Deploying Machine Learning Models in Python

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PyCon HK 2018
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What is this Talk About?

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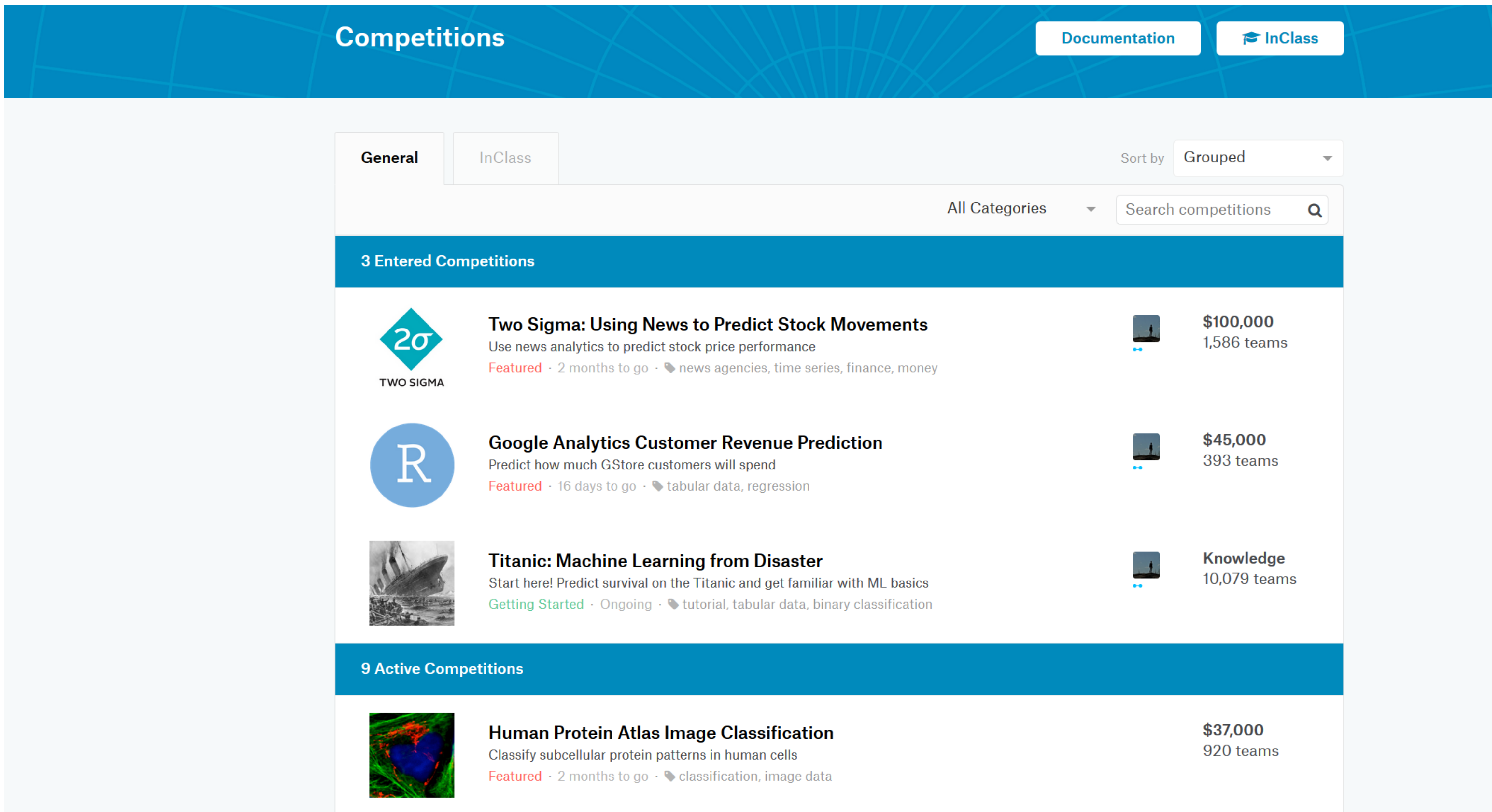
- The need to **deploy** machine learning models
- Different kinds of **workflows**
- Common **strategies**
- **Options** in Python
- Other **considerations**
- NOT about using docker/kubernetes

The "Kaggle" Way of Machine Learning

The "Kaggle" Way of Machine Learning

- Kaggle: a Website that host machine learning competitions
- You train machine learning models and generate predictions on the
- Everything is done **offline**



Machine Learning Applications

Machine Learning Applications

- In practice, generating predictions is only a **small part** of a machin
- Consider a system that uses machine learning to recognize hand-w

Common ML Systems Workflow (1)

- Train offline ➤ Predict offline ➤ Store predictions in DB
- Example: **Recommender systems**
  - A model is trained **offline**
  - For each user, generate (pre-compute) a list of recommended items, store in **database**
  - When the user visits the Website, return the list of items

Common ML Systems Workflow

Common ML Systems Workflow

- There are several common **workflows** for machine learning system
  1. Train offline ➤ Predict offline ➤ Store predictions in DB
  2. Train offline ➤ Embed model in a device ➤ Predict online
  3. Train offline ➤ Make model available as a service ➤ Predict online
- Notes:
  - **Offline**
    separate from a production system; does not have to be completed in real time
  - **Online**
    part of a production system; perform tasks in real time

Common ML Systems Workflow (1)

Common ML Systems Workflow (1)

- Train offline ➤ Predict offline ➤ Store predictions in DB
- Example: **Recommender systems**
    - A model is trained **offline**
    - For each user, generate (pre-compute) a list of recommended items, store in **data**
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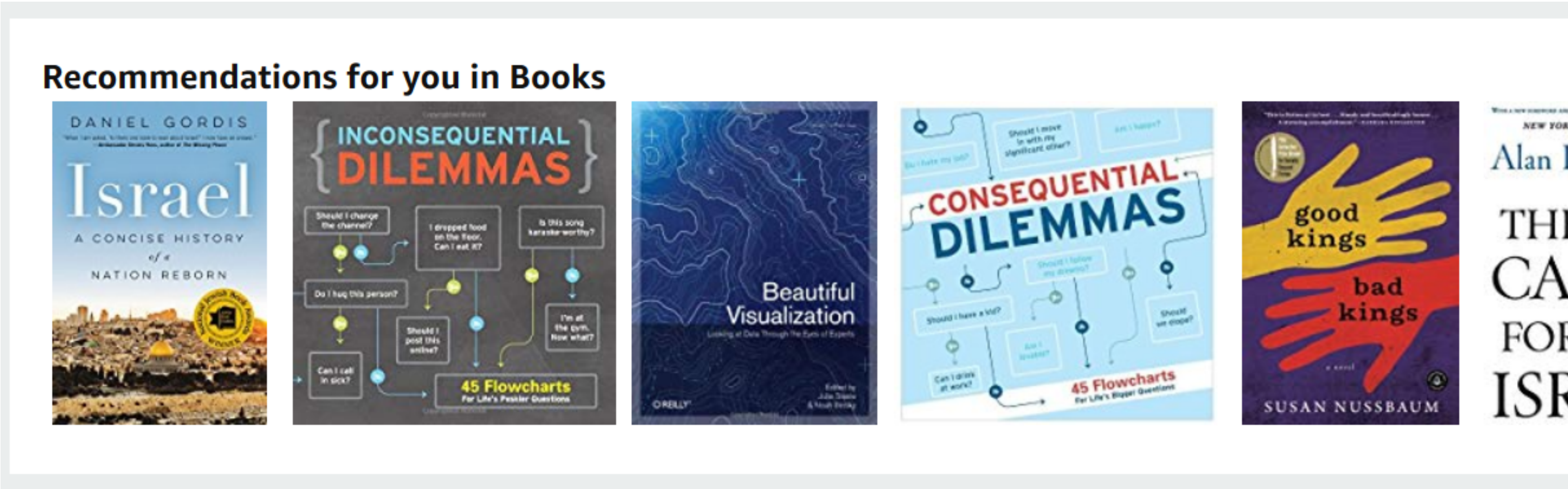


Common ML Systems Workflow (2)

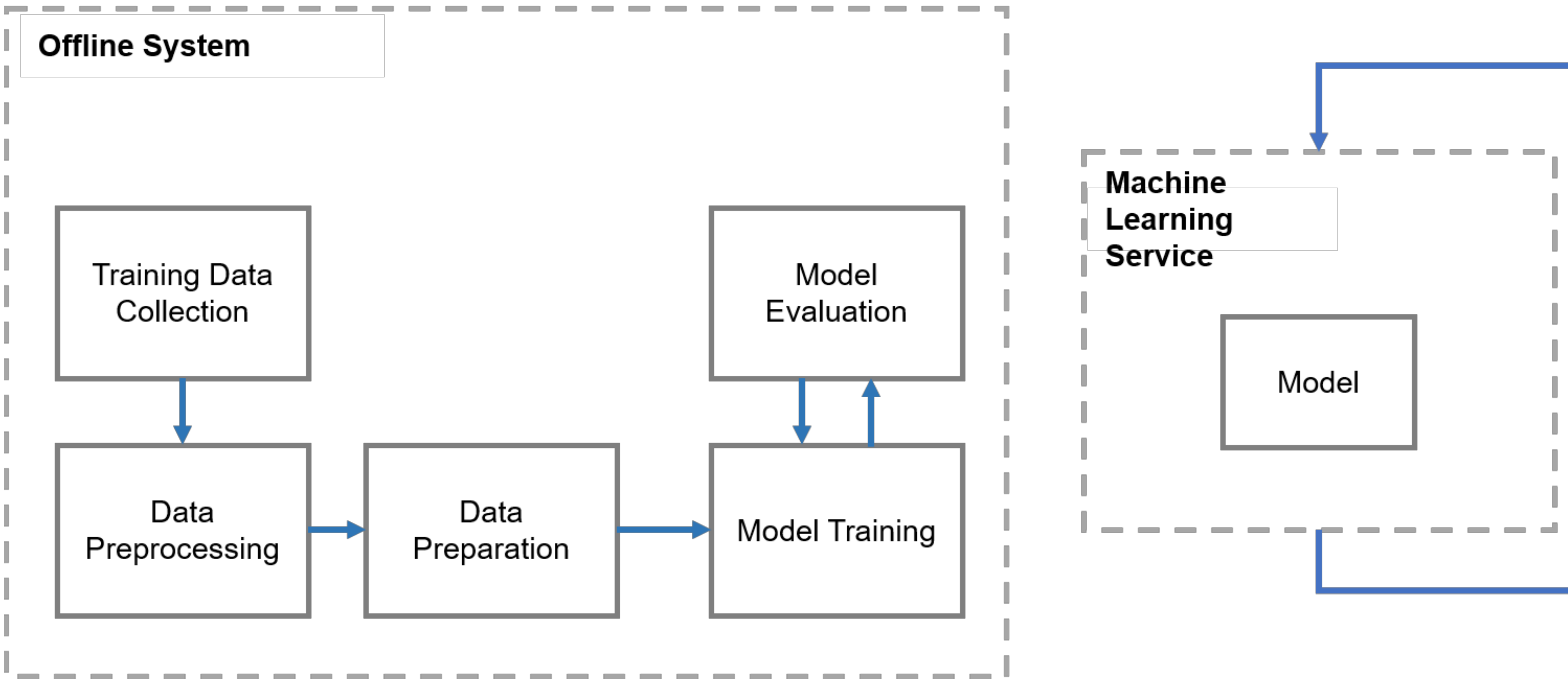
Common ML Systems Workflow (2)

- Train offline ➤ Embed model in a device ➤ Predict online
- Example: **Object detection using a drone**
  - A model is trained offline
  - The model together with other processing logic are downloaded to the drone's computer
  - The drone detects objects while it is in operation

Common ML Systems Workflow (3)

Common ML Systems Workflow (3)

- Train offline ➤ Make model available as a service ➤ Predict online
- Example: **Spam E-mail detection**
  - A classifier is trained offline with spam and non-span emails
  - Deployed as a service to serve users or other components in the system



Common ML Systems Workflow

Common ML Systems Workflow

- In (2) and (3), we need to think about how to **deploy** a machine lea
- Definition of **deploy**:

> *To place some resources into a position so as to be ready*
> *or use*

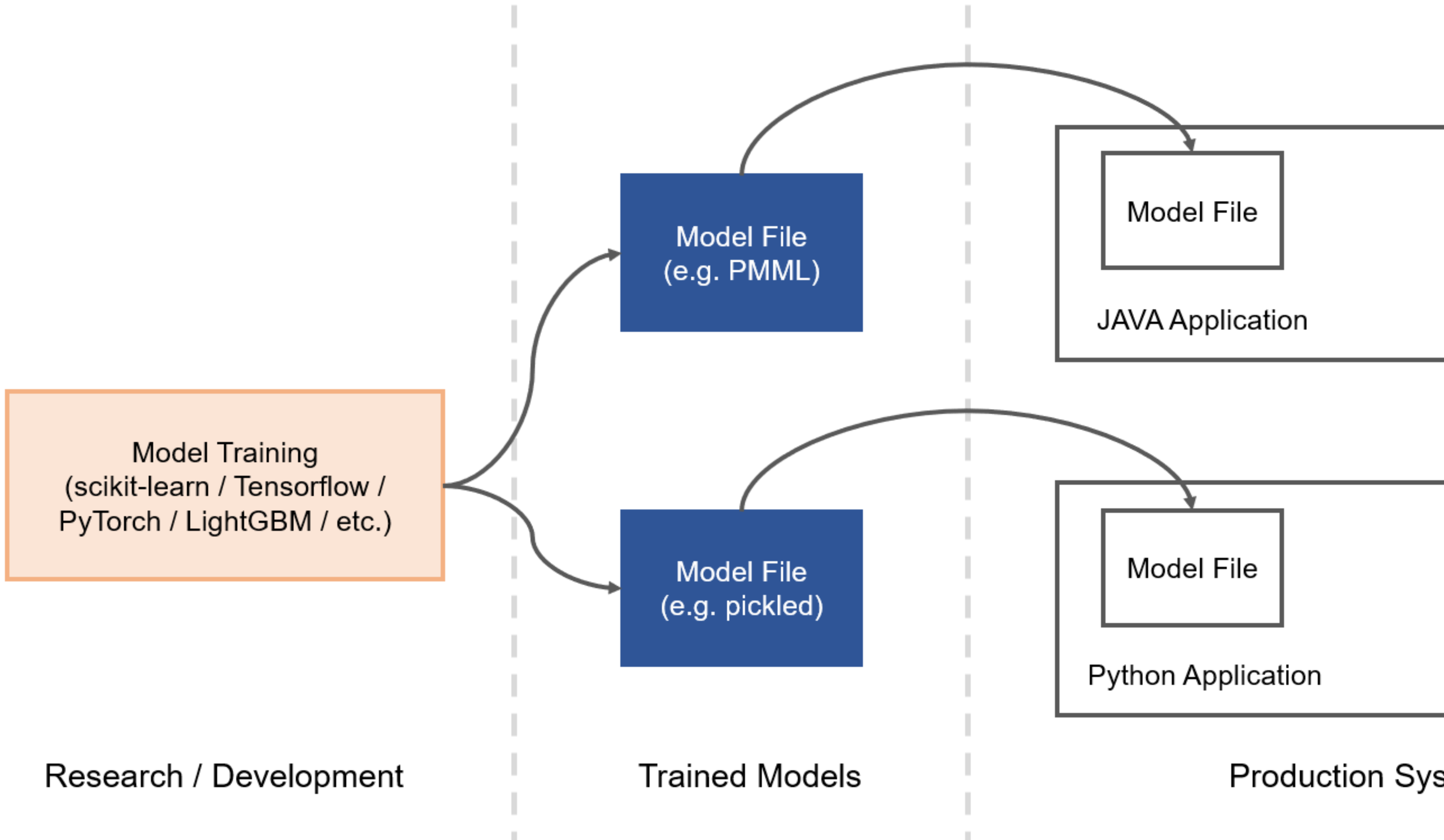
- In this talk, we will focus on **Use Case (3)**
- How to make machine learning models **available** to other users/sy

Common Strategies

Common Strategies

- **Persist** model in a **standard** format
- **Different languages** for development and production

- Serve models in r
- The **same** langua
used in developn



Persist Models in a Standard Format

Persist Models in a Standard Format

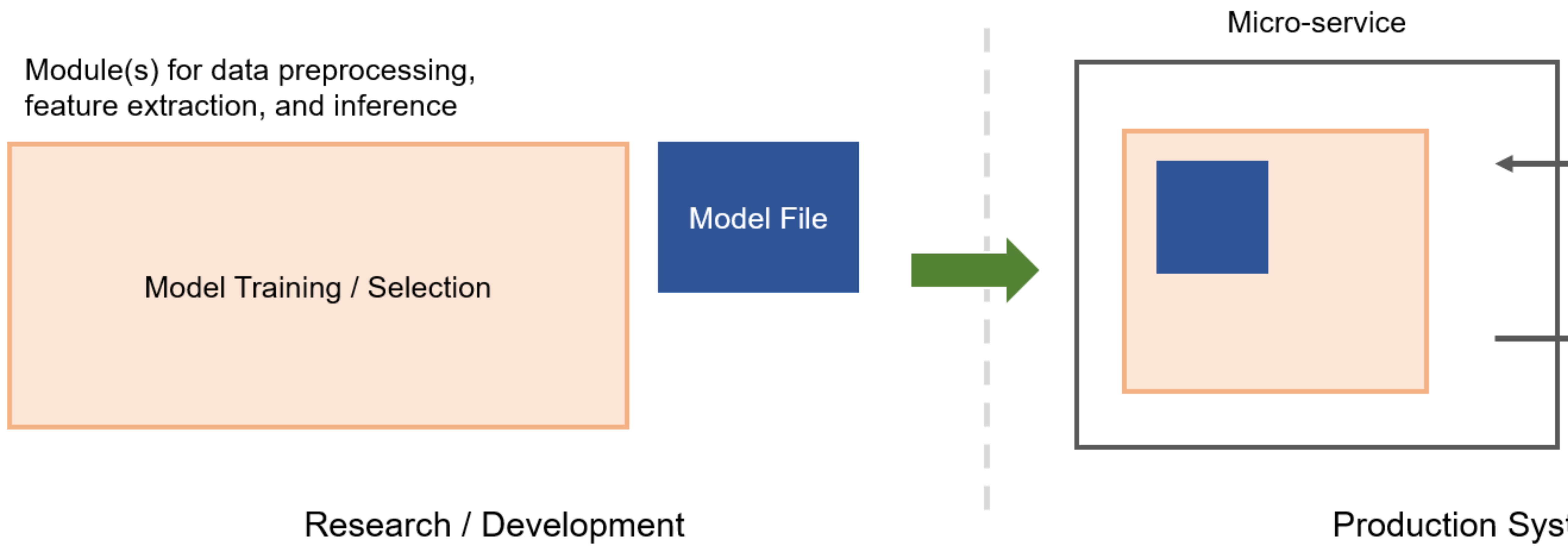
```
from sklearn.linear_model import LogisticRegression
from sklearn.feature_extraction.text import CountVectorizer
from sklearn2pmml import sklearn2pmml
from sklearn2pmml.pipeline import PMMLPipeline

# Load data ...

# Create pipeline and fit model
pipeline = PMMLPipeline([
  ("vec", CountVectorizer()),
  ("clf", LogisticRegression())
])
pipeline.fit(X, y)

# Write model in PMML format
sklearn2pmml(pipeline, "model.pmml", with_repr=True)
```

- **Predict**
  Langua
  - XML-b
    mode
  - scikit-
    sklear
  - Light(
    jpmm
- Referen
  Scikit-Le

Serve Models in Micro-services

Serve Models in Micro-services

- Models are persisted in a certain format specific to the language in
  (e.g. using `sklearn.externals.joblib`)
- The model (or even the module to load, pre-process and generate p
  wrapped in a **micro-service** that expose **endpoints** to receive requ



Options in Python

Options in Python

- XML-RPC
- HTTP REST micro-services
  - Flask: http://flask.pocoo.org/
  - Bottle: https://bottlepy.org/
  - Falcon: https://falconframework.org/
  - Vibora: https://github.com/vibora-io/vibora
  - AIOHTTP: https://aiohttp.readthedocs.io/en/stable/
- Asynchronous Messaging
  - Kafka: https://kafka.apache.org/
  - RabbitMQ: https://www.rabbitmq.com/
  - Redis: https://redis.io/

Wrapping Model Prediction in a Class

Wrapping Model Prediction in a Class

- Generating predictions can involve **pre-processing** and **post-proce**
- More convenient if everything is wrapped inside a **class**

```
class TextClassifier(object):
    """A Class wrapping the ML model"""

    def __init__(self):
        # Load the persisted model into memory
        self.model = joblib.load("model.pkl")

    def train(self):
        # Model training
        # ...

    def predict(self, x):
        y = self.model.predict([x])
        return y[0]
```

Tensorflow Models

Tensorflow Models

- For Tensorflow models, we need to keep a reference to the graph d

```
import tensorflow as tf
from keras.applications.resnet50 import ResNet50

class ImageClassifier(object):

    def __init__(self):
        self.graph = tf.get_default_graph()
        self.model = ResNet50(weights='imagenet')

    def preprocess(self, img):
        # preprocess the input image
        # ...

    def predict(self, img):
        x = self.preprocess(img)
        with self.graph.as_default():
            predictions = self.model.predict(x)
        ...
```

XML-RPC

XML-RPC

- XML-RPC: Remote procedure call based on HTTP and XML file forma
- The most straight-forward way if the **clients are also written in Py**

- Server

```
from xmlrpc.server import \
    SimpleXMLRPCServer
from model import TextClassifier

clf = TextClassifer()

address = ("localhost", 8000)
server = SimpleXMLRPCServer(address)
server.register_function(
    clf.predict, "predict")

server.serve_forever()
```

- Client

```
from xmlrpc.client imp

address = ("localhost"

# Create a proxy to t
with ServerProxy(addre
    server.predict("He
```

Flask

Flask

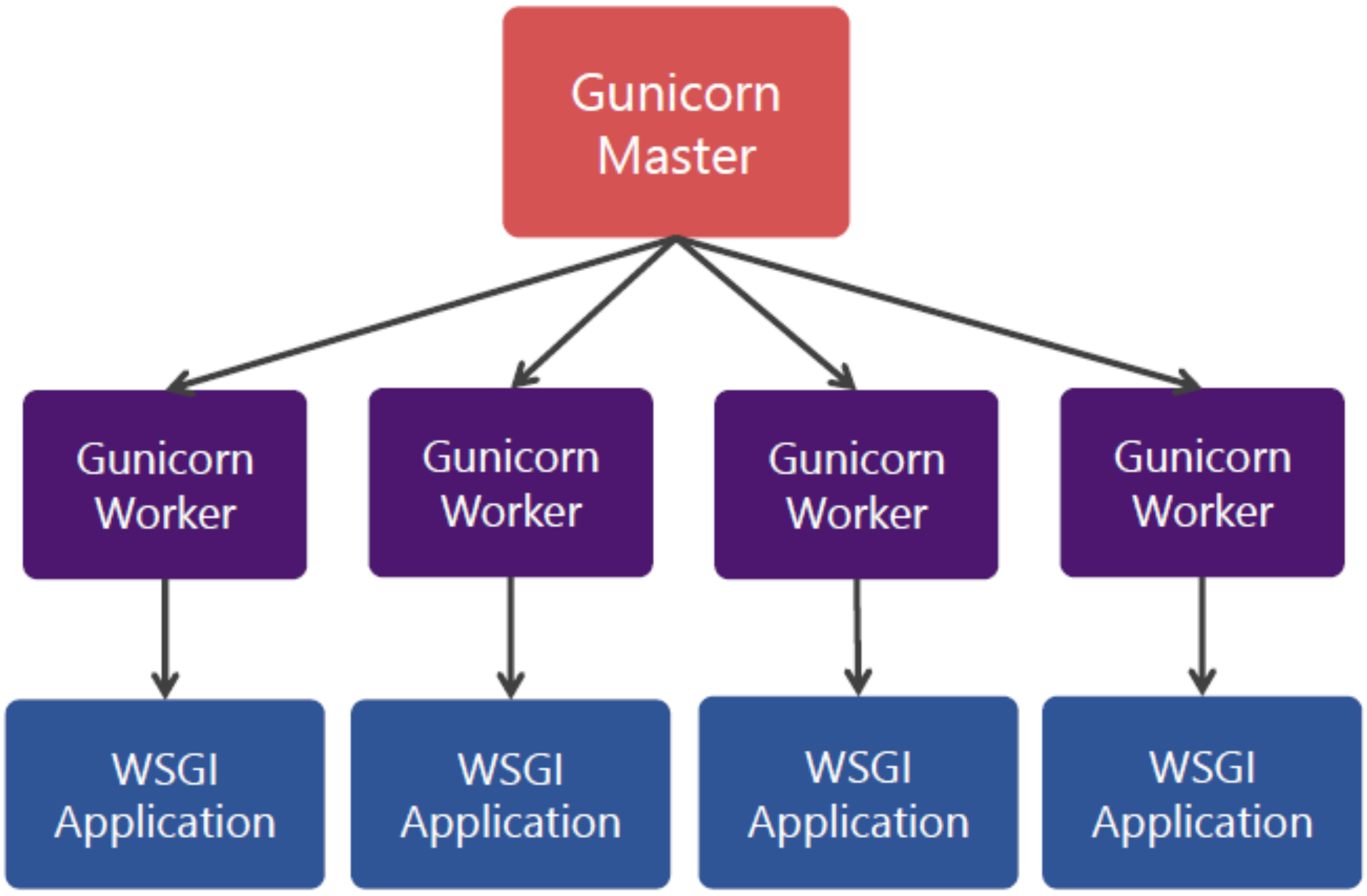
- A popular WSGI Web framework for creating HTTP APIs

```
from flask import Flask, current_app, request, jsonify
from model import TextClassifier

app = Flask(__name__)           # Create a Flask app
app.model = TextClassifier()  # Load model into the app

# Define the HTTP API for prediction
@app.route('/predict', methods=['POST'])
def predict():
    d = request.get_json()
    prediction = current_app.model.predict(d['x'])
    return jsonify(result=prediction)

# Start the Flask internal Web server
app.run()
```

Deploying

Deploying

- Flask is a **WSGI** Web Framework, it can be deployed using Gunicorn
- Gunicorn uses a **pre-fork worker** model (creates copies of your app
- `$ gunicorn app:app -b localhost:8000 -w 4`



Falcon

Falcon

- A Framework that focuses on REST APIs
- Falcon vs. Flask — Which one to pick to create a scalable deep learn

```
import falcon
from model import TextClassifier

class Handler(object):

    def __init__(self):
        self.model = TextClassifier()

    def on_post(self, req, resp):
        data = json.loads(req.stream.read())
        resp.media = {"result": self.model.predict(data['x'])}

app = falcon.API()
app.add_route('/predict', Handler())
app.run()
```

Vibora

Vibora

- Asynchronous HTTP client/server framework (requires Python 3.6+
- API very similar to Flask

```
from vibora import Vibora, Request
from vibora.responses import JsonResponse
from model import TextClassifier

app = Vibora()  # Create an Vibora application
app.add_component(TextClassifer())  # Add a globally available component

@app.route('/predict', methods=['POST'])
async def predict(request: Request):
    data = await request.json()
    model = app.get_component(TextClassifier)  # Get reference to the model
    prediction = model.predict(data['x'])
    return JsonResponse({"result": prediction})
```

AIOHTTP

AIOHTTP

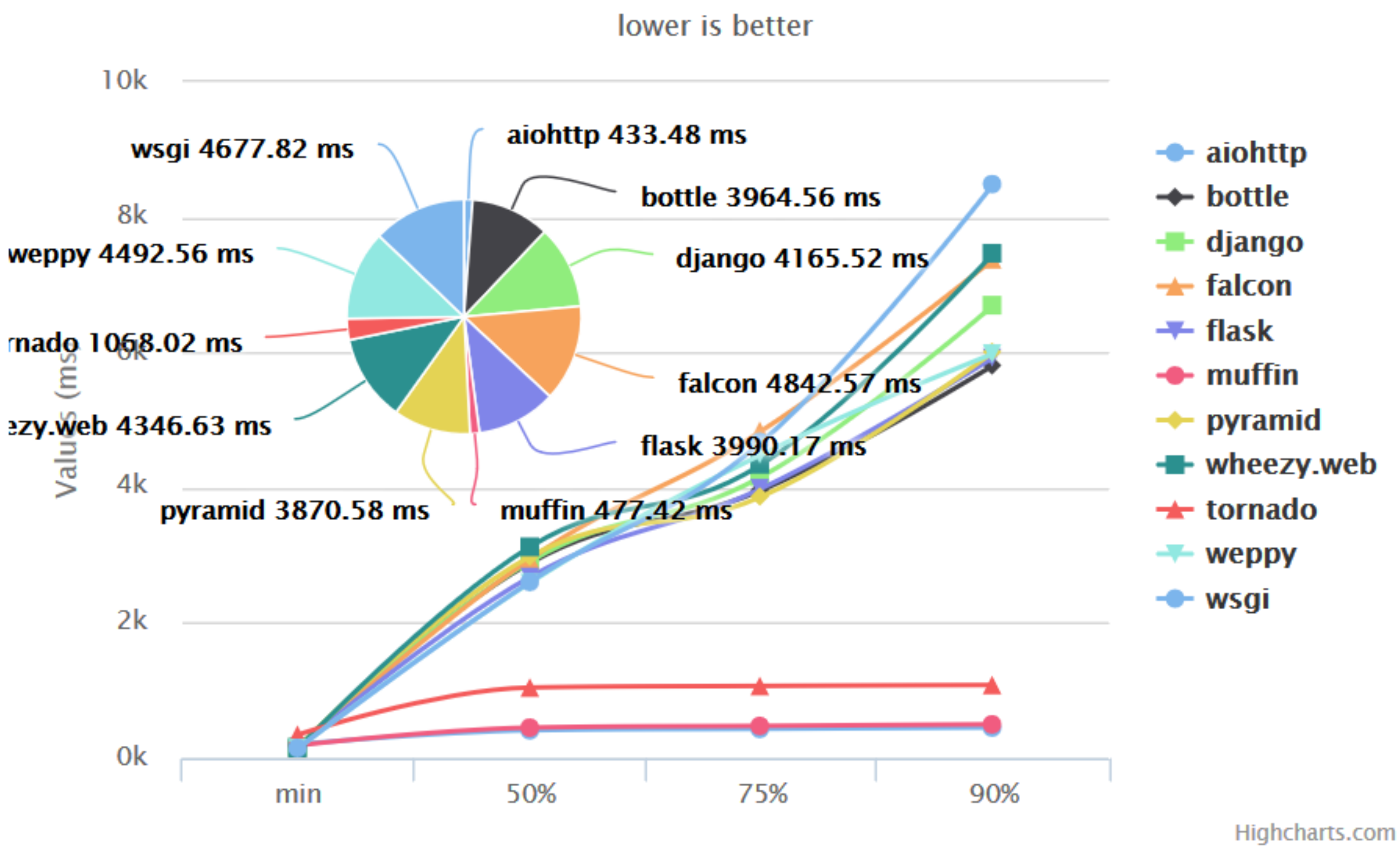
- Framework for implementing Asychronous HTTP client/server on t

```
from aiohttp import web
from model import TextClassifier

async def handle(request):
    data = await request.json()
    prediction = request.app['model'].predict(data['input'])
    return web.json_response({"result": prediction})

app = web.Application()
app.router.add_post('/predict', handle)
app["model"] = TextClassifier()

web.run_app(app, host='localhost', port=8000)
```

Comparing Web Frameworks

Comparing Web Frameworks

- Some benchmarking results can be found here or here
- For ML services, the choice of framework seems not too important,
  the time will be spent on data **processing** and **inference**



Simple request and response
http://klen.github.io/py-frameworks-bench/

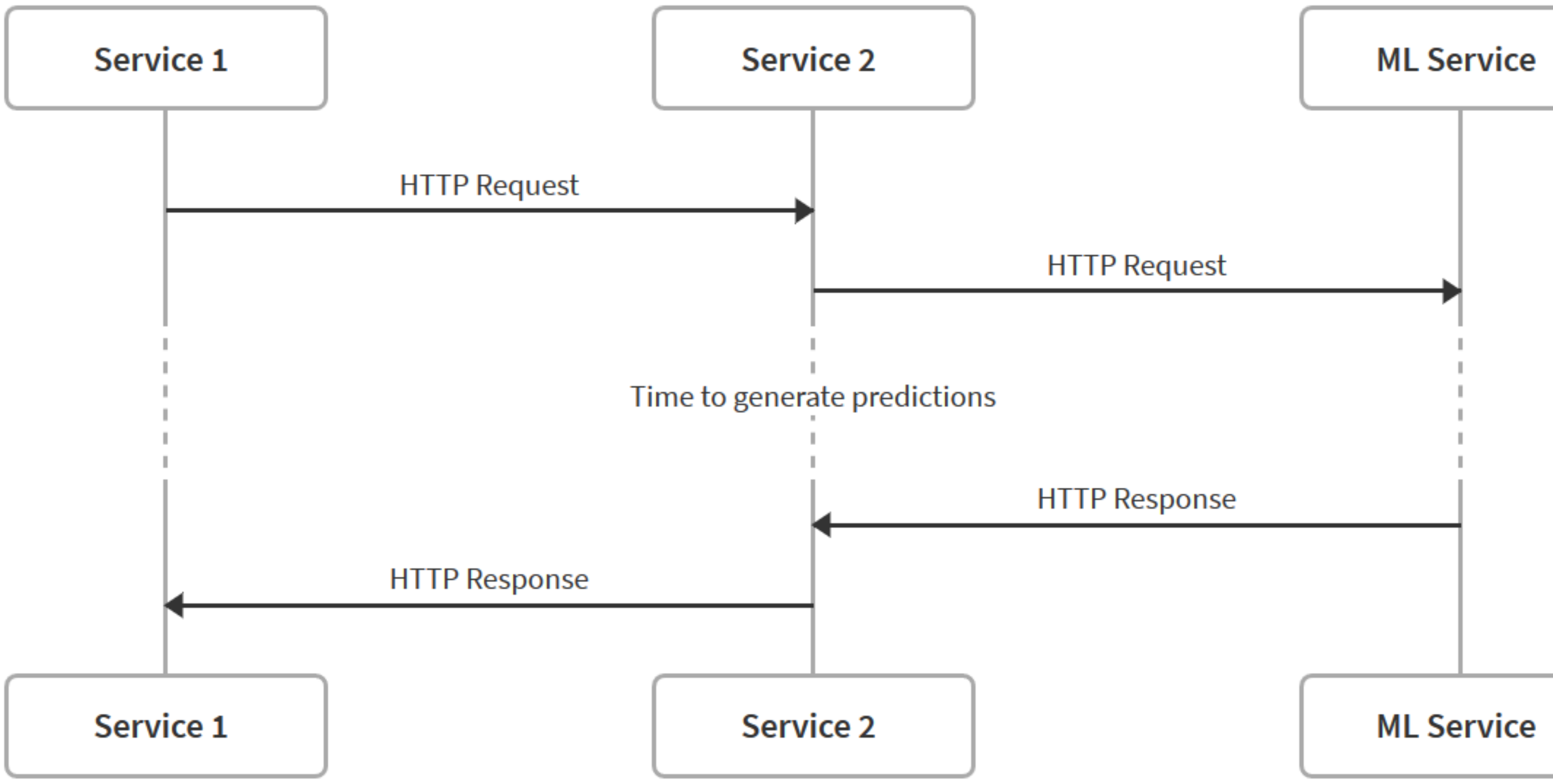
Frameworks	Requ
Tornado	1
Django	1
Flask	1
Aiohttp	2
Sanic	7
Vibora	13

POST JSON data
https://github.com/v

Disadvantage of Using HTTP APIs

Disadvantage of Using HTTP APIs

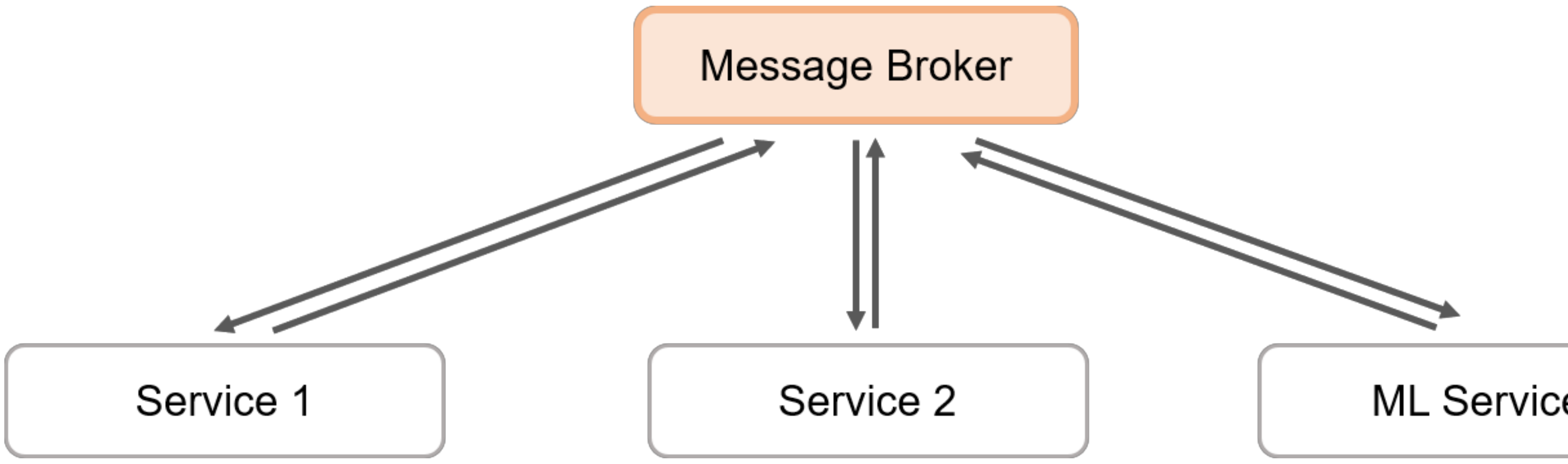
- HTTP REST APIs are simple to implement, however the process is **s**
- The client must **wait** until the ML service has finished the process o predictions
- In a complex system involving a lot of components, this may not be



Asynchronous Messaging

Asynchronous Messaging

- If components are relatively independent, using **asynchronous me** more efficient use of the services' resources
- Send requests and responses to a **message broker** instead of direc



- Options:
  - Redis https://redis.io/
  - RabbitMQ: https://www.rabbitmq.com/
  - Kafka: https://kafka.apache.org/

Rodis

Redis

- Redis is a key/value cache, but can also be used as a **message queu**

- Client Side

```
from redis import StrictRedis

# Get a connection to Redis
queue = StrictRedis(host='localhost',
                    port=6379)

# Create a message
message = "Hello!".encode("utf-8")

# Send the message to a channel
# named "prediction"
queue.publish("prediction", message)
```

- ML Service

```
from redis import Str
from model import Tex

queue = StrictRedis(ho
                    po
pubsub = queue.pubsub
pubsub.subscribe('pred

while True:
    x = p.get_message
    y_pred = model.pre
    # send result back
```

Kafka

Kafka

- A scalable and distributed message queue
- Two Python packages available: kafka-python and confluent-kafka

- Producer of messages

```
from kafka import KafkaProducer

# Create a message producer
address = 'localhost:1234'
producer = KafkaProducer(
    bootstrap_servers=address)

# Send message to a topic
producer.send('prediction', # topic
              '{"x": "Hello!"}') # msg
...
```

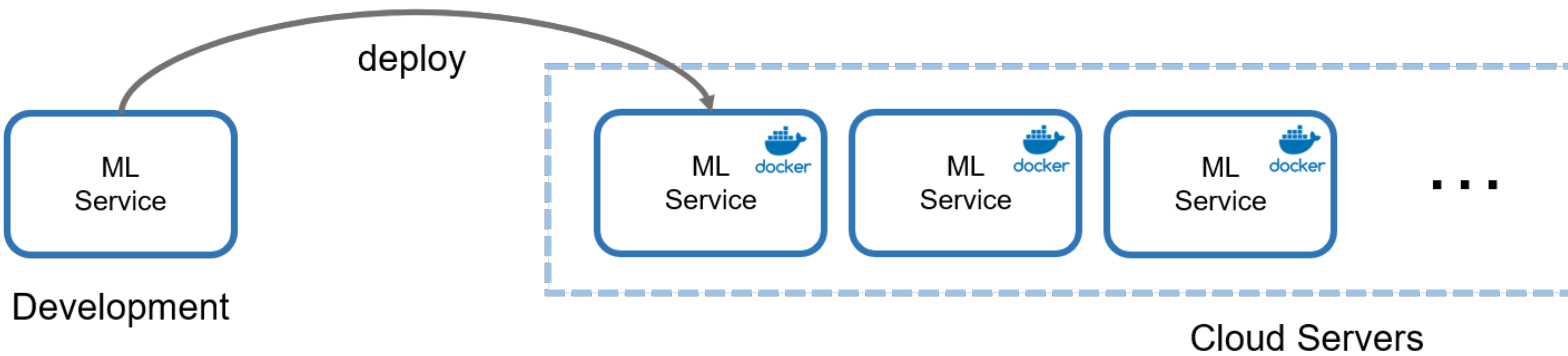
- Consumer of mes

```
from kafka import Kafk

# Create a consumer o
consumer = KafkaConsun

# Get message from bro
for msg in consumer:
    # Decode message
    content = msg.valu
    data = json.loads
    ...
```

Scaling ML Services

Scaling ML Services

- Nowadays micro-services are usually deployed as docker containe
systems such as Kubernetes
- **Scaling** involves creating multiple containers, each container runn
service
- Challenge: How to configure **resources allocated to each containe**



Scaling ML Services

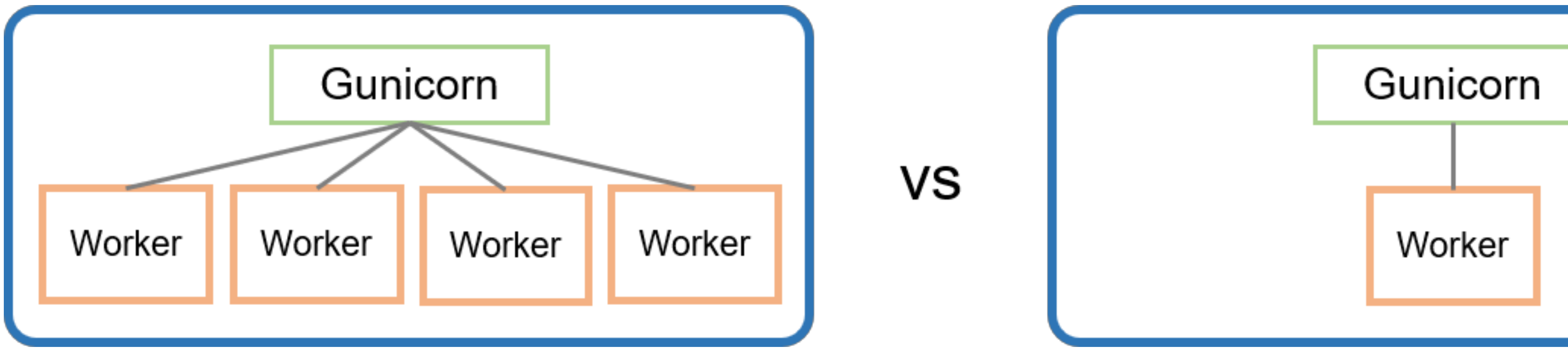
Scaling ML Services

- Some models can benefit from **multiple cores** using multi-threadin
  processing, e.g.:
  - scikit-learn's RandomForestClassifier
  - Facebook's fastText
  - Deep learning models built using Tensorflow or PyTorch
- Some models are huge and consume a lot of **RAM**
- Some models can only run on **single cores**
- Using GPUs, sometimes **batch processing** can be faster

Single vs. Multiple Workers

Single vs. Multiple Workers

- Example: using **Flask** and **Gunicorn** to deploy a Tensorflow model
- Tensorflow models can utilize **multiple cores** during inference
- Would be better to scale using multiple containers, each allocated
rather than having multiple workers in a single container



Summary

Summary

- When using a model in a **production system**, in addition to the per
(i.e. accuracy / precision / recall of the model, we need to consider:

1. **Model Size** ➤ would it be too big to be copied around?
2. **Memory** ➤ how much memory will it take up after loaded?
3. **CPU** ➤ how much CPU resources needed to generate a prediction?
4. **Time to Predict** ➤ time requried to generate a prediction
5. **Preprocessing** ➤ how complicated are the preprocessing steps?

Thank You!

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Slides Avaliable at:
http://talks.albertauyeung.com/pycon2018-deploy-