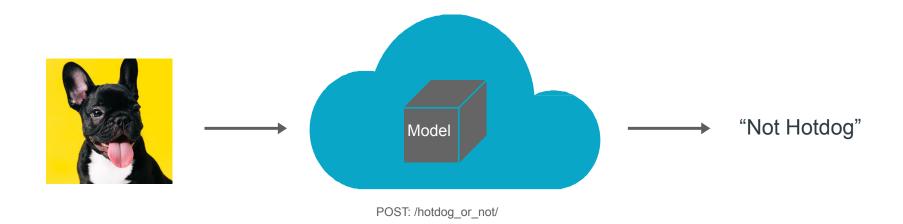
Model Serving systems

From the ground up



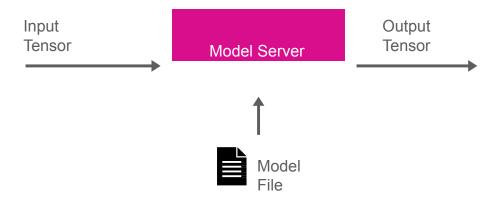
I have a trained model!





Using a Model Server

- TF-Serving
- Triton Inference Server
- TorchServe





Real world ML application

{ "user_id": 10010 }

Business Logic

Database Query

RPC/REST calls

Data Validation

Embedding Lookup

Feature Transformation

Model Inference

Output Transformation

Business Logic

{ "approval": true}



Using a web serving framework

HTTP Request

Business Logic

Feature Transformation

Model Inference

Output Transformation

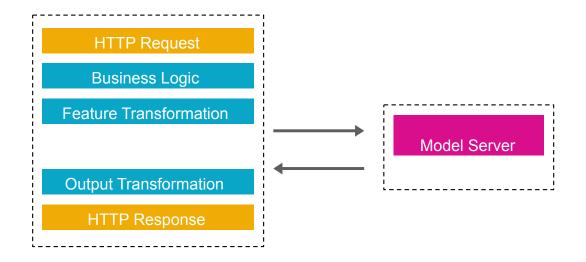
HTTP Response

FastAPI worker

- Scale by replicating process
- Low resource utilization, limited by GIL
- No batching

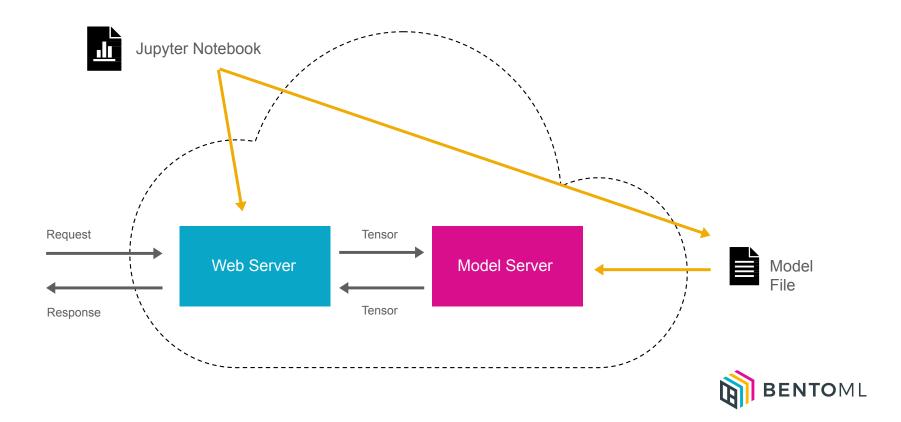


Web Server + Model Server, best from both worlds?

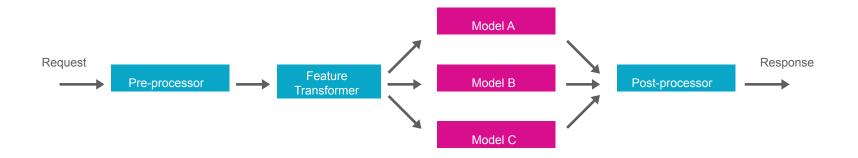




Model and code are tightly coupled



Serving Complex Pipelines



- Complex micro-services or task-queue based architecture
- Hard to optimize performance and eliminate bottleneck
- Hard to evaluate model performance end-to-end



Day 1 and Day 2 problems veren higher infrastructure cost

- New ML Framework support?
- Fine-tune batching behavior for each model
- Retrain model and CI/CD pipeline
- Model performance monitoring
- A/B Testing, Canary rollout, Multi-armed bandit

•



Introducing BentoML The Unified Model Serving Framework



Save and version all your models in one place

```
model = train_model()
import bentoml
bentoml.pytorch.save('recommender', model)
```

- One model store that works for all ML frameworks
- Model registry backed by cloud blob storage
- Preserve model dependency versions, metadata, and labels



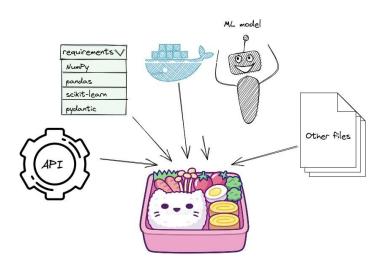
Describe entire serving pipeline in Python

```
import asyncio
import bentoml
from bentoml io import Image, Text
from mylib import pre_process, post_process
svc = bentoml.Service("my_ml_service")
model a runner = bentoml.xqboost.ModelRunner('model a:latest')
model_b_runner = bentoml.pytorch.ModelRunner('model_b:latest')
@svc.api(input=Image(), output=Text())
async def predict(input_image):
   model input = pre process(input image)
    results = asyncio.gather(
        model_a_runner.async_run(model_input),
        model_b_runner.async_run(model_input),
    return post_process(results)
```



Build Bento for deployment

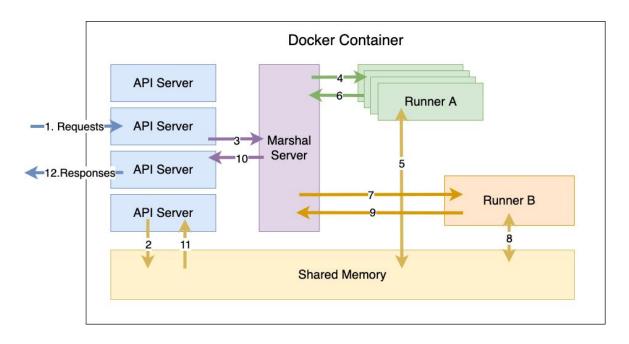




- Bento is just like docker for ML deployment
- Package all your models, serving pipeline code, and dependencies into a bento
- Easy to test and ready for deployment



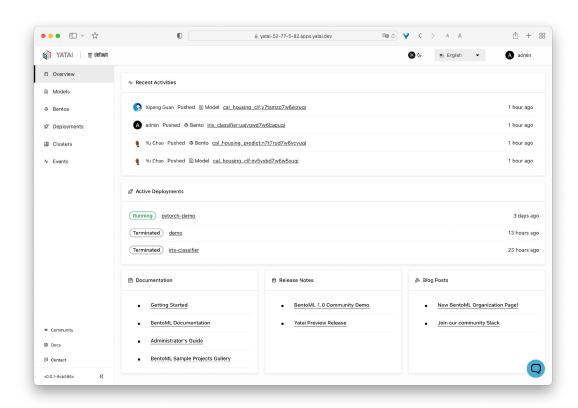
High-performance serving out-of-the-bento



Single-node deployment architecture



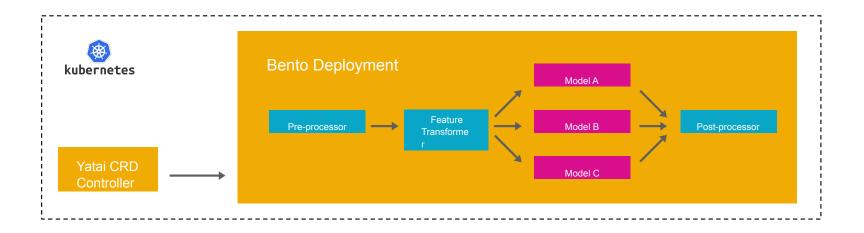
Yatai: BentoML at scale on Kubernetes



```
apiVersion: yatai.bentoml.org/v1beta1
kind: BentoDeployment
metadata:
spec:
  bento_tag: 'fraud_detector:dpijemevl6nlhlg6'
  autoscaling:
    minReplicas: 3
    maxReplicas: 20
    metrics:
    - type: Resource
      resource:
        name: cpu
  resources:
    limits:
      cpu: 500m
    requests:
      cpu: 200m
  runners:
    model runner a:
      autoscaling:
       minReplicas: 1
        maxReplicas: 5
        metrics:
       type: Requests
          resource:
           name: backlog
```



High-performance model serving at scale



- Auto-scale at individual runner level to eliminate bottleneck
- Automatically adjust batching parameter based on traffic
- Kubernetes native, advanced CI/CD made easy



Thank you!

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