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Model Serving Patterns

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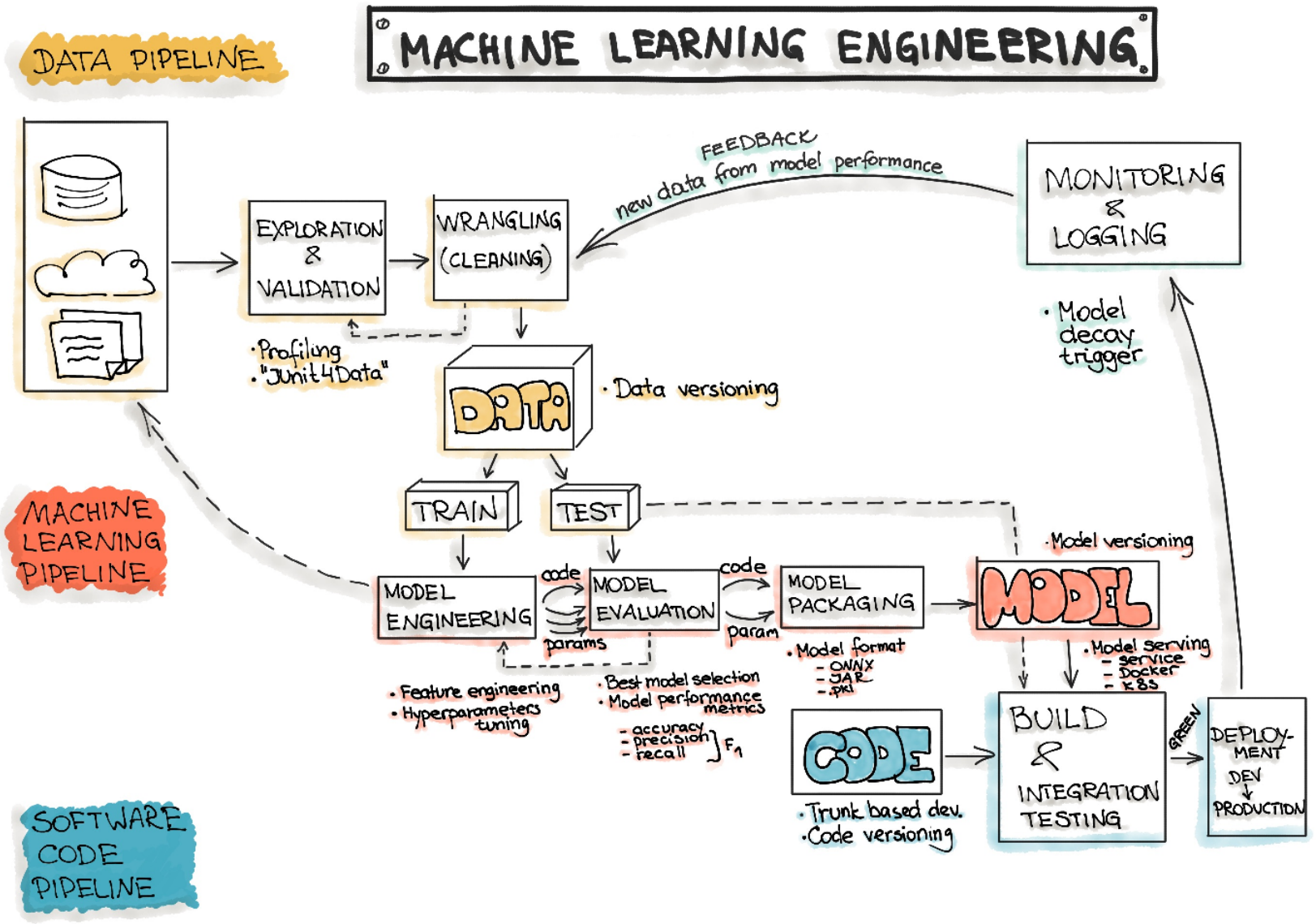
Extracted from
Three Levels of ML Software

Machine Learning Workflow



Code: Deployment Pipelines

- The final stage of delivering an ML project includes the following three steps:
  - Model Serving
  - Model Performance Monitoring
  - Model Performance Logging

- Model Serving
  - The process of deploying the ML model in a production environment

- Model Performance Monitoring
  - The process of observing the ML model performance based on live and previously unseen data, such as prediction or recommendation
  - interested in ML-specific signals, such as prediction deviation from previous model performance
  - signals might be used as triggers for model re-training

- Model Performance Logging
  - Every inference request results in a log-record.

Model Serving Patterns

- Three components should be considered when ML model is served in a production environment
  - The inference is the process of getting data to be ingested by a model to compute predictions
  - requires a model, an interpreter for the execution, and input data

- Deploying an ML system to a production environment includes two aspects,
  - First deploying the pipeline for automated retraining and ML model deployment
  - Second, providing the API for prediction on unseen data

- Model serving is a way to integrate the ML model in a software system

- Five patterns to put the ML model in production:
  - Model-as-Service
  - Model-as-Dependency
  - Precompute
  - Model-on-Demand
  - and Hybrid-Serving

Model Serving Patterns(2)

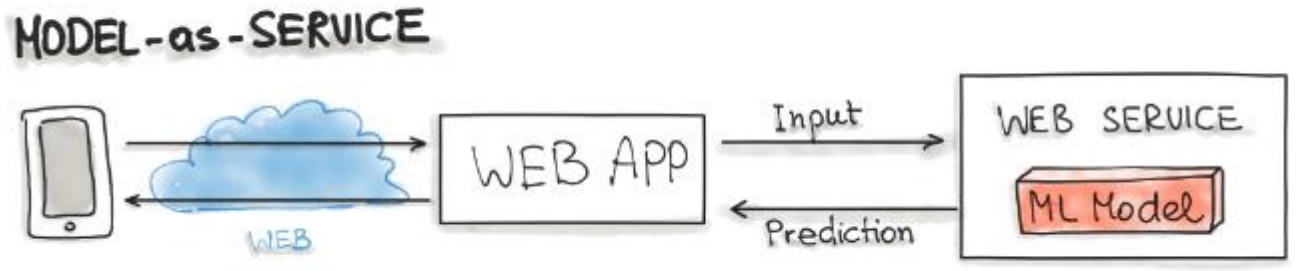
Machine Learning Model Serving Taxonomy

Machine Learning Model Serving Taxonomy			
	ML Model		
Service & Versioning	Together with the consuming application	Independent from the consuming application	
Compile/ Runtime Availabilty	Build & runtime available	Available re-motely through REST API/RPC	Available at the runtime scope
Serving Patterns	"Model-as-Dependency"	"Model-as-Service"	"Precompute" and "Model on Demand"
	Hybrid Model Serving (Federated Learning)		

Model-as-Service

- A common pattern for wrapping an ML model as an independent service
  - can wrap the ML model and the interpreter within a dedicated web service
  - applications can request through a REST API or consume as a gRPC service

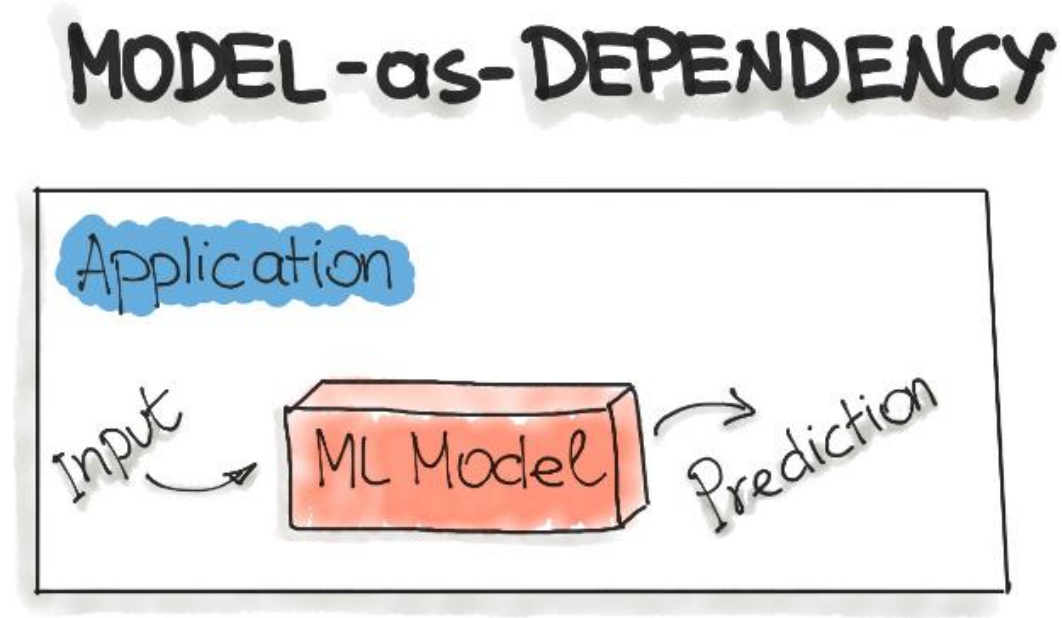
- Used for various ML workflows
  - Forecast
  - Web Service
  - Online Learning



Model-as-Dependency

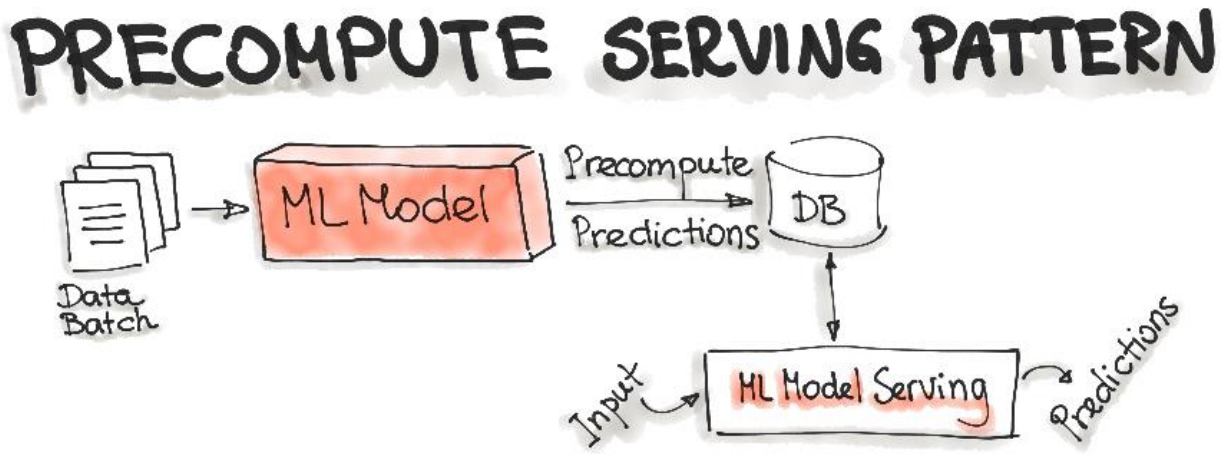
- Probably the most straightforward way to package an ML model
  - mostly used for implementing the Forecast pattern.

- A packaged ML model is considered as a dependency within the software application
  - For example, the application consumes the ML model like a conventional jar dependency by invoking the prediction method and passing the values
  - The return value of such method execution is some prediction that is performed by the previously trained ML model



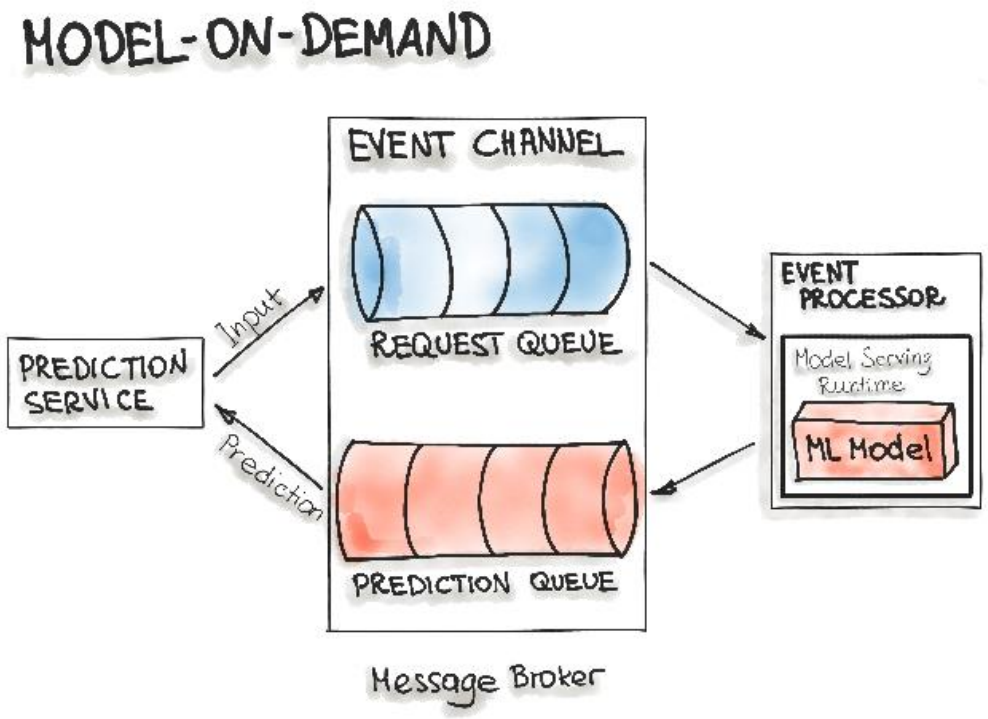
Precompute Serving Pattern

- Tightly related to the Forecast ML workflow
- Use an already trained ML model and precompute the predictions for the incoming batch of data
  - Resulting predictions are persisted in the database
  - For any input request, query the database to get the prediction result



Model-on-Demand

- Treats the ML model as a dependency that is available at runtime
  - contrary to the Model-as-Dependency pattern, has its own release cycle and is published independently
- Message-broker architecture is typically used for such on-demand model serving
  - contains two main types of architecture components:
    - a broker component
    - an event processor component
  - Broker component is the central part that contains the event channel that are utilised within the event flow
  - The event channels, which are enclosed in the broker component, are message queues
  - Message broker allows one process to write prediction-requests in a input queue
  - Event processor contains the model serving runtime and the ML model
    - connects to the broker, reads these requests in batch from the queue and sends them to the model to make the predictions
- The model serving process runs the prediction generation on the input data
  - writes the resulted predictions to the output queue
  - queued prediction results are pushed to the prediction service that initiated the prediction request



Hybrid-Serving (Federated Learning)

- Unique in the way it does, there is not only one model that predicts the outcome, but there are also lots of it
  - Exactly spoken there are as many models as users exist, in addition to the one that’s held on a server

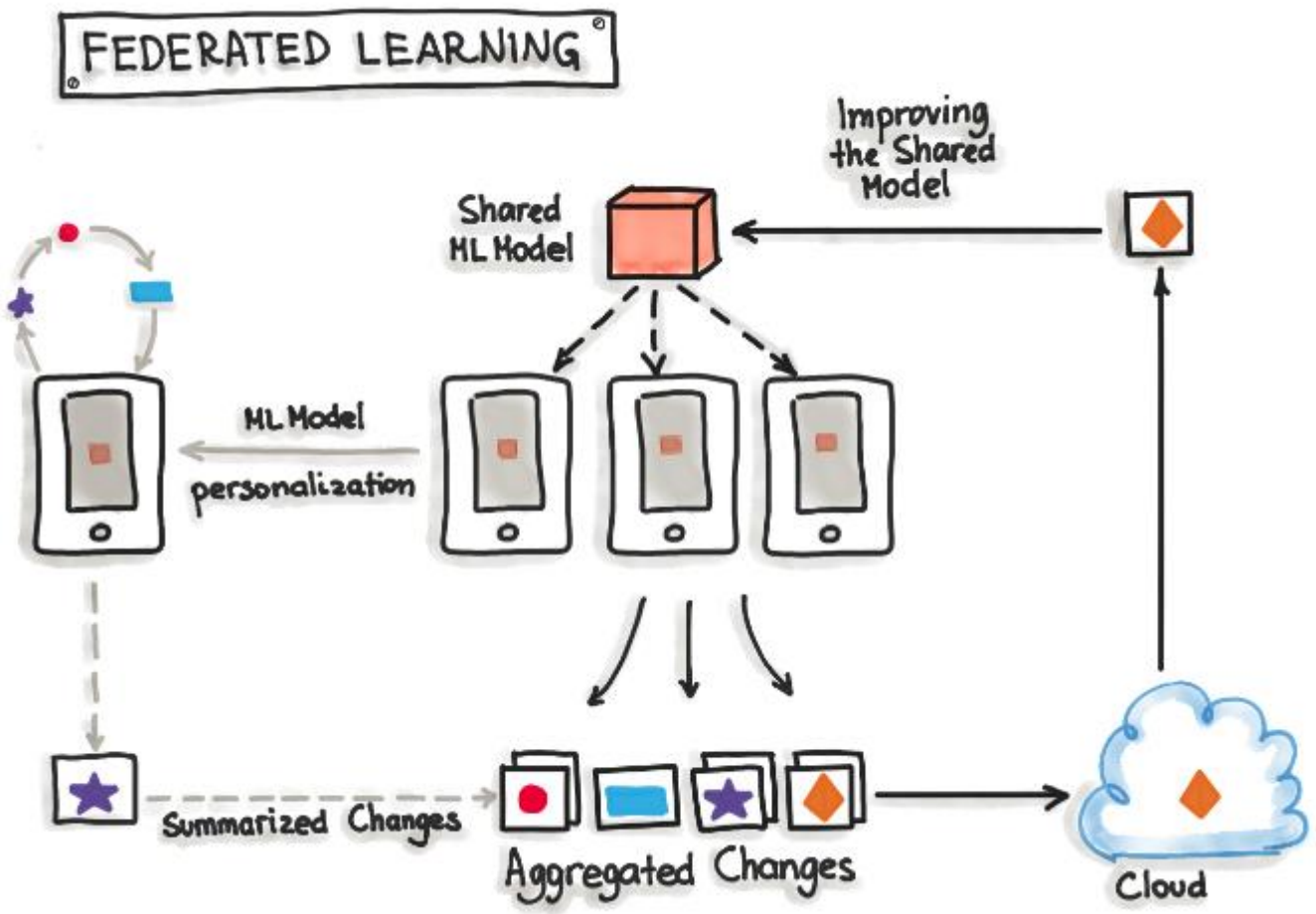
- Start with the unique model, the one on the server
  - Model on the server-side is trained only once with the real-world data
  - sets the initial model for each user
  - a relatively general trained model so it fits for the majority of users

- On the other side, there are the user-side models - really unique models
  - possible for the devices to train their own models due to hardware enhancements
  - devices will train their own highly specialized model for their own user
  - Once in a while, the devices send their already trained model data (not the personal data) to the server

- Then the server model will be adjusted
  - the actual trends of the whole user community will be covered by the model
  - this updated server model is set to be the new initial model that all devices are using

Hybrid-Serving (Federated Learning) 2

- Not having any downsides for the users, while the server model gets updated, this happens only when the device is idle, connected to WiFi and charging
  - testing is done on the devices, therefore the newly adopted model from the server is sent to the devices and tested for functionality
- Big benefit
  - data used for training and testing, which is highly personal, never leaves the devices while still capturing all data that is available
  - possible to train highly accurate models while not having to store tons of (probably personal) data in the cloud
- Constraints
  - mobile devices are less powerful
  - the training data is distributed across millions of devices and these are not always available for training
  - Exactly for this TensorFlow Federated (TFF) has been created - lightweight form of TensorFlow

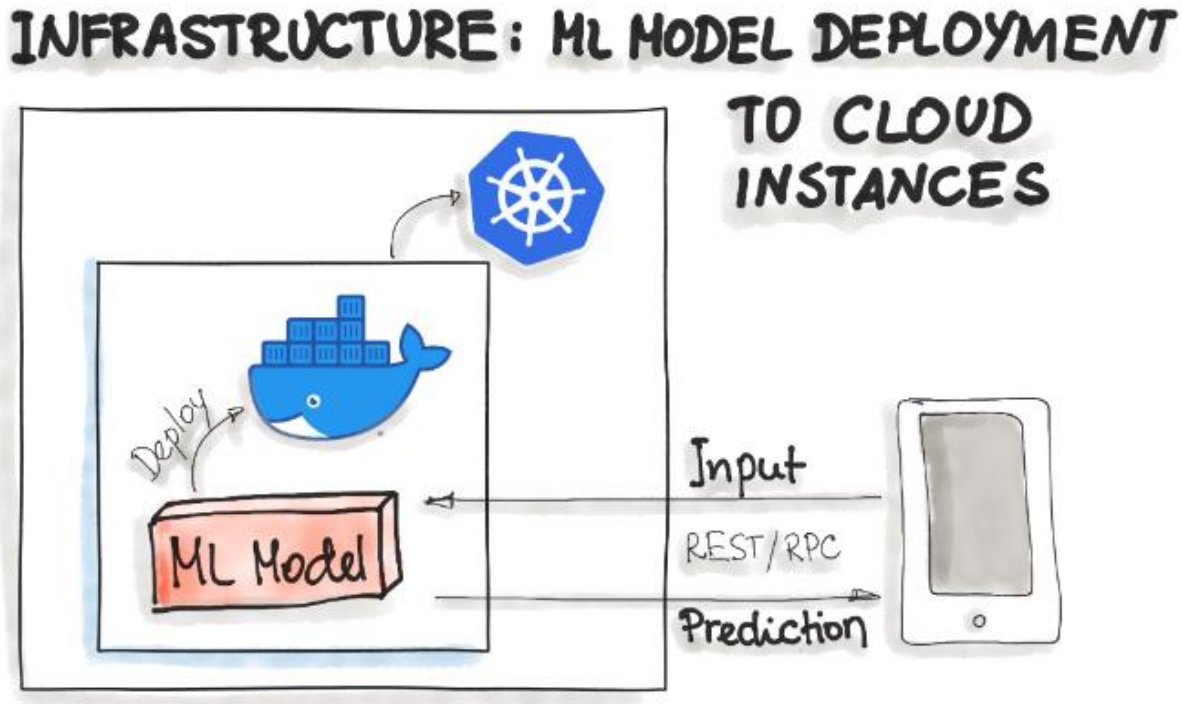


Deployment Strategies

- Common ways for wrapping trained models as deployable services, namely deploying ML models as
  - Docker Containers to Cloud Instances
  - Serverless Functions

Deploying ML Models as Docker Containers

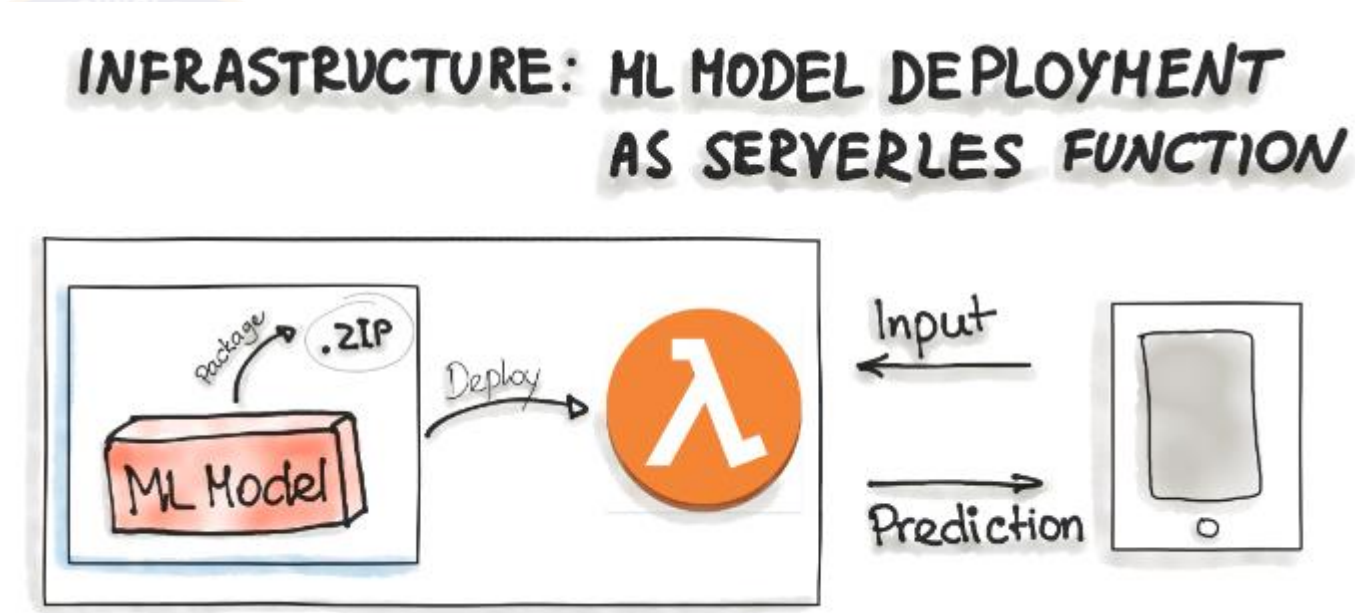
- No standard, open solution to ML model deployment!
- Containerization becomes the de-facto standard for delivery
  - as ML model inference being considered stateless, lightweight, and idempotent
  - means deploy a container that wraps an ML model inference code
- Docker is considered to be de-facto standard containerization technology
  - for on-premise, cloud, or hybrid deployments
- One ubiquitous way is to package the whole ML tech stack (dependencies) and the code for ML model prediction into a Docker container
  - Then Kubernetes or an alternative (e.g. AWS Fargate) does the orchestration
  - The ML model functionality, such as prediction, is then available through a REST API (e.g. implemented as Flask application)



Deploying ML Models as Serverless Functions

- Various cloud vendors already provide machine-learning platforms - can deploy model with their services
  - Amazon AWS Sagemaker, Google Cloud AI Platform, Azure Machine Learning Studio, and IBM Watson Machine Learning
  - Commercial cloud services also provide containerization of ML models such as AWS Lambda and Google App Engine servlet host

- In order to deploy an ML model as a serverless function,
  - the application code and dependencies are packaged into .zip files, with a single entry point function
  - could be managed by major cloud providers such as Azure Functions, AWS Lambda, or Google Cloud Functions
  - However, attention should be paid to possible constraints of the deployed artifacts such as the size of the artifacts



Thank You!

In our next session: