HP云的模型服务自动化实践

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Content

目录

Part 01

HP云介绍

HP云介绍

- 惠普云主要架在Amazon上，提供惠普内部项目**所有服务**的部署、监控、运维及管理。
  - Kubernetes
  - Istio
  - Harbor
  - Azure Pipeline

- **全方位自动化**
  - 基础设施全面实现即代码化（Infrastructure as Code）
    - Terraform
  - 服务自动化部署，项目组可自助完成部署。
    - Helm, Flux2

Part 02

模型推理平台的需求与设计

模型推理平台的需求

- 模型推理需求日益增长，云端部署与管理：
  - 生成式 AI：Llama3、QWen ...
  - 传统机器学习：Scikit-learn、XGBoost
  - 深度学习：TensorFlow Serving、PyTorch ONNX 模型
  - 其他：Hugging Face Transformers
- 模型存储需支持：Hugging Face、S3、PVC、EFS ... ...
- 任何项目都能**方便**发布自己的模型推理
- 所有模型推理不用任何额外实现，就**自动拥有** 权限管理，限流，动态扩展，可观测性 等功能

模型推理平台的设计

- KServe 为基础 (不用 Knative)
- 不依赖于 KServe, 自己实现
  - 模型访问权限控制 (Istio)
  - HPA 动态扩展 (Prometheus Adapter)
  - 可观测性
  - LLM Token 限流和统计 (enovyfilter)
  - 金丝雀发布 (Istio)
  - API 限流 (Envoy ratelimit)
  - … …

Part 03

基于 KServe/Istio/Envoy 的架构实现

- 模型部署
- 模型访问权限控制
- HPA 动态扩展
- 可观察性
- API Rate Limit
- LLM Token 限流和统计
- 金丝雀发布

Part 03 - 01

实现 – 模型部署

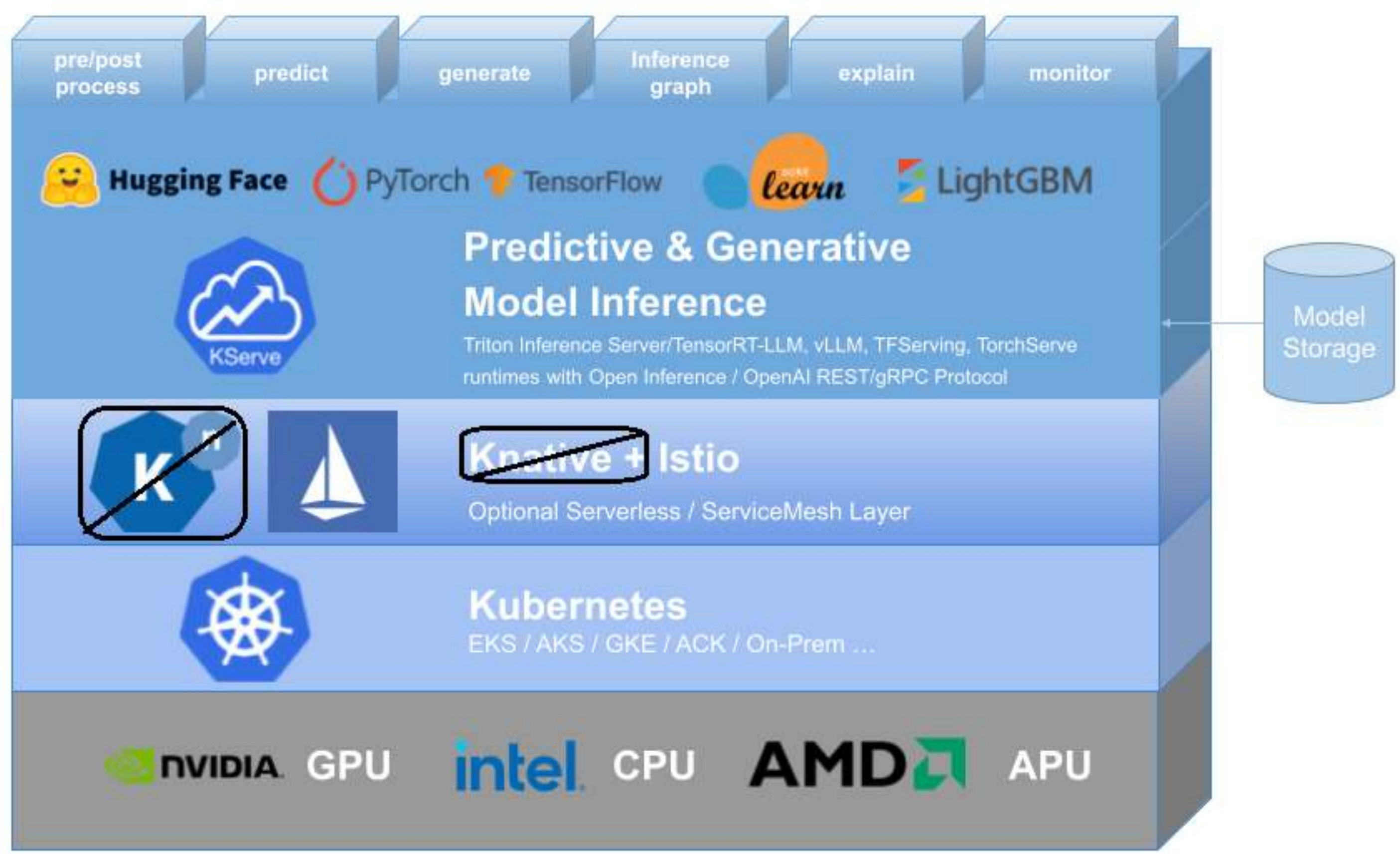
模型部署

KServe：标准化模型推理平台

- 支持多种模型
- 自动化部署

运行环境：Amazon EKS

无服务架构 Knative 不适合我们，所以不用



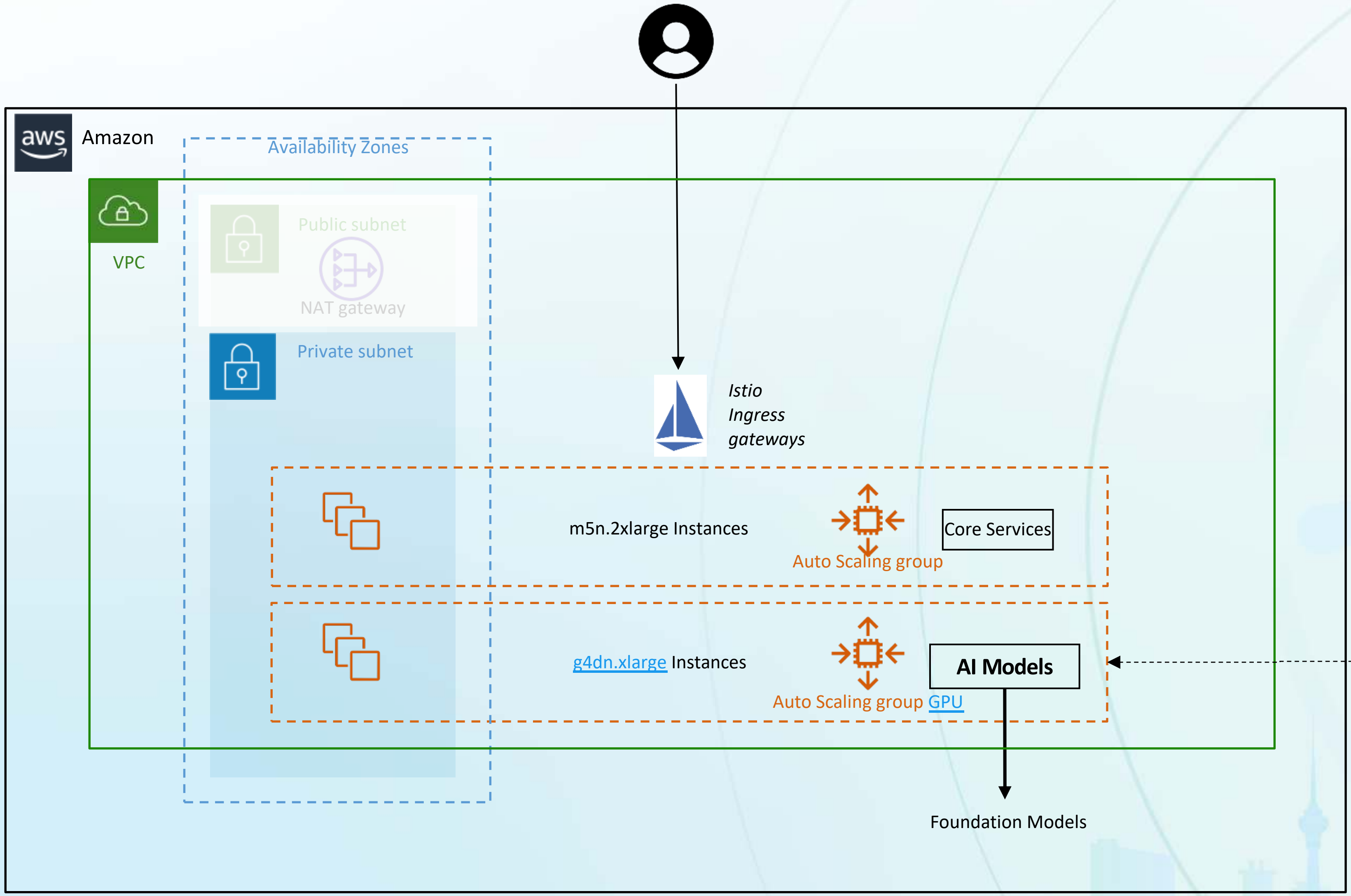
模型部署

- KServe 核心功能：
  - 支持各种推理模型，如： Hugging Face, PyTorch, Scikit-learn … …

    （支持**自定义**推理模型，这样可发布我们自己的模型， 也可以原生使用 vllm 等框架）
  - 支持各种模型存储，如：Hugging Face、S3、PVC、EFS … …
  - 支持 Model Explainability (模型可解释性)
  - 支持 Multi Model Serving(多模型) 和 Inference Graph(推理工作流)

- 集成Helm 和 Flux2，实现自动化部署 [Sample Code]

支持 GPU Node



Install NVIDIA k8s-device-plugin

*Add “nodegroup gpu” in **terragrunt** file:*

```
nodegroup = {
  gpu = {
    node_labels = {
      "node-group" = "gpu",
    }
    node_taints = [
      {
        key    = "nvidia.com/gpu"
        value  = "1"
        effect = "NO_SCHEDULE"
      },
    ]
    instance_type = "g4dn.xlarge"
  },
}
```

支持 GPU Node

模型如何申请 GPU资源？

Enterprise

Model owner 在 配置文件定义：

```
resources:
  requestGPU: 1
  limitGPU: 1
```

HelmRelease Value

```
{{- if or .Values.resources.requestGPU .Values.resources.limitGPU }}
tolerations:
  - key: nvidia.com/gpu
    operator: Exists
{{- end }}
```

```
affinity:
  nodeAffinity:
    requiredDuringSchedulingIgnoredDuringExecution:
      nodeSelectorTerms:
      - matchExpressions:
        - key: eks.amazonaws.com/nodegroup
          {{- if or .Values.resources.requestGPU .Values.resources.limitGPU }}
          operator: In
          {{- else }}
          operator: NotIn
          {{- end }}
          values:
          - {{ .Values.clusterName }}-gpu
  {{- end }}
```

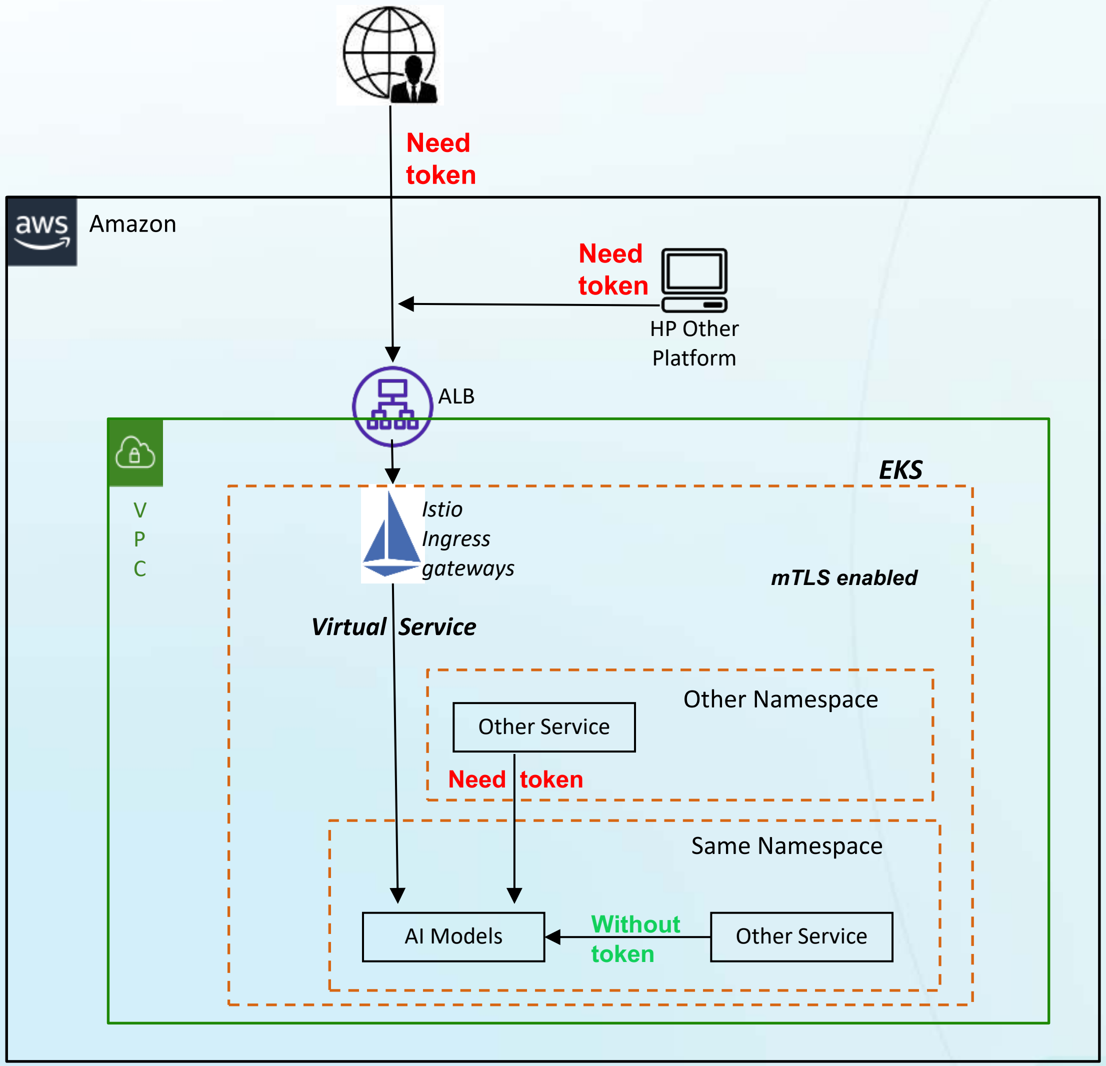
Helm Charts

需要 GPU 的 POD
跑在 GPU Node

Part 03 - 02

实现 – 模型服务访问控制 (通过Istio)

模型服务访问控制



$ curl -X POST -H "Content-Type: application/json" -d payload.json \

https://sample-svc.dev.int.example.com/v2/models/test_model/infer

< HTTP/2 403

RBAC: access denied

$ curl -X POST -H "Content-Type: application/json" -d payload.json \

https://sample-svc.dev.int.example.com/v2/models/test_model/infer \

-H "Authorization: Bearer $token"

< HTTP/1.1 200 OK

{ … ….

模型服务访问控制

1. 启用 Istio mTLS

   详情链接

2. 通过 Istio Virtual Service 发布模型服务

   详情链接

3. Authentication And Authorization by Istio

   - 外部访问需Token
   - 同Namespace不需Token
   - CUSTOM Authorization 增强保护

   详情链接

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Part 03 - 03

实现 – HPA 动态扩展

HPA 动态扩展

需求：支持模型配置 Horizontal Pod Autoscaler (动态扩展)，基于：

- CPU utilization
- Memory utilization
- **Requests per second**
- **GPU utilization**

设计：

- 基于 CPU utilization, Memory utilization 是 HPA 默认支持的
- 使用 Prometheus adapter, 支持 HPA 基于 Custom metrics

Prometheus Adaptor

HPA 动态扩展

- Prometheus adapter 的架构和安装 详细

- 如何实现 HPA based on "Requests per second"

  基于 Istio metrics **istio_requests_total**

  具体例子

- 如何实现 HPA based on " HPA - GPU utilization "

  安装 NVIDIA gpu-operator

  基于 Nvidia metrics **DCGM_FI_DEV_GPU_UTIL**

  具体例子

HPA 动态扩展

Flux: Install Prometheus adaptor [Code]

```yaml
---
apiVersion: helm.toolkit.fluxcd.io/v2beta2
kind: HelmRelease
metadata:
  name: prometheus-adapter
  namespace: infra
spec:
  releaseName: prometheus-adapter
  chart:
    spec:
      chart: prometheus-adapter
      version: 4.10.0
      sourceRef:
        kind: HelmRepository
        name: prometheus
  values:
    prometheus:
      url: http://prometheus-server.infra.svc.cluster.local
      port: 80
    rules:
      default: false
      custom:
      - seriesQuery: istio_requests_total{pod!="", namespace!=""}
        resources:
          overrides:
            namespace:
              resource: namespace
            pod:
              resource: pod
        name:
          matches: "istio_requests_total"
          as: "requests_per_second"
        metricsQuery: sum(rate(<<.Series>>{<<.LabelMatchers>>}[2m])) by (<<.GroupBy>>)
      - seriesQuery: '{__name__=~"^DCGM_FI_DEV_GPU_UTIL$", app="nvidia-dcgm-exporter", containe
        resources:
          overrides:
            exported_namespace:
              resource: namespace
            pod:
              resource: pod
        name:
          matches: DCGM_FI_DEV_GPU_UTIL
          as: "gpu_utilization"
        metricsQuery: avg(avg_over_time(<<.Series>>{<<.LabelMatchers>>}[1m])) by (<<.GroupBy>>)
```

Helm Chart: HPA template [Code]

```yaml
apiVersion: autoscaling/v2
kind: HorizontalPodAutoscaler
metadata:
  name: {{ .Release.Name }}-predictor
  namespace: {{ .Release.Namespace }}
  labels:
    app: {{ .Release.Name }}
spec:
  scaleTargetRef:
    apiVersion: apps/v1
    kind: Deployment
    name: {{ .Release.Name }}-predictor
  {{- with .Values.autoscaling.targetGPUUtilizationPercentage }}
  - type: Pods
    pods:
      metric:
        name: gpu_utilization
      target:
        averageValue: {{ . }}
        type: Value
  {{- end }}
  {{- with .Values.autoscaling.targetRequestRate }}
  - type: Pods
    pods:
      metric:
        name: requests_per_second
      target:
        averageValue: {{ . }}
        type: Value
  {{- end }}
```

Helm Release Values [Example]

```yaml
replicaCount: 1
autoscaling:
  maxReplicaCount: 10
  targetCPUUtilizationPercentage: 80
  targetMemoryUtilizationPercentage: 70
  targetGPUUtilizationPercentage: 75
  targetRequestRate: 100
```

Part 03 - 04

实现 – 可观测性 (Observability)

可观测性

如何实现 AI 模型的可观测性？

- 日志
  - KServe 日志组件
  - Istio Access log
- Metrics
  - Enable KServe metrics for Prometheus
  - Model metrics (vLLM)
  - GPU Metrics
  - Istio Metrics

可观测性

日志

- KServe 日志组件 [详细]

With **KServe Inference Logger, all predict header/ body of requests/ response** can be sent to your "message handle" service, for save to S3, database, or just print out.

```yaml
apiVersion: serving.kserve.io/v1beta1
kind: InferenceService
metadata:
  name: sklearn-iris
spec:
  predictor:
    logger:
      mode: all
      url: http://message-dumper.default/
    model:
      modelFormat:
        name: sklearn
      storageUri: gs://kfserving-examples/models/sklearn/1.0/model
```

Configure

```
{  "instances": [    [6.8,  2.8,  4.8,  1.4],    [6.0,
Received Request:
x-request-id: e4123d01-5d29-9ab8-8f4a-76761d62d18b
x-b3-traceid: 4933d0bdf218ca0c3b514339c0f9fd9f
x-b3-spanid: 2d576fcb7dd00f52
x-b3-flags: Not provided
Payload:
{"predictions":[1,1]}
```

Logs in message service

- Istio Access log [详细]
  - Include API host, method, path, response code, duration ... ...

可观测性

Metrics – Enable KServe metrics for Prometheus [文档]

所有推理服务都有相应的 metrics, 如：

- KServe 默认支持的模型定义在 kserve/config/runtimes

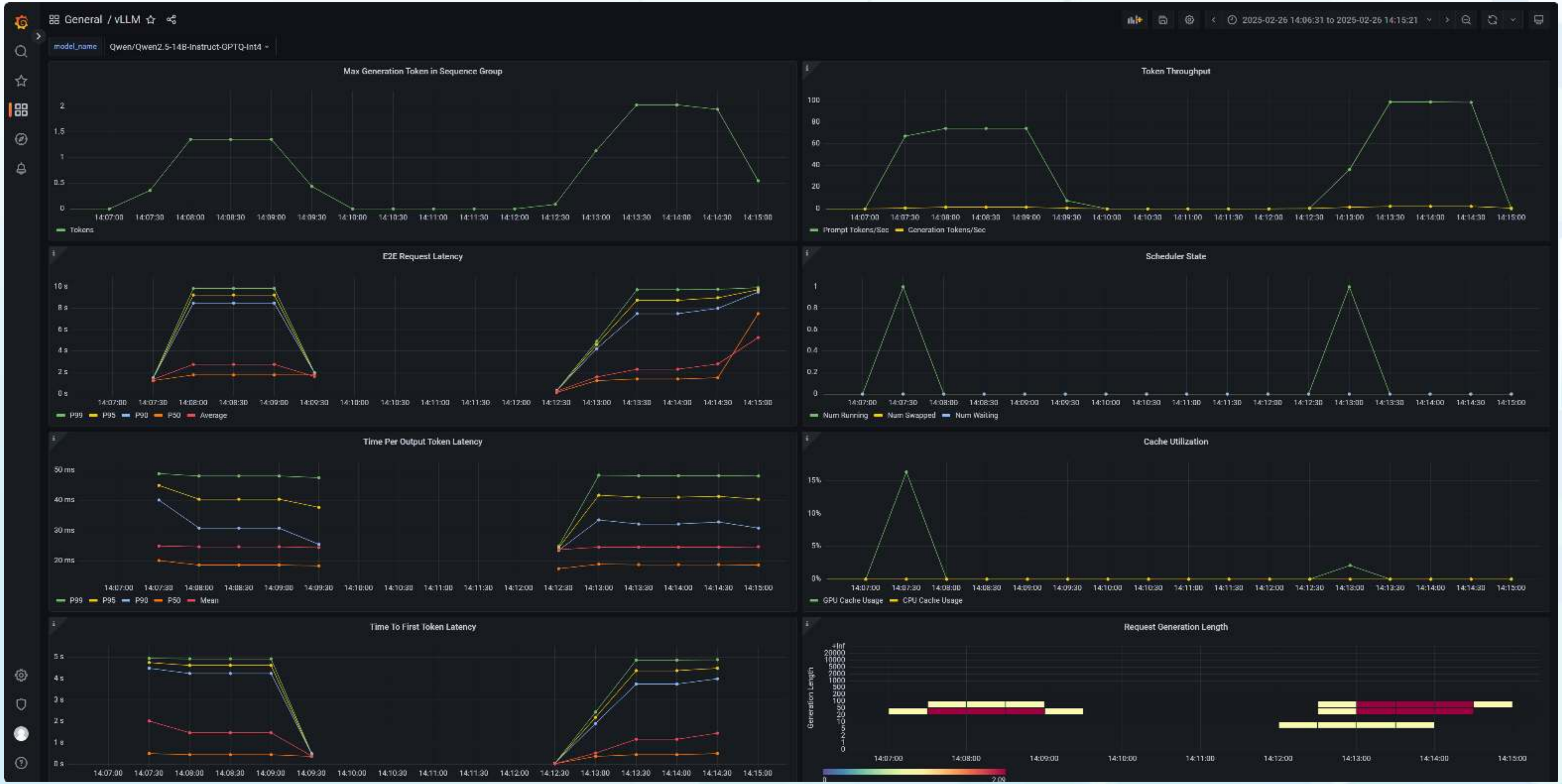
```yaml
metadata:
  name: kserve-torchserve
spec:
  annotations:
    prometheus.kserve.io/port: '8082'
    prometheus.kserve.io/path: "/metrics"
```

- 自定义模型 (Custom Model) 可以自己定义在 Helm Chart

```yaml
apiVersion: serving.kserve.io/v1beta1
kind: InferenceService
metadata:
  annotations:
    {{- if and .Values.metrics .Values.metrics.enabled }}
    prometheus.io/scrape: 'true'
    prometheus.io/port: {{ .Values.metrics.port | default 8082 | quote }}
    prometheus.io/path: {{ .Values.metrics.path | default "/metrics" }}
    {{- end }}
  name: {{ .Release.Name }}
```

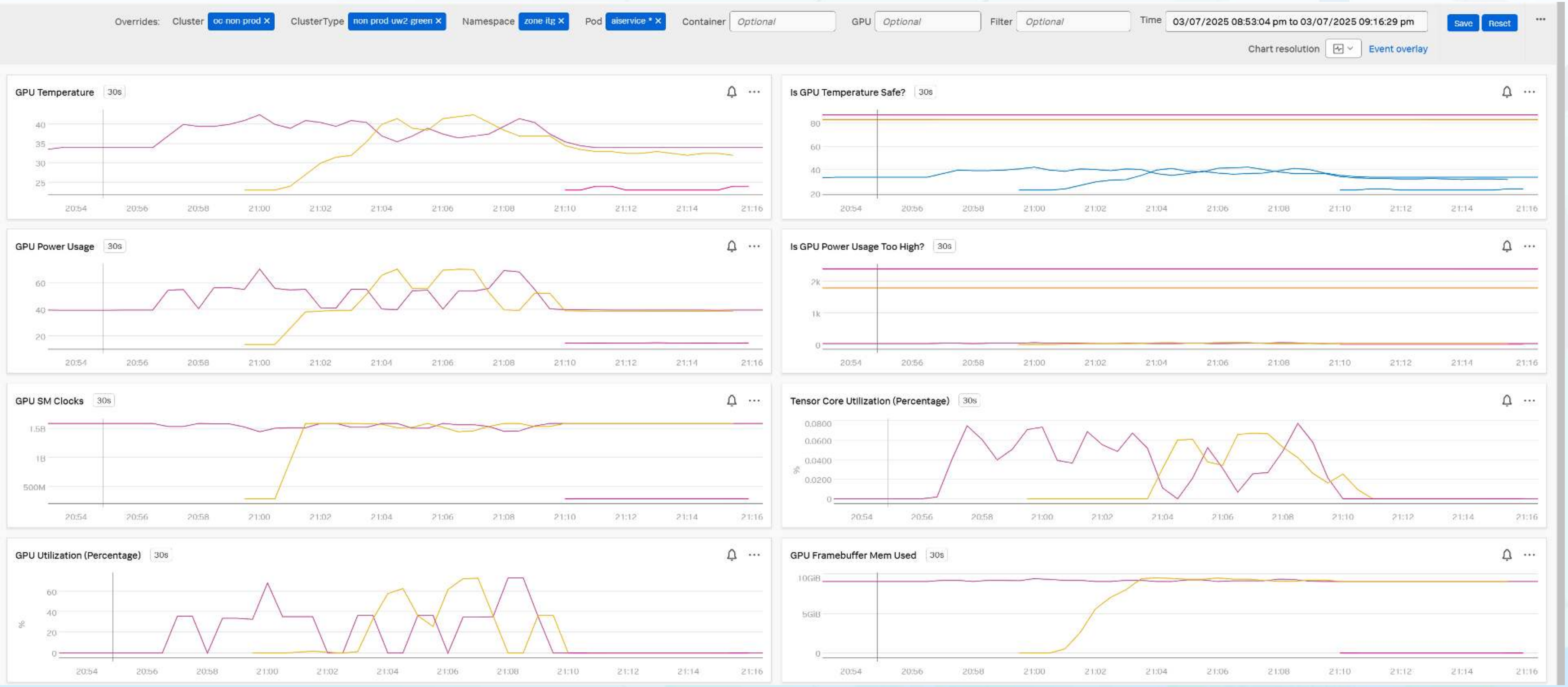
可观测性

例子： Custom Model 千问的 metrics [配置]



可观测性

例子：GPU metrics



Part 03 - 05

实现 – API Rate Limit

API Rate Limit

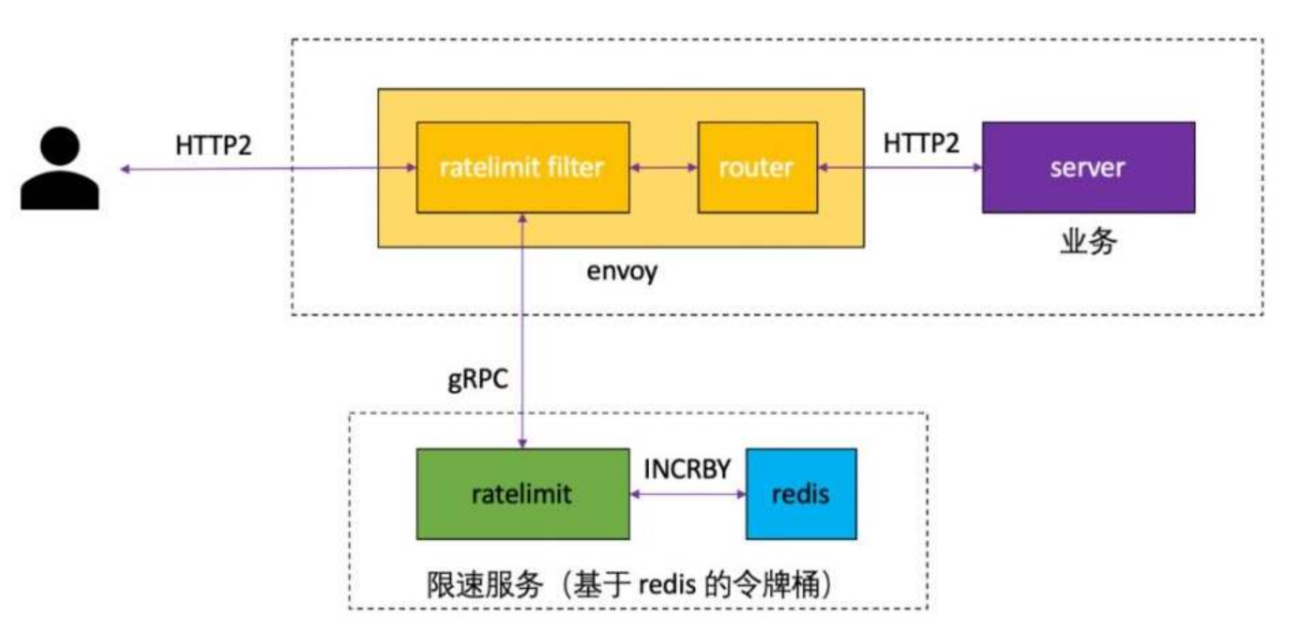
目的： API 级别的限流

- 每一个 IP 限制每分钟的 API 访问量
- 每一个 tenant 限制每分钟的 API 访问量

配置：

```
ratelimitIPPerMinute: 10
ratelimitEachSAPerMinute: 100
```

如何实现： [详细]



Part 03 - 06

实现 – LLM Token 限流和统计

LLM Token 限流和统计

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Invoke API: (under token limitation)

curl https://qwen-predictor-default.api.sandbox-uw2.sample.io/v1/chat/completions -H "Content-Type: application/json" -H 'Authorization: Bearer **$token**' -d '{ "model": "Qwen/Qwen2.5-14B-Instruct-GPTQ-Int4", "messages": [{"role": "system", "content": "You are a helpful assistant."}, {"role": "user", "content": "**1 + 1 =?**"}] }'

{"id":"chatcmpl-3634b846-bf56-9c98-ae57-8252df864ff7","object":"chat.completion","created":1740653385,"model":"Qwen/Qwen2.5-14B-Instruct-GPTQ-Int4","choices":[{"index":0,"message":{"role":"assistant","reasoning_content":null,"content":"**1 + 1 = 2**", "tool_calls":[]},"logprobs":null,"finish_reason":"stop","stop_reason":null}],"usage":{"**prompt_tokens":25**,"**total_tokens":33**,"**completion_tokens":8**,"prompt_tokens_details":null},"prompt_logprobs":null}

Invoke API: (Over token limitation)

curl https://qwen-predictor-default.api.sandbox-uw2.sample.io/v1/chat/completions -H "Content-Type: application/json" -H 'Authorization: Bearer **$token**' -d '{ "model": "Qwen/Qwen2.5-14B-Instruct-GPTQ-Int4", "messages": [{"role": "system", "content": "You are a helpful assistant."}, {"role": "user", "content": "**1 + 1 =?**"}] }'

< HTTP/2 400
Usage over limit -- serviceAccount + IP.

[Envoyfilter 代码]

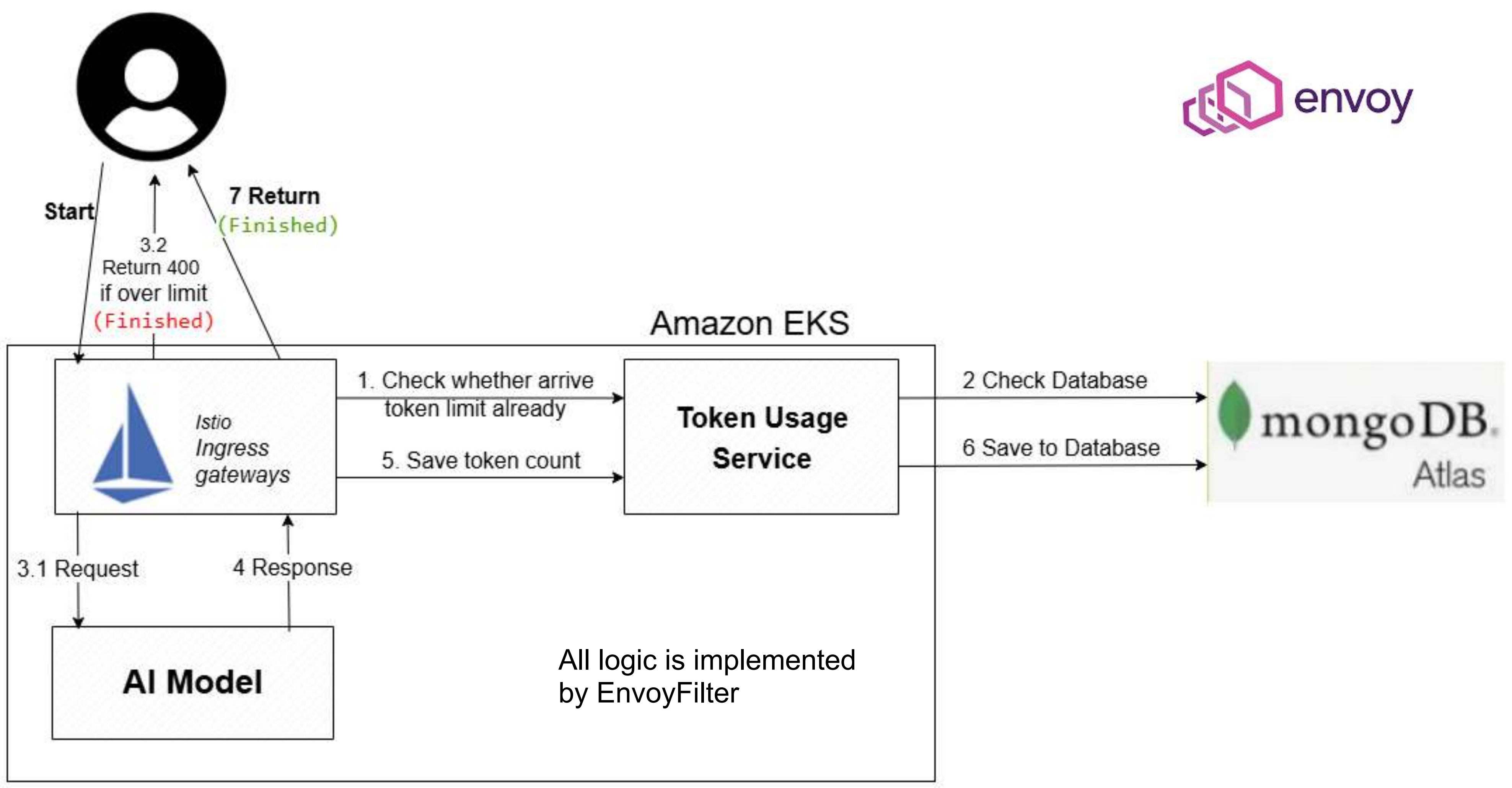
modelToken.tenantLimitation

```
_id: ObjectId('67b9e35ea2876d5f86c7c29b')
sa_limit : 12000
ip_limit : 400
tenant_id : "tenant01"
```

modelToken.sa_ip_usage_daily

```
_id: ObjectId('67c042e4317d13162b21de16')
serviceAccount : "console@zone-prod.hpoc-sa.com"
clientIP : "15.65.196.24"
date : "2025-02-27"
usage : 421
```

LLM Token 限流和统计



Envoyfilter 代码

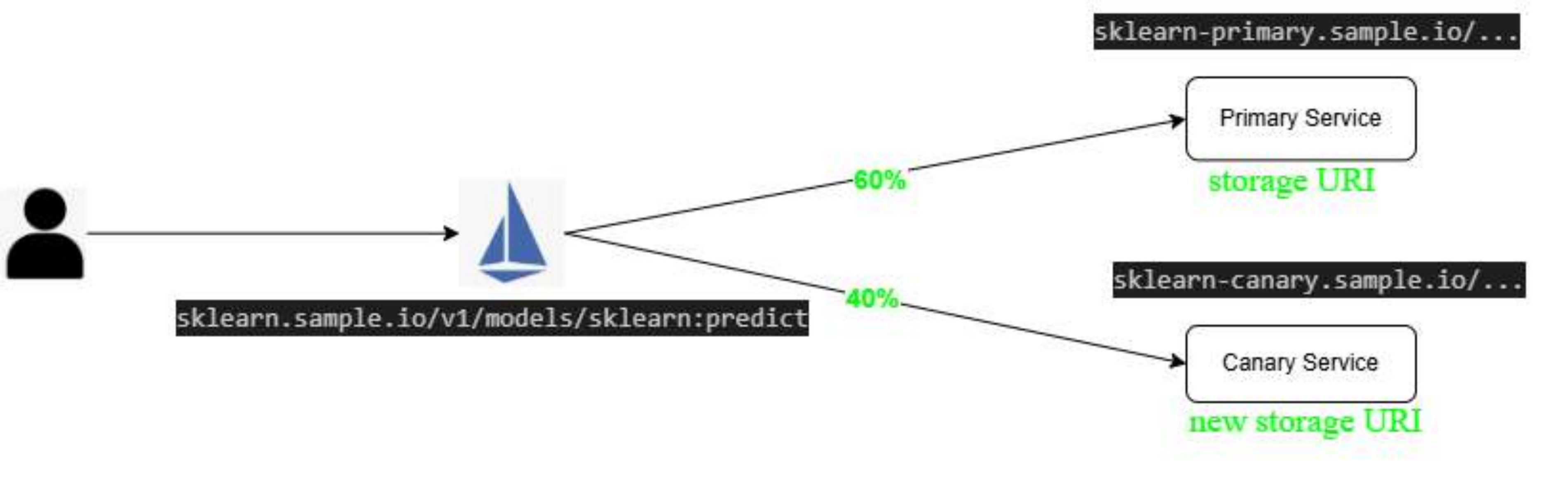
Part 03 - 07

实现 – 金丝雀发布 (Canary)

金丝雀发布 (Canary)

需求：与传统的金丝雀发布只注重 container image 不同，模型的金丝雀发布更要注重模型的版本。

设计：创建两个 inference service。
他们所有值，对象都一样，除了 storage Uri 和 container image tag.
两个 inference service 的流量分配 用 Istio virtual service 来实现。



金丝雀发布 (Canary)

Helm Chart 设计：建立新的 kserve-general Chart
[详细]

分流的实现：Istio Virtual Service
[详细]

原 Chart 改动: 兼容直接调用
[详细]

Flux调用
[详细]

测试
[详细]

```yaml
apiVersion: networking.istio.io/v1
kind: VirtualService
metadata:
  name: sklearn-predictor
  namespace: project
spec:
  gateways:
  - istio-system/apigee-gateway
  hosts:
  - sklearn-predictor-project.int.dev-us.sample.io
  http:
  - match:
    - uri:
        regex: ^/.+$
    name: sklearn-predictor
    route:
    - destination:
        host: sklearn-primary-predictor
        port:
          number: 80
      weight: 60  #{{ .Values.primaryLoad }}
    - destination:
        host: sklearn-canary-predictor
        port:
          number: 80
      weight: 40 # {{ sub 100 .Values.primaryLoad }}
```

总结

总结

- 实现统一的模型推理平台，除了选择 KServe 这样的工具发布模型，更要让各个模型自动获得模型访问权限控制， HPA 动态扩展， 可观测性，LLM Token 限流和统计， 金丝雀发布， API 限流。 我们集成 Istio, Envoy, Prometheus Adaptor, GPU Operate, 很好地实现了这些功能。

- 由于是自己实现， 非常灵活，可以根据自己的需求方便地定制。

- 利用 Helm, Flux，实现全方位自动化。用户通过配置，方便地发布各种模型。

实现简单，架构清晰。欢迎大家参考，同样地实现 [代码]

问 答

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