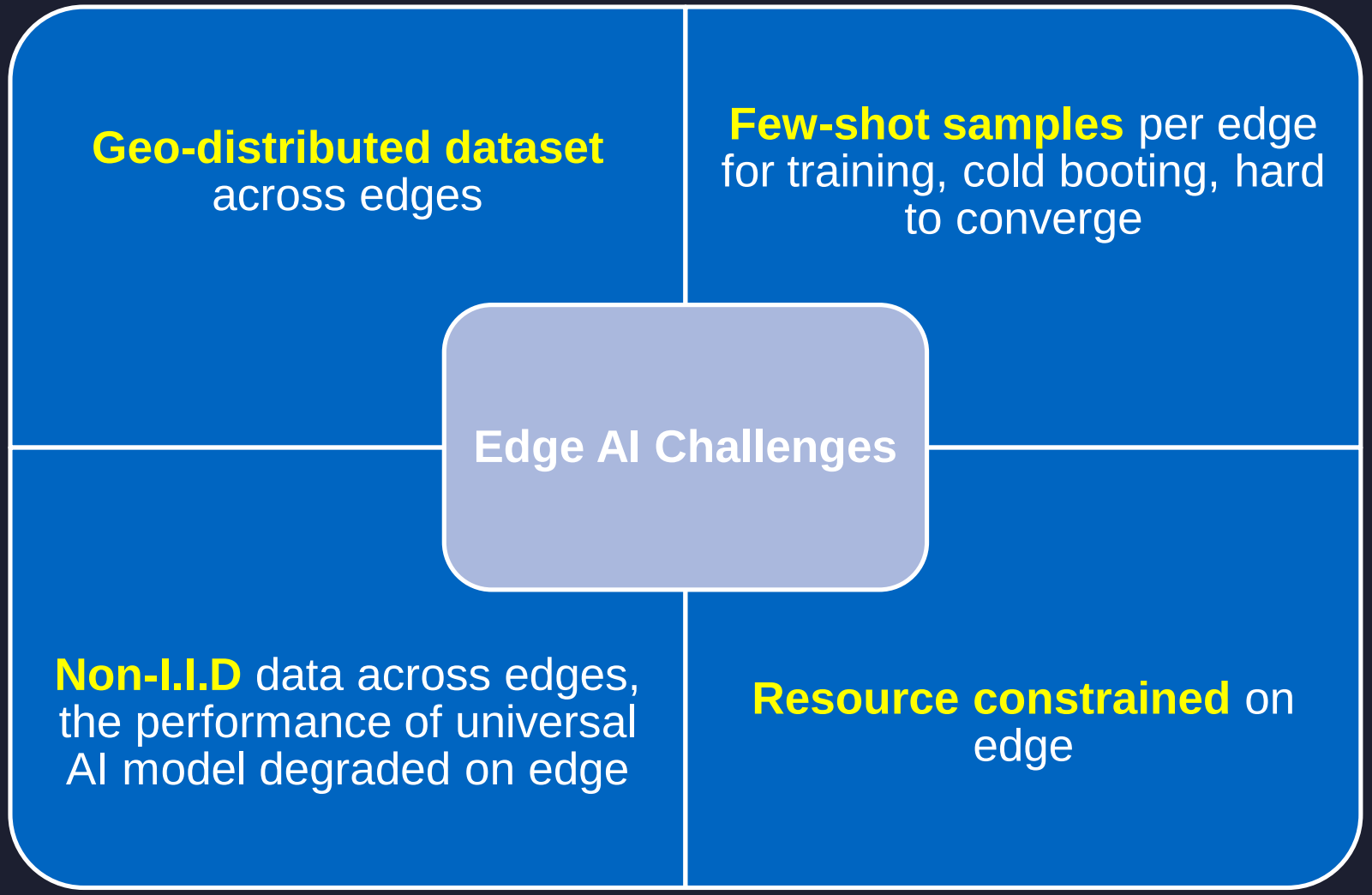
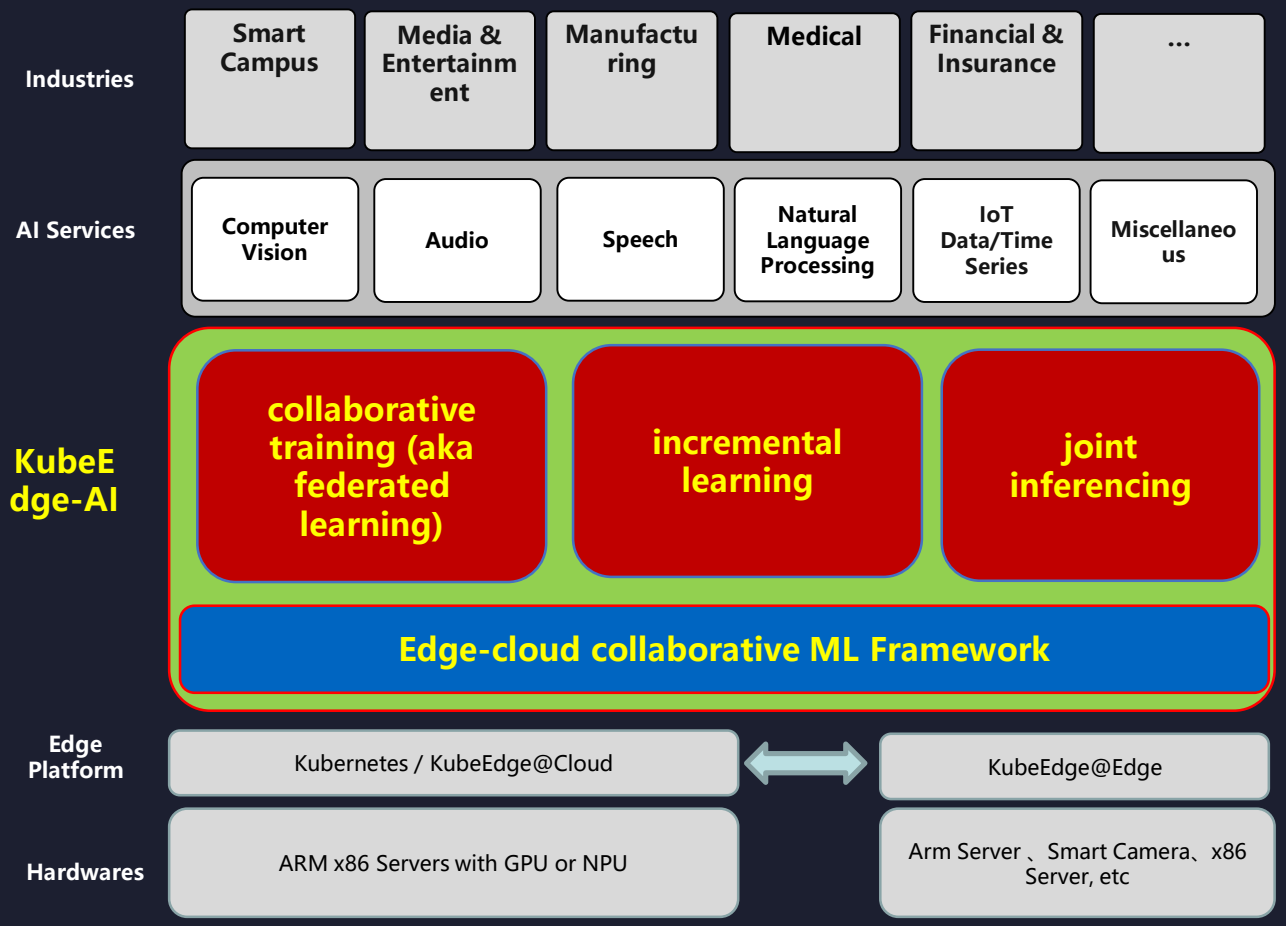
KubeEdge-AI Intro

Edge AI Challenges



KubeEdge-AI



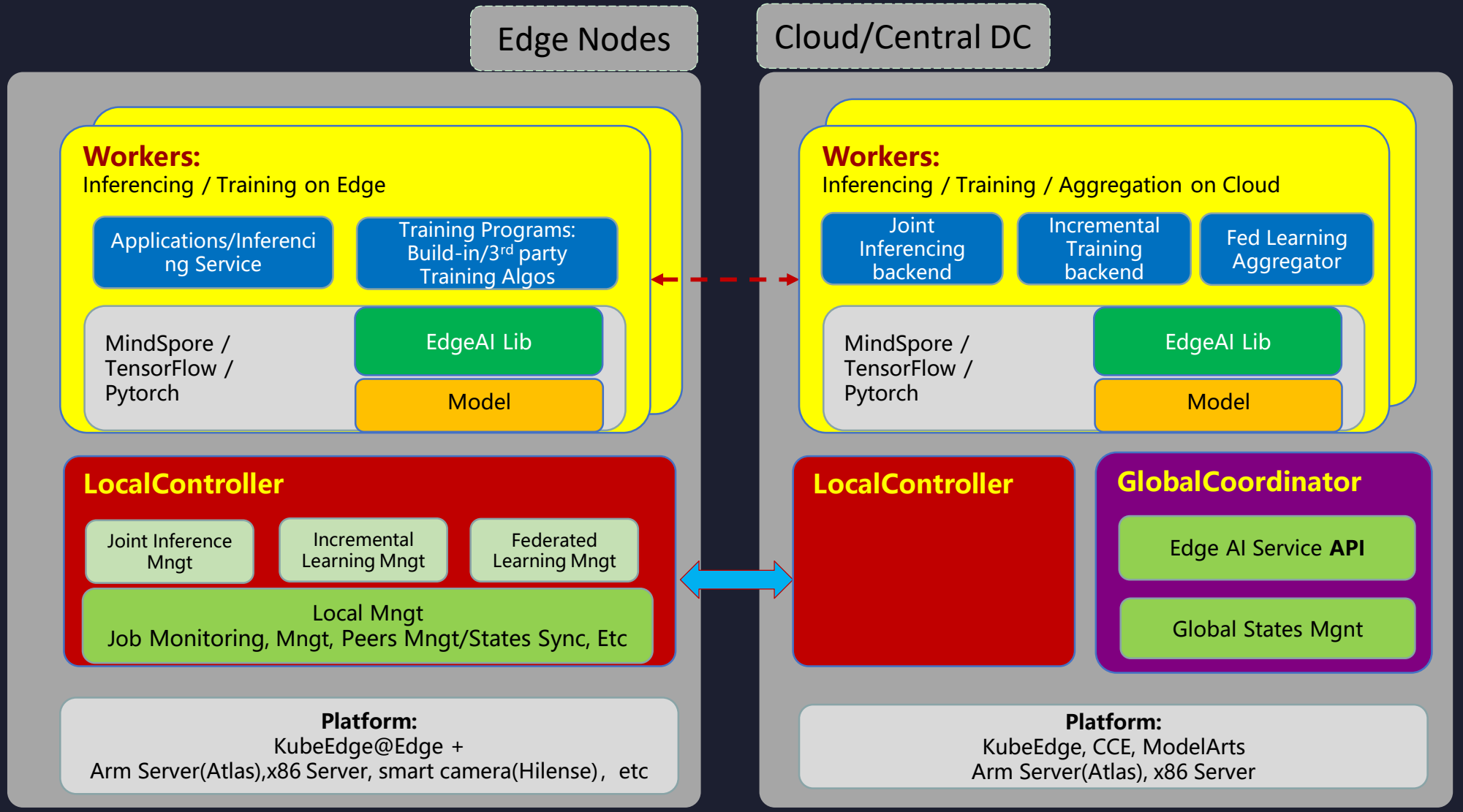
- What we propose：
  - ① an edge-cloud collaborative ML framework based on KubeEdge
  - ② with embed collaborative training and joint inferencing algorithm, which can
  - ③ working with existing AI framework like Tensorflow, etc
- 3 Features：
  - ① joint inferencing
  - ② incremental learning
  - ③ collaborative training (aka federated learning)
- Targeting Users：
  - ① Domain-specific AI Developers: build and publish edge-cloud collaborative AI services/functions easily
  - ② Application Developers: use edge-cloud collaborative AI capabilities.

We are NOT:

- ① to re-invent existing ML framework, i.e., tensorflow, pytorch, mindspore, etc.
- ② to re-invent existing edge platform, i.e., kubeedge, etc.
- ③ to offer domain/application-specific algorithms, i.e., facial recognition, text classification, etc.

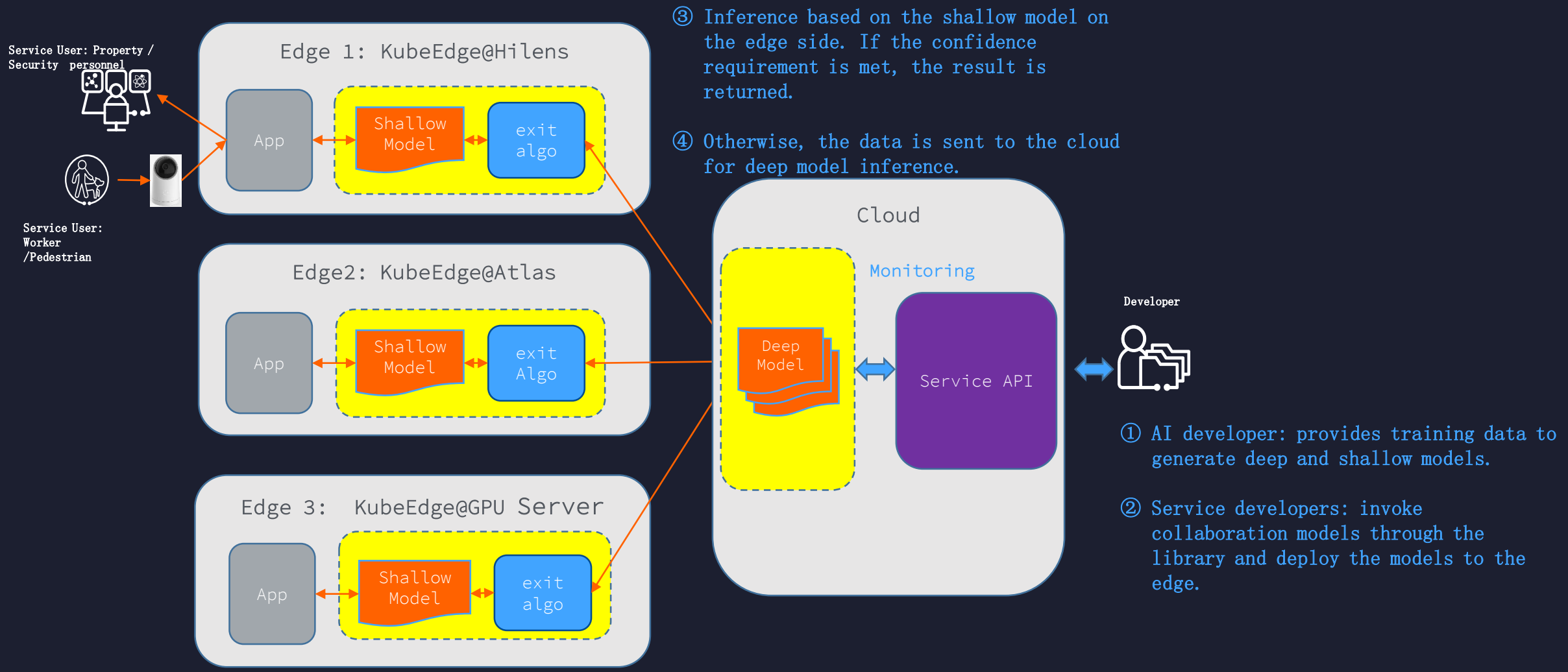
Service Architecture

- **Workers:**
  - do inferencing or training, based on existing ML framework;
  - launch on demand, imagine they are docker containers;
  - different workers for different features;
  - could run on edge or cloud.
- **Lib:**
  - expose the Edge AI features to applications, i.e. training or inferencing programs.
- **GlobalCoordinator**
  - uniportal of EdgeAI,
  - across-edges coordination
- **LocalController**
  - local controller
  - manage local dataset and models



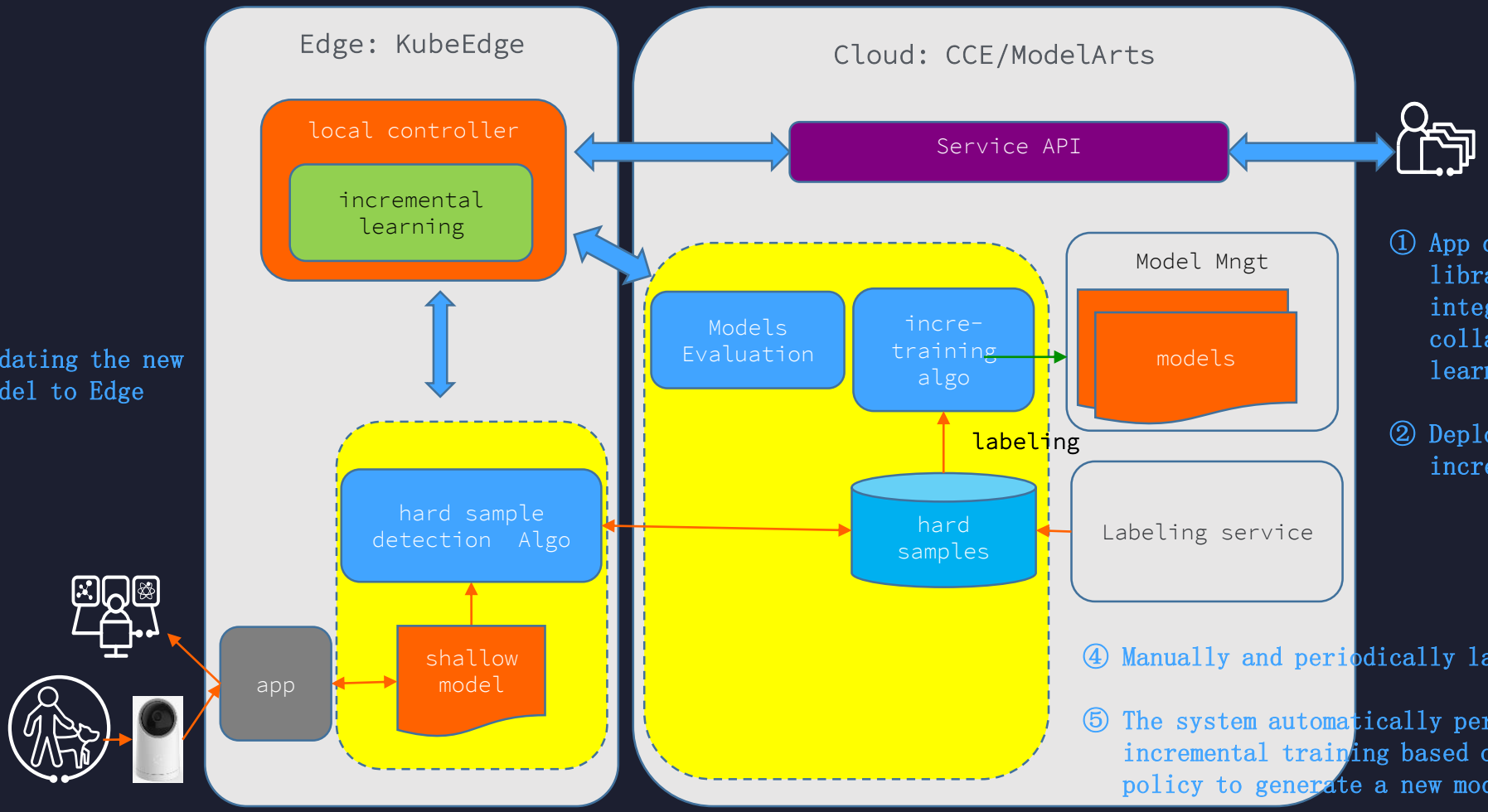
Edge-cloud Collaborative JOINT INFERENCE

Improve the inference performance, when edge resources are limited.



Edge-cloud Collaborative INCREMENTAL LEARNING

The more models are used, the smarter they are.



① App developers: Use the Edge AI library during development to integrate the edge-cloud collaborative incremental learning function.

② Deploy the app and start incremental learning.

③ The hard sample detection algorithm in the Edge AI library identify the samples with low inference confidence, and upload them to the cloud labeling service.

④ Manually and periodically label samples.

⑤ The system automatically performs incremental training based on the preset policy to generate a new model.

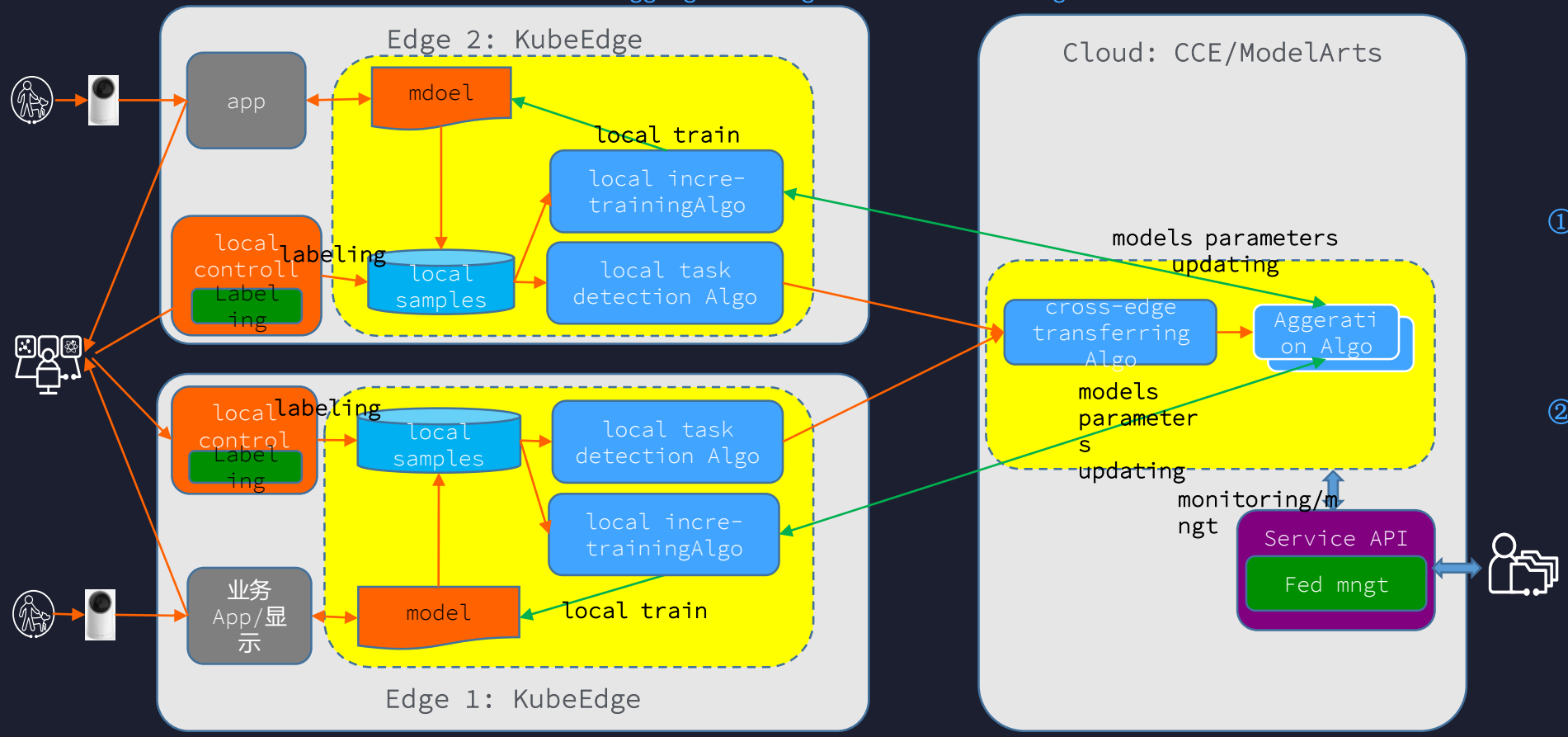
⑥ Updating the new model to Edge

Edge-cloud collaborative FEDERATED LEARNING

Raw data is not transmitted out of the edge, and the model is generated by knowledge aggregation.

③ Multi-task detection: Divide non-IID sample sets and work with the cloud to identify similar tasks.

④ Local training: Model parameters are uploaded to the cloud, and the cross-edge transferring and model aggregation algorithms are running on the cloud.



① Developer: Import the Edge AI library and develop the edge-cloud collaborative federated learning program.

② Start the federated learning task and deploy the training program to the edge.

Developer perspective: JOINT INFERENCE

Design Objectives: Try not to change the existing code of developers and do not require developers to learn new frameworks, reducing learning costs.

How To Use:

- Importing the Edge AI library: Developers use the familiar ML framework (such as TensorFlow) to import the edge AI library (solar_corona library in the figure).
- JOINT INFERENCE: Replace the original load model object part, configure and generate the edge-cloud synergy model, and the background automatically generates a large model on the cloud. Developers do not need to change other parts of the code.

JOINT INFERENCE code example
(Based on TensorFlow)

```python
import hilens

import solar_corona


def pre_fun():
    """
    Preprocessing function may be, for example, image rotation or resize.
    """
    return


def post_fun():
    """
    Post-processing function may be, for example, a post-processing module NMS in the object detection framework.
    """
    return


def run():
    # endpoint may be :  1. Services started by users' own models 2. Existing cloud services
    big_model_endpoint = solar_corona.joint_inference.get_big_model_endpoint()      # deep model on cloud
    ibt = solar_corona.joint_inference.IBT(upload_ratio=0.5)                        # "transfer to cloud" algorithm
    model_path = solar_corona.context.get_model_path()

    # Configure the edge-cloud model, including:
    # the local path of the model,
    # local pre-processing,
    # post-processing methods,
    # cloud migration algorithm,
    # cloud migration endpoint.
    model = solar_corona.load_model(model_path, pre_fun, post_fun,
                                    cloud_offload_algorithm=ibt,
                                    big_model_endpoint=big_model_endpoint)

    # Service parameters settings.
    camera_address = solar_corona.context.get_parameters('ip_camera_address')
    camera = hilens.VideoCapture(camera_address)

    # Service related code.
    while True:
        image = read_one_frame_from_camera(camera)
        predictions = model.predict(image)


if __name__ == "__main__":
    run()
```

Developer perspective: FEDERATED LEARNING

Design Objectives: Try not to change the existing code of developers and do not require developers to learn new frameworks, reducing learning costs.

How To Use:

- Importing the Edge AI library: Developers use the familiar ML framework (such as TensorFlow) to import the edge AI library (solar_corona library in the figure).
- FEDERATED LEARNING: Import the local training loss function, optimizer, and the collaborative_train function from the solar_corona library.

FEDERATED LEARNING code example
(Based on TensorFlow)

```python
def main():
    tf.random.set_seed(22)

    # load dataset.
    (x, y) = solar_corona.load_train_dataset()
    (x_test, y_test) = solar_corona.load_eval_dataset()
    x, x_test = normalize(x, x_test)

    # read parameters from deployment config.
    epochs = solar_corona.context.get_parameters('epochs')
    batch_size = solar_corona.context.get_parameters('batch_size')
    aggregation_algorithm = solar_corona.context.get_parameters('aggregation_algorithm')

    train_loader = tf.data.Dataset.from_tensor_slices((x, y))
    train_loader = train_loader.map(prepare_cifar).shuffle(50000).batch(batch_size)
    test_loader = tf.data.Dataset.from_tensor_slices((x_test, y_test))
    test_loader = test_loader.map(prepare_cifar).shuffle(10000).batch(batch_size)
    model = VGG16([32, 32, 3])

    # you can use the loss/metric function defined in keras
    # loss = keras.losses.CategoricalCrossentropy(from_logits=True)
    # metric = keras.metrics.CategoricalAccuracy()
    # also you can use the loss/metric function defined in solar_corona
    loss = solar_corona.losses.ADifferentCategoricalCrossentropy()
    metric = solar_corona.metrics.ADifferentCategoricalAccuracy()
    # again, you can use either.
    # optimizer = keras.optimizers.Adam(learning_rate=0.0001)
    optimizer = solar_corona.optimizers.ADifferentAdam(learning_rate=0.0001)

    model = solar_corona.collaborative_training.fit(train_loader=train_loader,
                                                    test_loader=test_loader,
                                                    model=model,
                                                    loss=loss,
                                                    metric=metric,
                                                    optimizer=optimizer,
                                                    batch_size=batch_size,
                                                    epochs=epochs,
                                                    # config the aggregation_algorithm
                                                    aggregation_algorithm=aggregation_algorithm)

    # Save the model based on the config.
    solar_corona.save_model(model)


if __name__ == '__main__':
    main()
```

Thank you