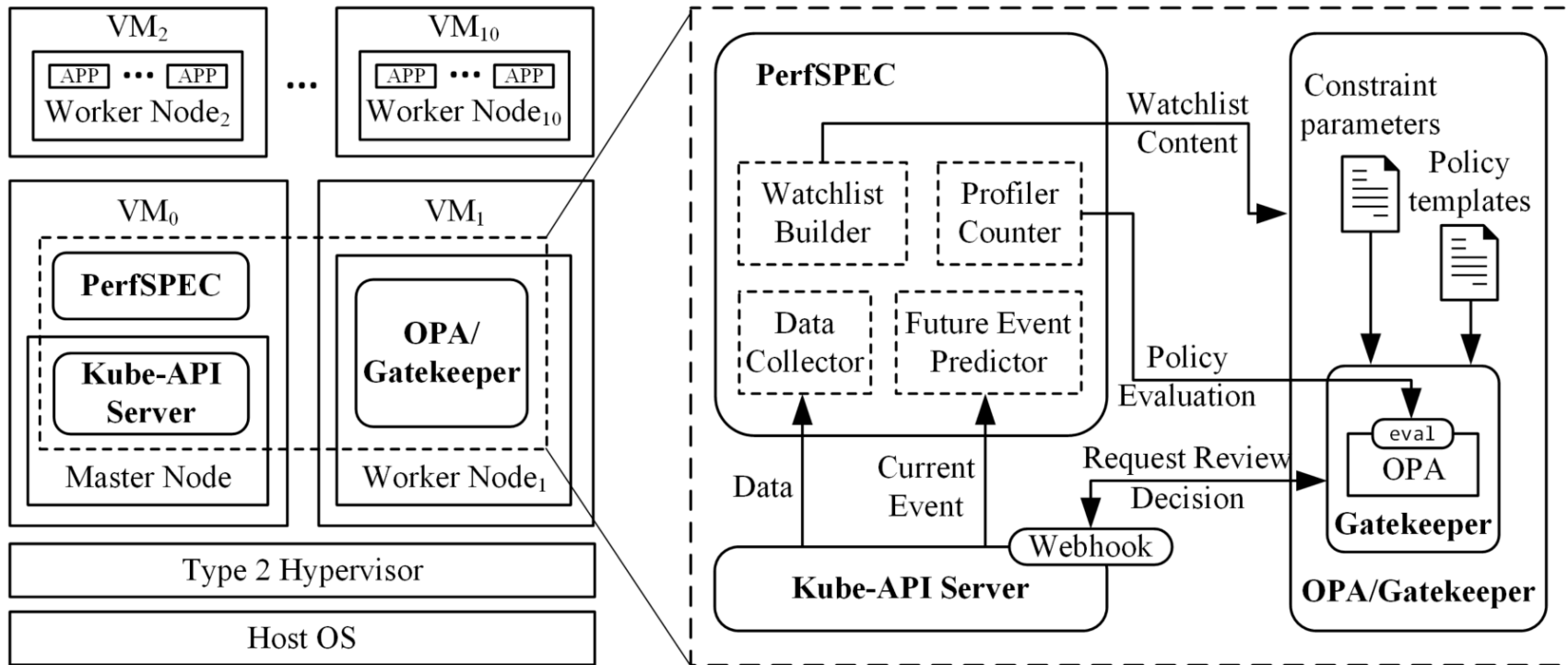
TensorFlow Machine learning



-  Python package and project manager in **Rust**
-  Polars Polars DataFrames **Rust**
-  Nushell + **Dataframes** a **Rust** shell
-  Deep Learning Framework **Rust**

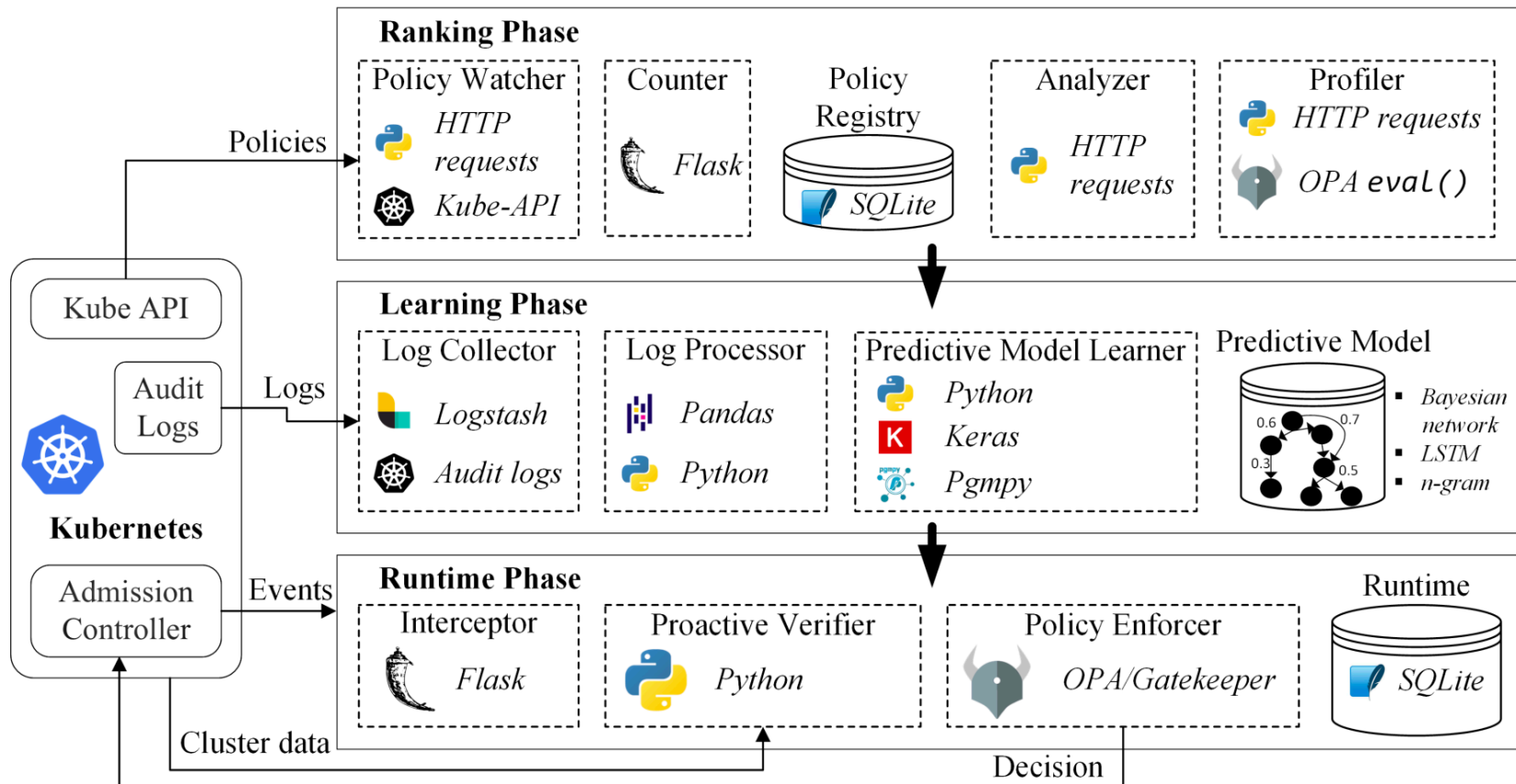
PrefSPEC Runtime Phase

Integración con Kubernetes



Arquitectura inicial

PerfSPEC





 Repositorio **PerfSPEC Learning Phase**

repo.jesusperez.pro/prefspec-learning

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