

# Kubeflow: Multi-Tenant, Self-Serve,

# **ML Platform**

kunming@google.com kam.d.kasravi@intel.com

## Enabling the end user

- Multi-tenant self-serve workspaces for developers and data scientists
- Do not saddle the end user with k8s details
- Deploy job to the right CPU/Accelerated hardware
- Kustomize overlays for different cpu/accelerated hardware combinations



## **Kubeflow: A platform for building ML products**

- Leverage containers and Kubernetes to solve the challenges of building ML products
  - Reduce the time and effort to get models launched
- Why Kubernetes
  - Kubernetes has won
  - Kubernetes runs everywhere
  - Enterprises can adopt shared infrastructure and patterns for ML and non ML services
  - Knowledge transfer across the organization
- Kubeflow is open
  - $\circ \quad \text{No lock in} \quad$
  - 200 Members
  - 20+ Organizations
  - Stats available @ <u>http://devstats.kubeflow.org</u>



## **Kubeflow Cloud Providers**

- Google Kubernetes Engine
- AWS
- Azure

## **Kubeflow Native K8**

• Deployable to any k8 existing cluster



## **ML** Applications

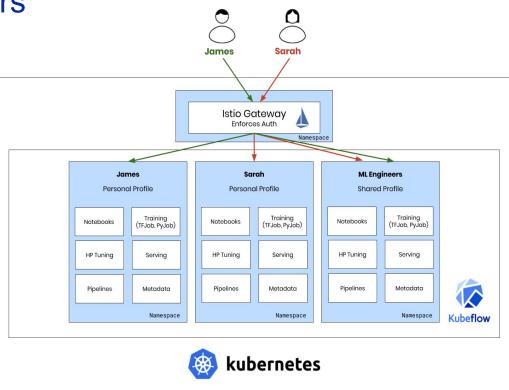
- Goal: applications for every stage of ML
- Examples:
  - Experimentation / Data Exploration
    - Jupyter / Notebook Spawner
  - $\circ$  Training
    - Tensorflow & Pytorch distributed training managed through K8s CRDs
    - Katib HP Tuning
  - Workflows:
    - Pipelines
  - o Metadata
    - Tracking and managing metadata of ML workflows
  - Feature Store
    - Feast (from GOJEK)





## Multi Tenancy for End Users

Users will operate on same k8s cluster while each user has their own workspace hosting their services. Workspaces are logically isolated: each user can only access services to their own workspace.





## K8s Multi-Tenancy Challenges

- Define clear user workspace boundary for access isolation
- K8s in-cluster network is transparent
  - Services are by default visible from all pods
  - Need to establish network access control
- Access control around traffic through shared ingress
  - Users might access services in their own workspaces through same ingress.
  - Need to establish access control behind ingress: user can only access workspace after permission check
- Workspace access sharing & revoke
  - Each workspace owner should be able to share/revoke workspace access
  - Access sharing should not leak owner privilege while allow invited user operating on CRs
- All policies, roles and bindings involved should behave in consistency.



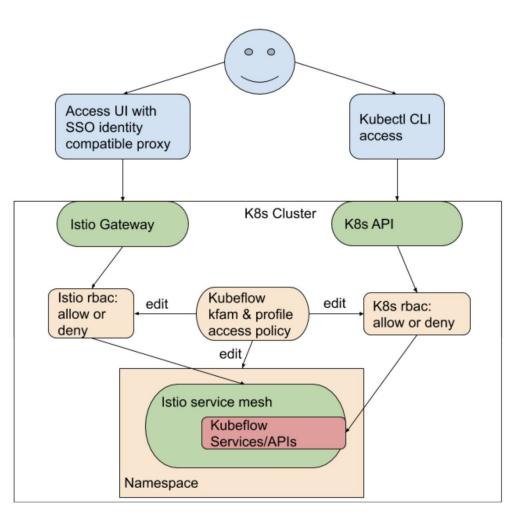
# Kubeflow Multi-Tenancy (Profiles)

- Define user workspace as namespace and build access control around it
  - Manage user access to namespace through k8s rbac policy.
- Leverage Istio to control in-cluster traffic
  - By default requests to user workspaces are denied unless allowed by Istio Rbac
- Leverage Identity-Aware Proxy and Istio to control traffic through ingress
  - Identity user request through Identity-Aware Proxy.
  - Istio then do rbac check on request target workspace and identity
- Enable workspace access sharing & revoke
  - Workspace owners can share/revoke workspace access with other users through kubeflow UI
  - Invited users will have k8s edit permission plus permission to operate kubeflow CRs
- Self-serve
  - New user can self-register to create and own their workspace through kubeflow UI
- Kubeflow Profile CR to control all policies, roles and bindings involved and guarantee consistency.
  - Offer plugin interface to manage external resource/policy outside k8s, eg. access control of public cloud APIs



## **Kubeflow Access Control**

- User access through kubectl: controlled by k8s rbac policy.
- User access through browser: controlled by istio rbac policy.
- Kubeflow multi-tenancy is implemented k8s-native way, new services can be integrated easily.





## **Kubeflow Profile**

## Created by the user via cli: kubectl apply -f myprofile.yaml or kubeflow UI

apiVersion: kubeflow.org/v1alpha1 kind: Profile metadata: name: \$(name) spec: owner: \$(owner)

Data scientists use Profiles to create various types of workspaces, where they can run training, inference, etc.



## Create Kubeflow Profile -

## yaml

apiVersion: kubeflow.org/v1beta1 kind: Profile

kind: Profi

metadata:

name: demo-namespace # profile name is also namespace name spec:

#### owner:

#### kind: User

name: user1@email.com # replace with the email of the user plugins:

- kind: WorkloadIdentity

spec:

gcpServiceAccount: user1-gcp@project-id.iam.gserviceaccount.com

## Kubeflow

#### Namespace

ui

A namespace is a collection of Kubeflow services. Resources created within a namespace are isolated to that namespace. By default, a namespace will be created for you.

#### Namespace Name

demo-namespace





## Share Kubeflow Profile with other users





## Kubeflow Device Overlays (accelerators, cpus)

- Device Overlays into Profiles, Pods
- Uses Profile extensions, Tekton Pipelines
- Can also be applied to Argo workflows and other pipeline engines



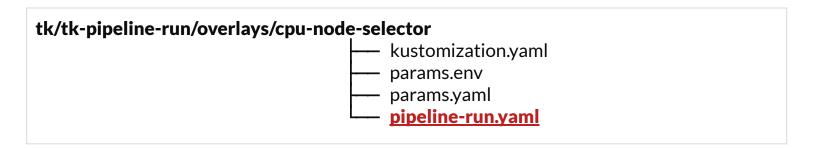
## Kubeflow Profile adds cpu/accelerator quotas

Has a quotas section that is added to the namespace

```
apiVersion: kubeflow.org/v1alpha1
kind<sup>.</sup> Profile
metadata:
 name: $(name)
spec:
 owner: $(owner)
                                         This could be added by an admission-controller or
 quota:
                                         gitops
  hard:
   requestsCpu: $(requestsCpu)
   requestsMemory: $(requestsMemory)
   requestsGpu: $(requestsGpu)
   limitsCpu: $(limitsCpu)
   limitsMemory: $(limitsMemory)
   <vendor/device>: <value>
```



kfctl can deploy manifest files from different repos or on disk





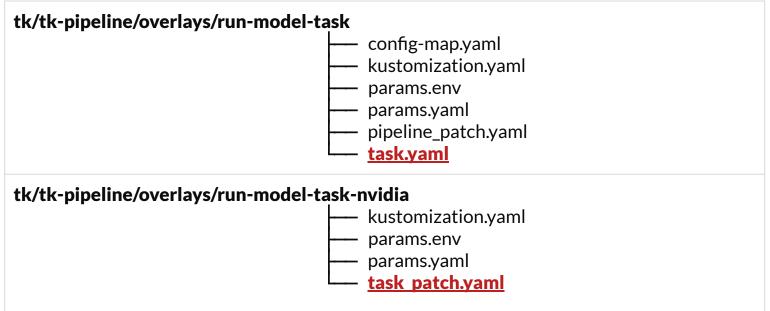
Adds a podTemplate.nodeSelector.cpu value

tk/tk-pipeline-run/overlays/cpu-node-selector/pipeline-run.yaml

apiVersion: tekton.dev/v1alpha1 kind: PipelineRun metadata: name: \$(generateName) spec: podTemplate: nodeSelector: cpu: "\$(cpuType)"



kfctl can deploy manifest files from different repos or on disk





## run-model example

### tk/tk-pipeline-run/overlays/run-model-task/task.yaml

apiVersion: tekton.dev/v1alpha1 kind: Task metadata: name: run-model spec: inputs: params: - name: imageName type: string steps: - name: run-model image: \$(inputs.params.imageName) command: ["/bin/bash", "/run-model/run-model.sh"]



task is patched to add gpu info

tk/tk-pipeline-run/overlays/run-model-task-nvidia/task\_patch.yaml

 op: add path: /spec/steps/0/resources value: limits: nvidia.com/gpu: \$(accelerator\_count)



config file to run a model on a node with cpu=skylake, nvidia.com/gpu

- kustomizeConfig:	- kustomizeConfig:
overlays:	overlays:
- run-model-task	- application
- run-model-task-nvidia	- cpu-node-selector
parameters:	parameters:
- name: accelerator_count	- name: cpuType
value: 1	value: skylake
repoRef:	repoRef:
name: manifests	name: manifests
path: tk/tk-pipeline	path: tk/tk-pipeline-run
name: <b>tk-pipeline</b>	name: tk-pipeline-run



## DEMO

- A kubeflow deployment that created a GKE cluster with 2 nodes

CPU Platform	Accelerator Type	Machine Type	Image Type
Intel Skylake	gpu nvidia-tesla-t4	n1-standard-8	cos
Intel Cascade Lake	-	c2-standard-8	ubuntu

- Run the same tensorflow model within a Profile but with different overlays

Pod limits selects the accelerator type (nvidia.com/gpu: '1') Pod affinity selects the cpu platform (cpu: cascadelake)



# Kubeflow

# **Thank You**

- Kubeflow website <u>https://www.kubeflow.org/</u>
- Code <u>https://github.com/kubeflow/kubeflow</u>