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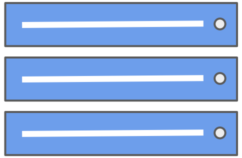
DeepLearning.AI

Model Serving Architecture

Model Serving: Patterns and Infrastructure

ML Infrastructure

On Prem



- Train and deploy on your own hardware infrastructure
- Manually procure hardware GPUs, CPUs etc
- Profitable for large companies running ML projects for longer time

On Cloud

- Train and deploy on cloud choosing from several service providers
    - Amazon Web Services, Google Cloud Platform, Microsoft Azure, etc

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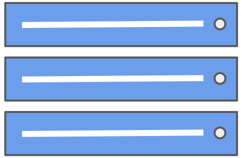

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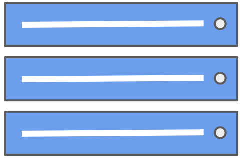

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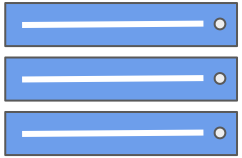

- Can use open source, pre-built servers
    - TF-Serving, KF-Serving, NVidia and more...

On Cloud

- Create VMs and use open source pre-built servers
- Use the provided ML workflow

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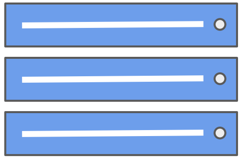

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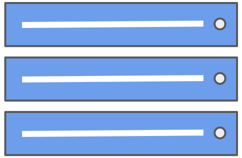

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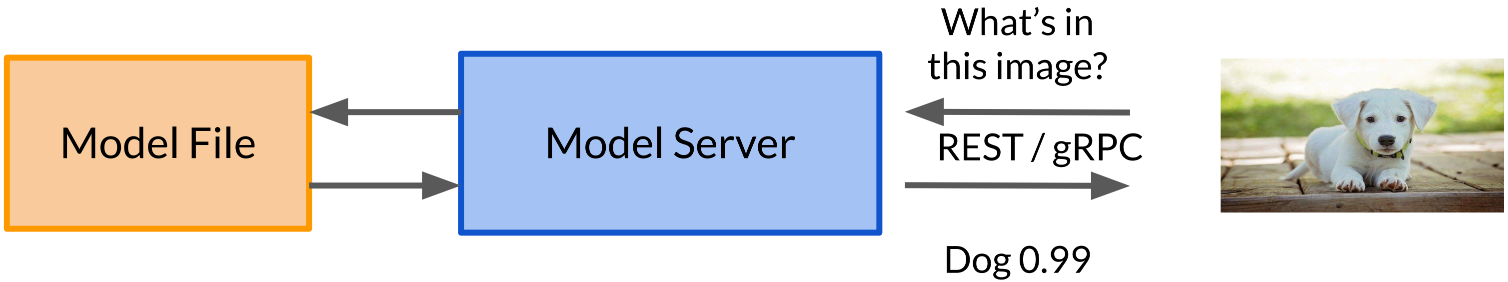
Model Servers

- Simplify the task of deploying machine learning models at scale.
- Can handle scaling, performance, some model lifecycle management etc.,



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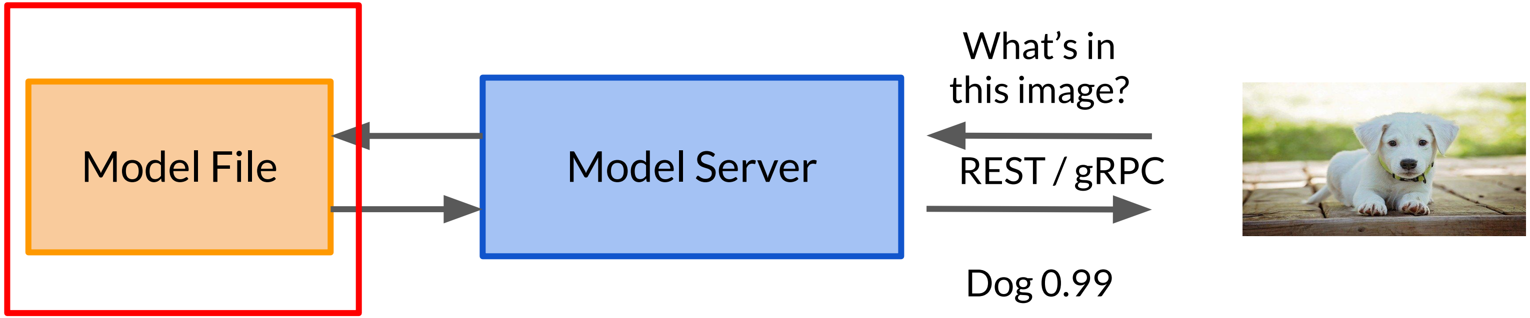

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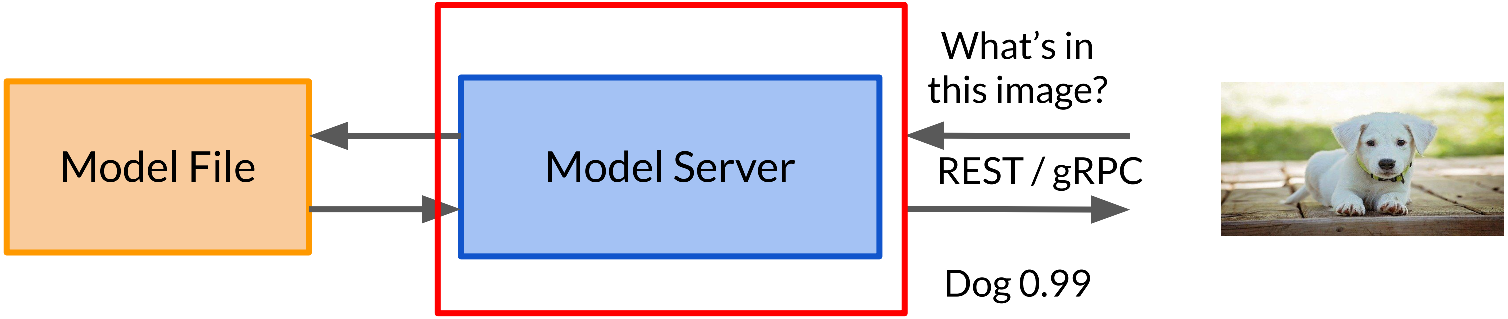

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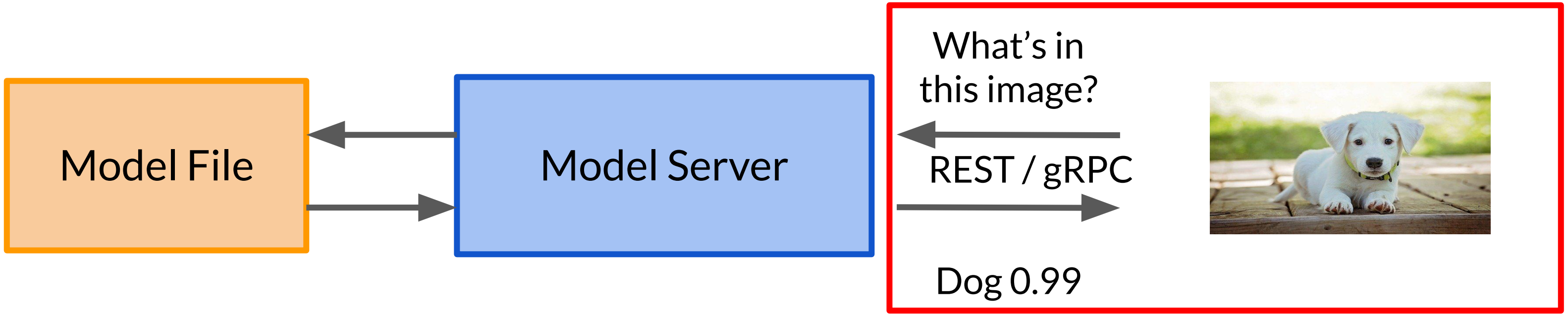

Model Servers

TensorFlow

TensorFlow Serving

PyTorch

TorchServe

Kubeflow

KF Serving

NVIDIA

TRITON INFERENCE SERVER

TensorFlow Serving

TensorFlow

Supports many servables

TF Models	Non TF Models	Word Embeddings	Vocabularies	Feature Transformations

Out of the box integration with TensorFlow Models

Batch and Real-time Inference

Multi-Model Serving

Exposes gRPC and REST endpoints

TensorFlow Serving

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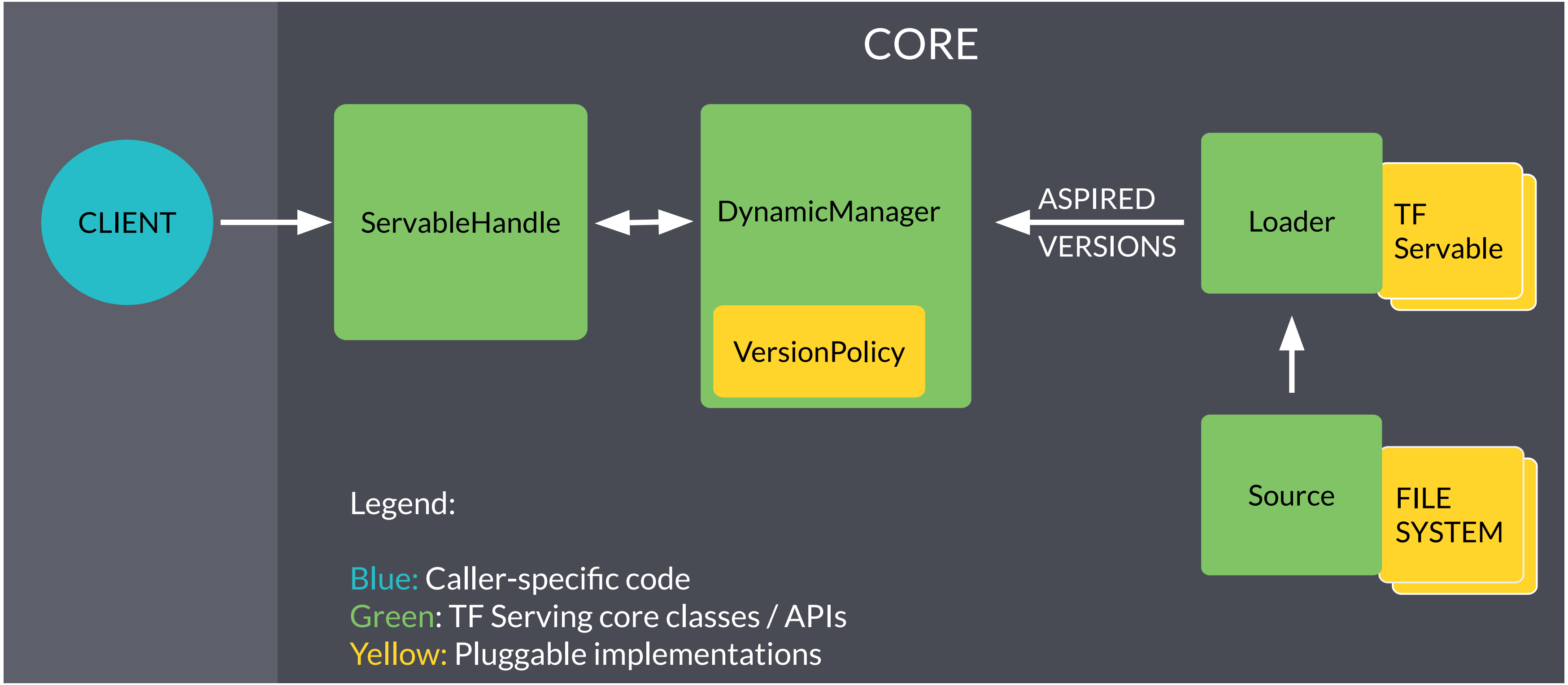
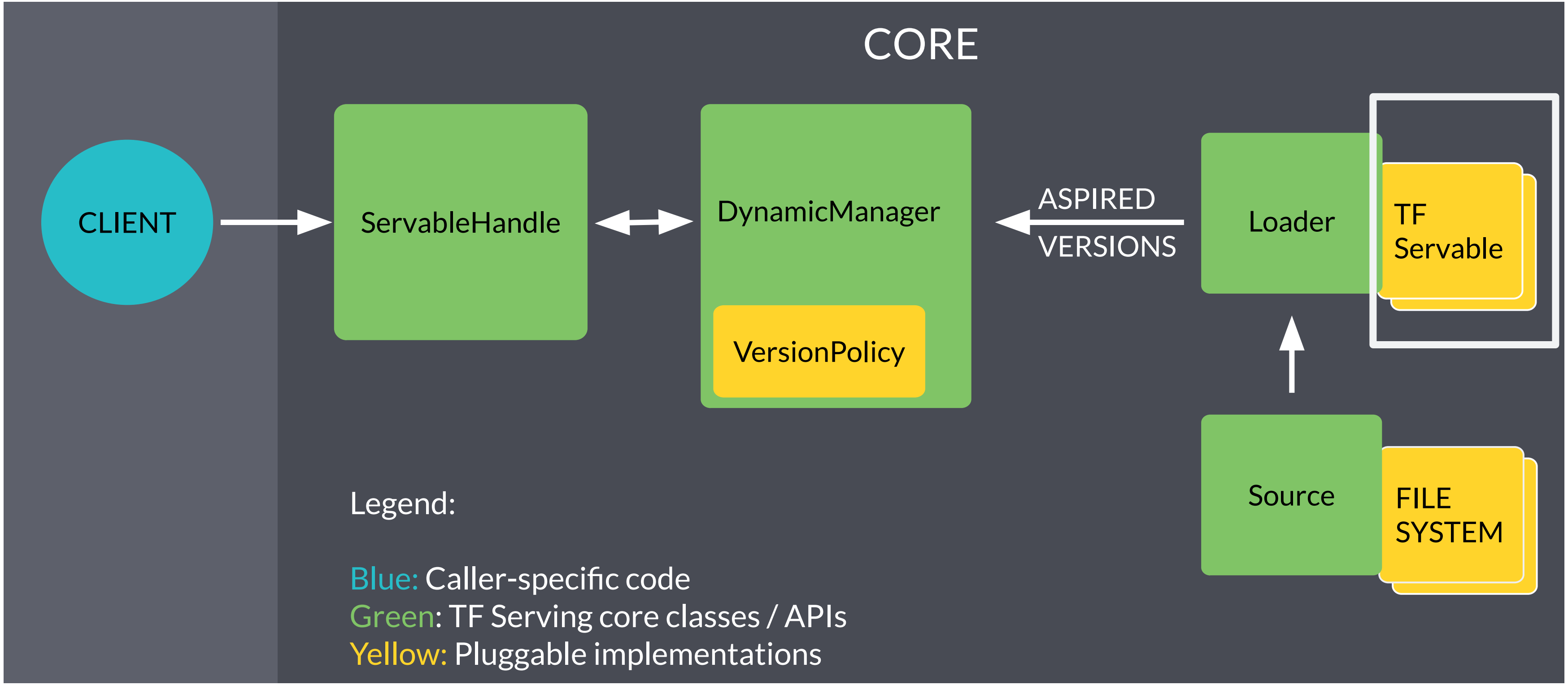


TensorFlow Serving Architecture



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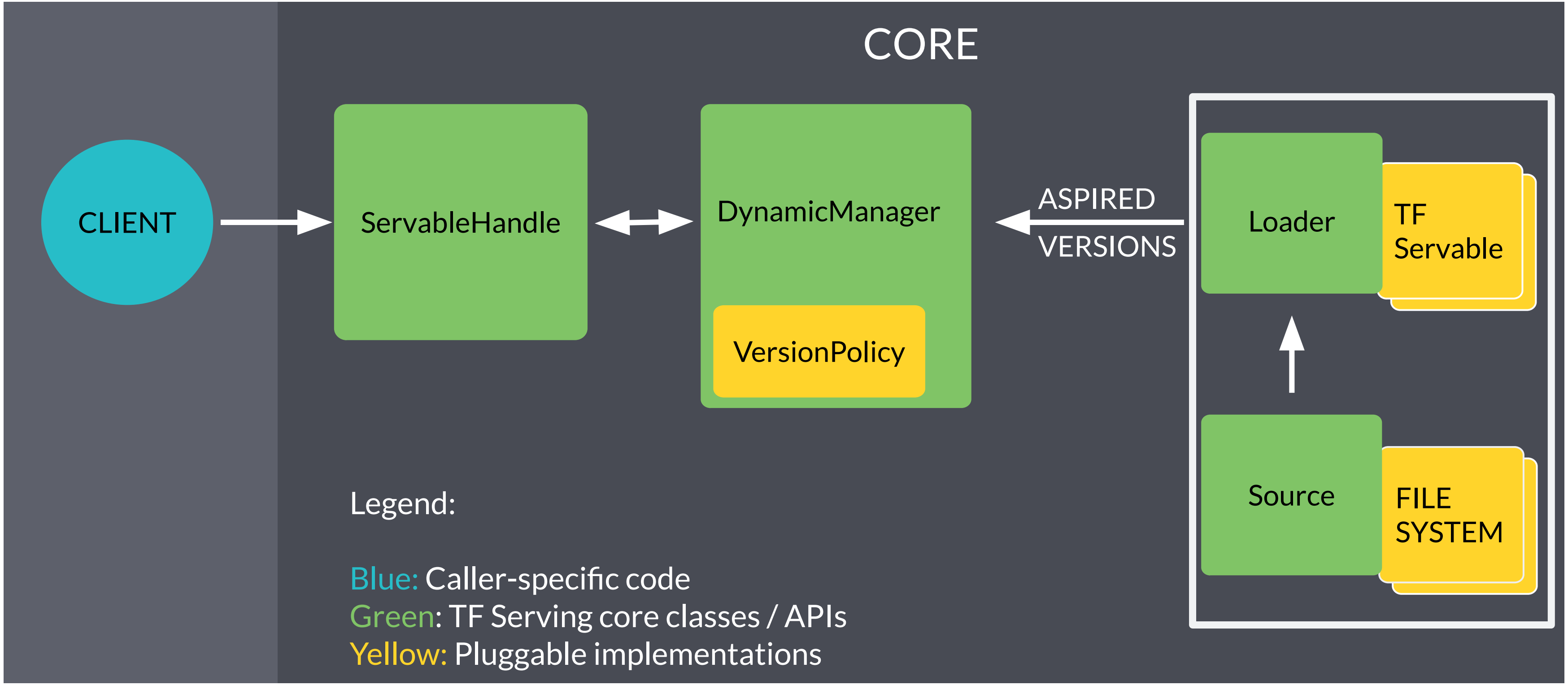

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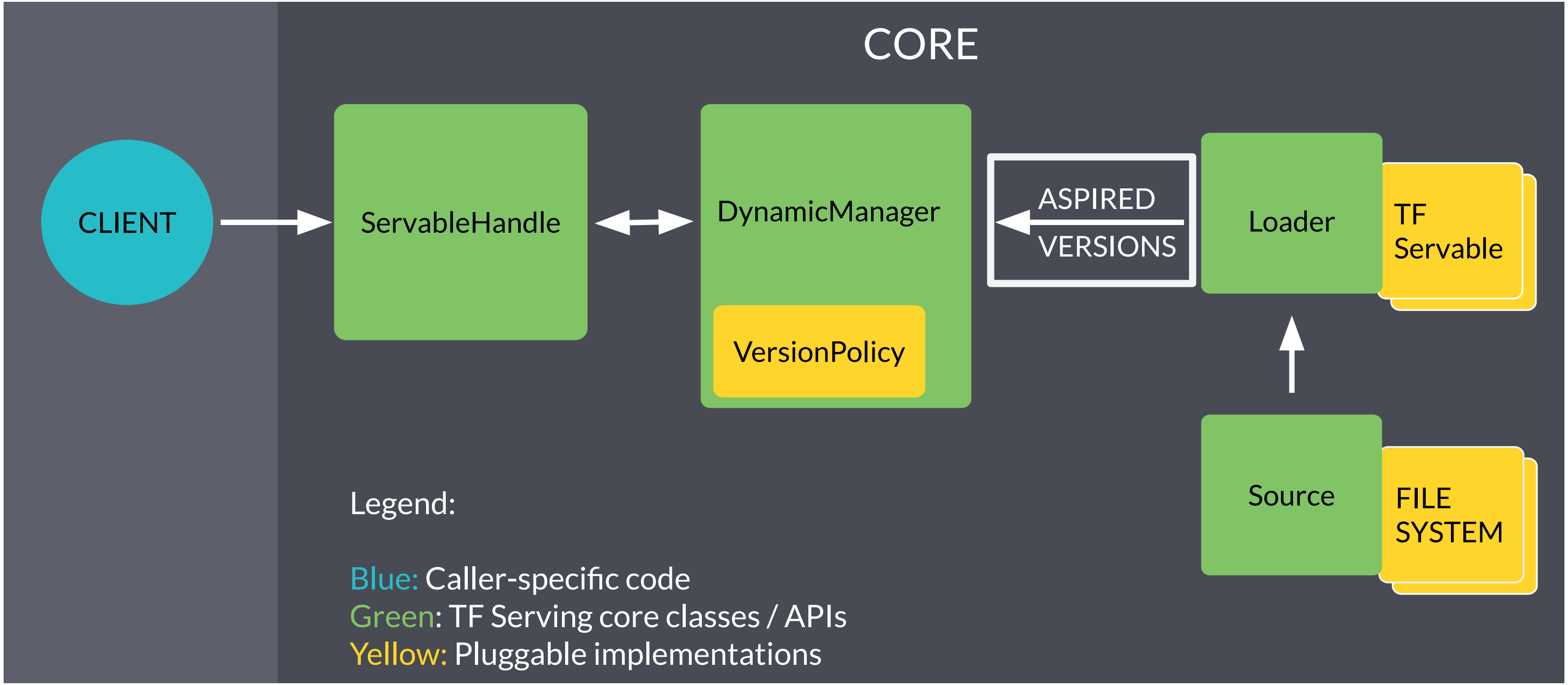

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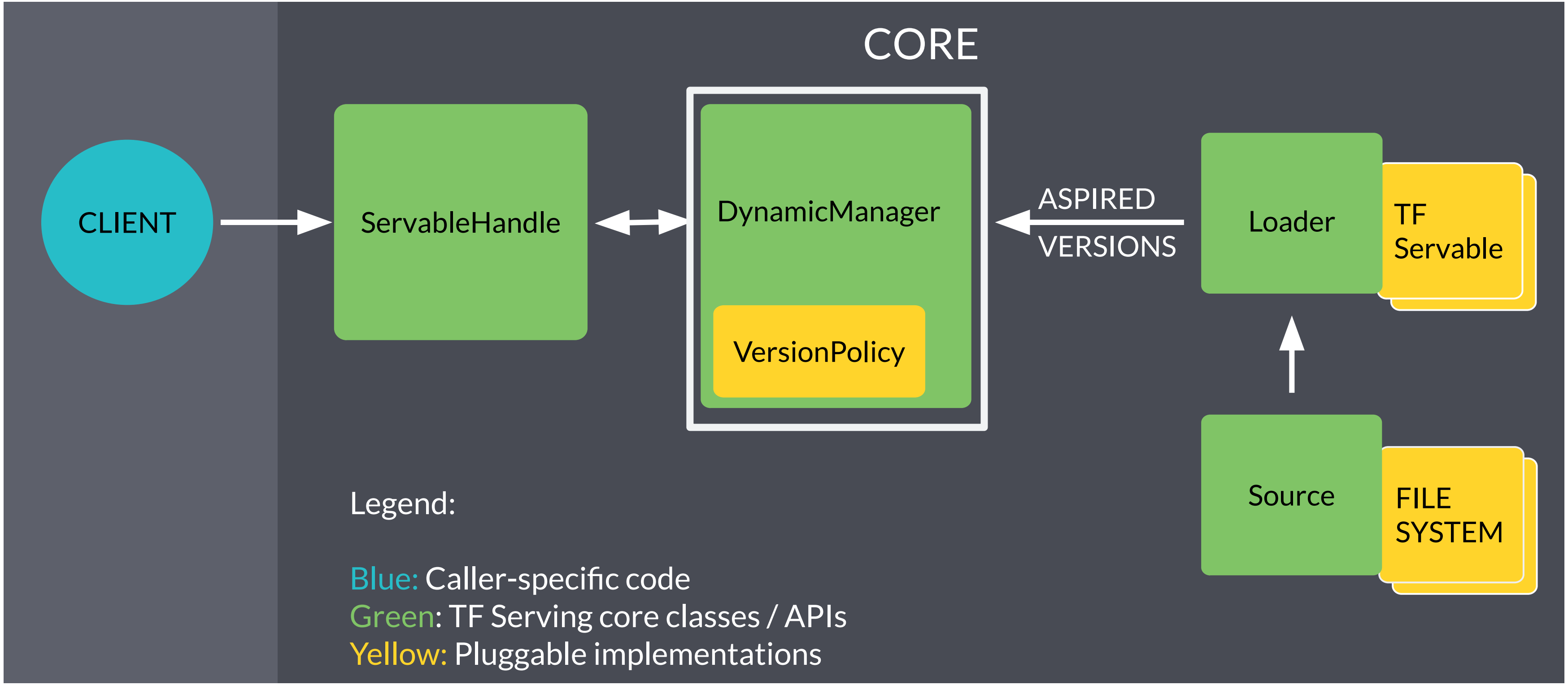

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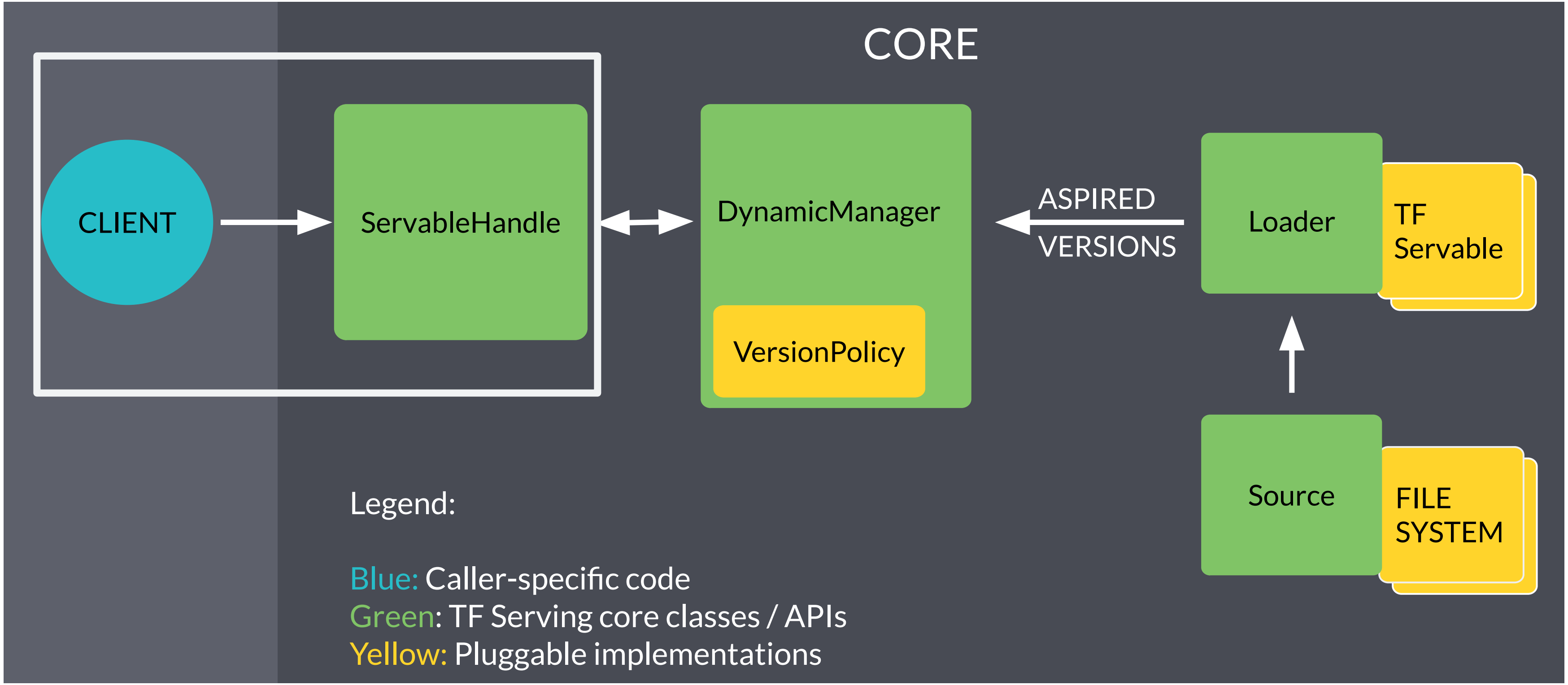

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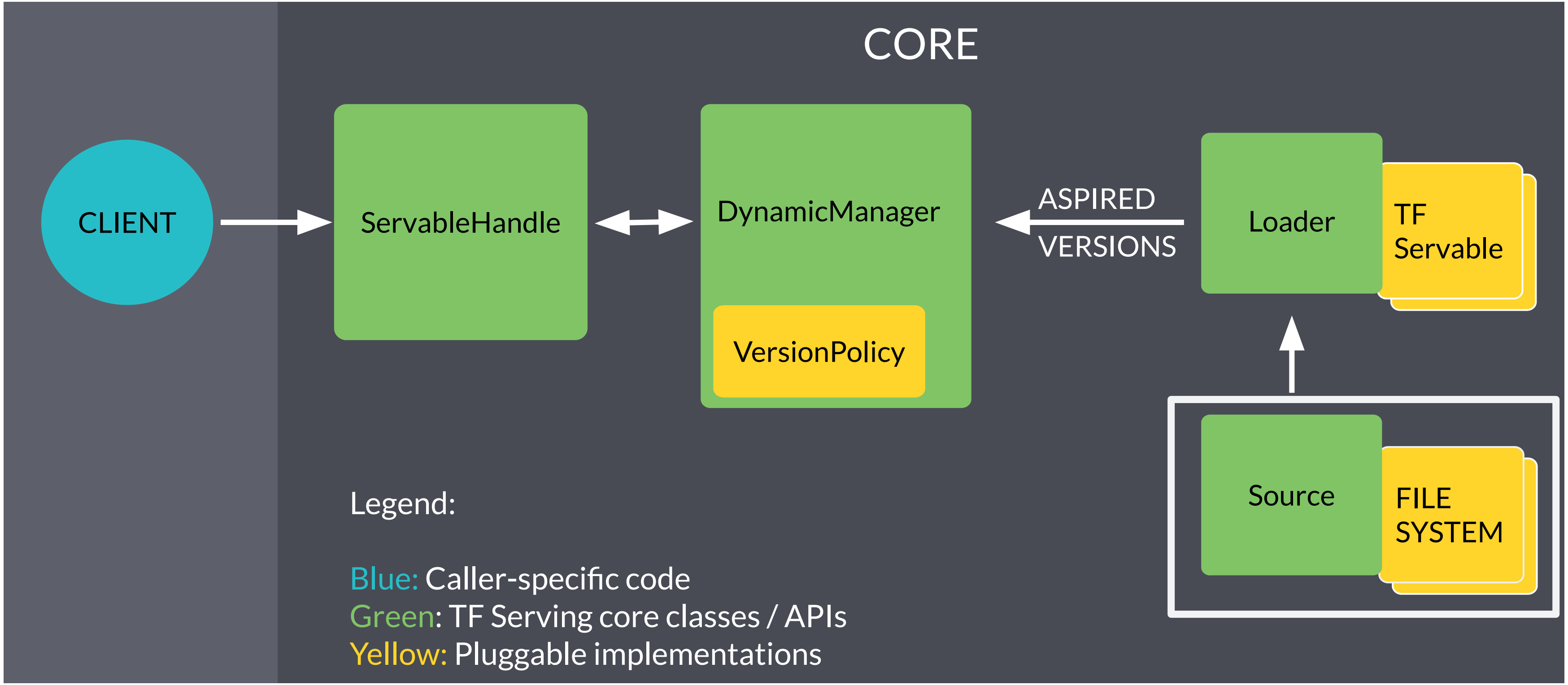

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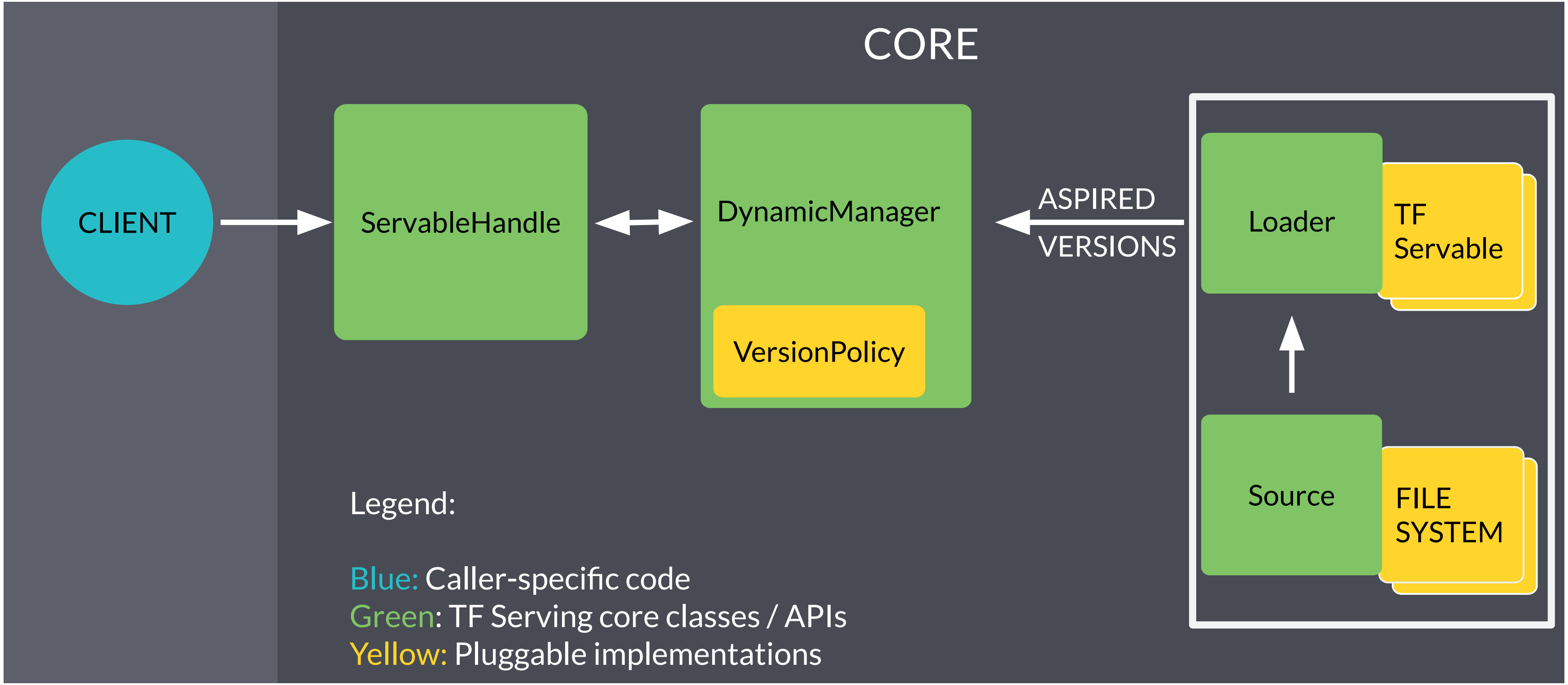

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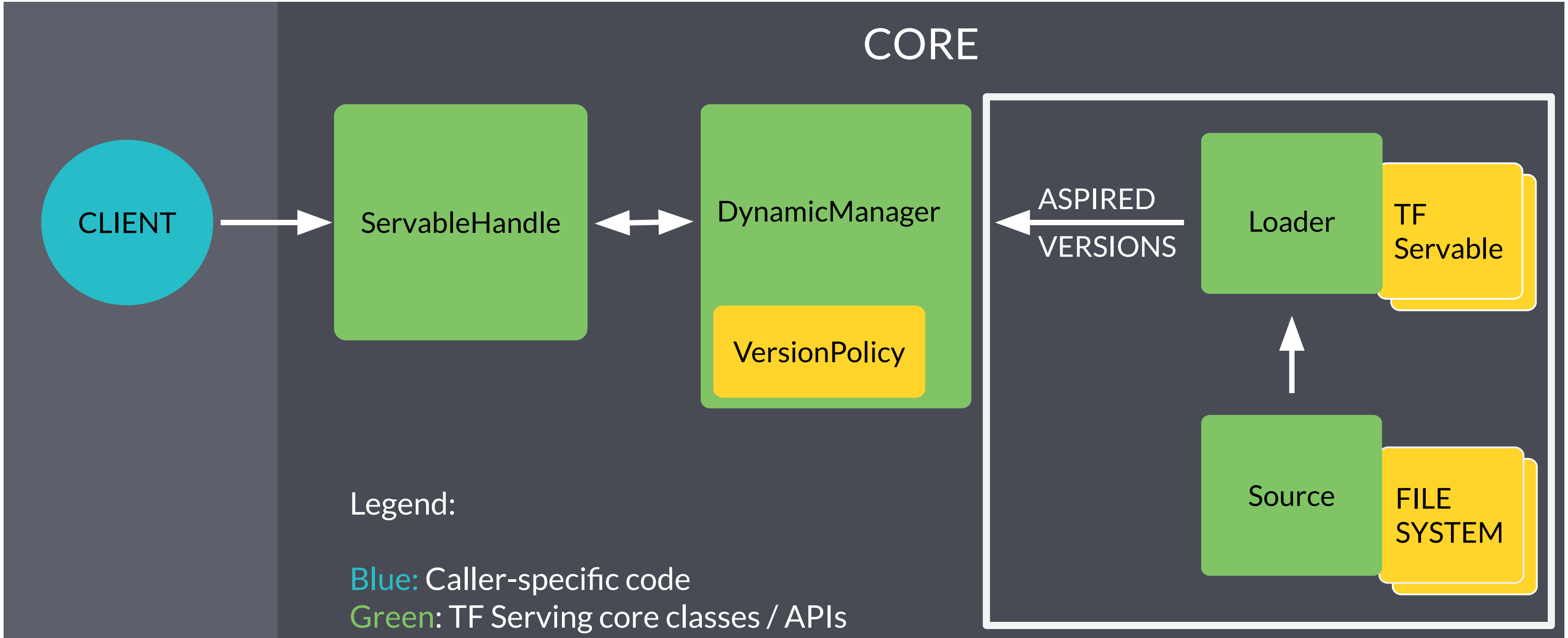
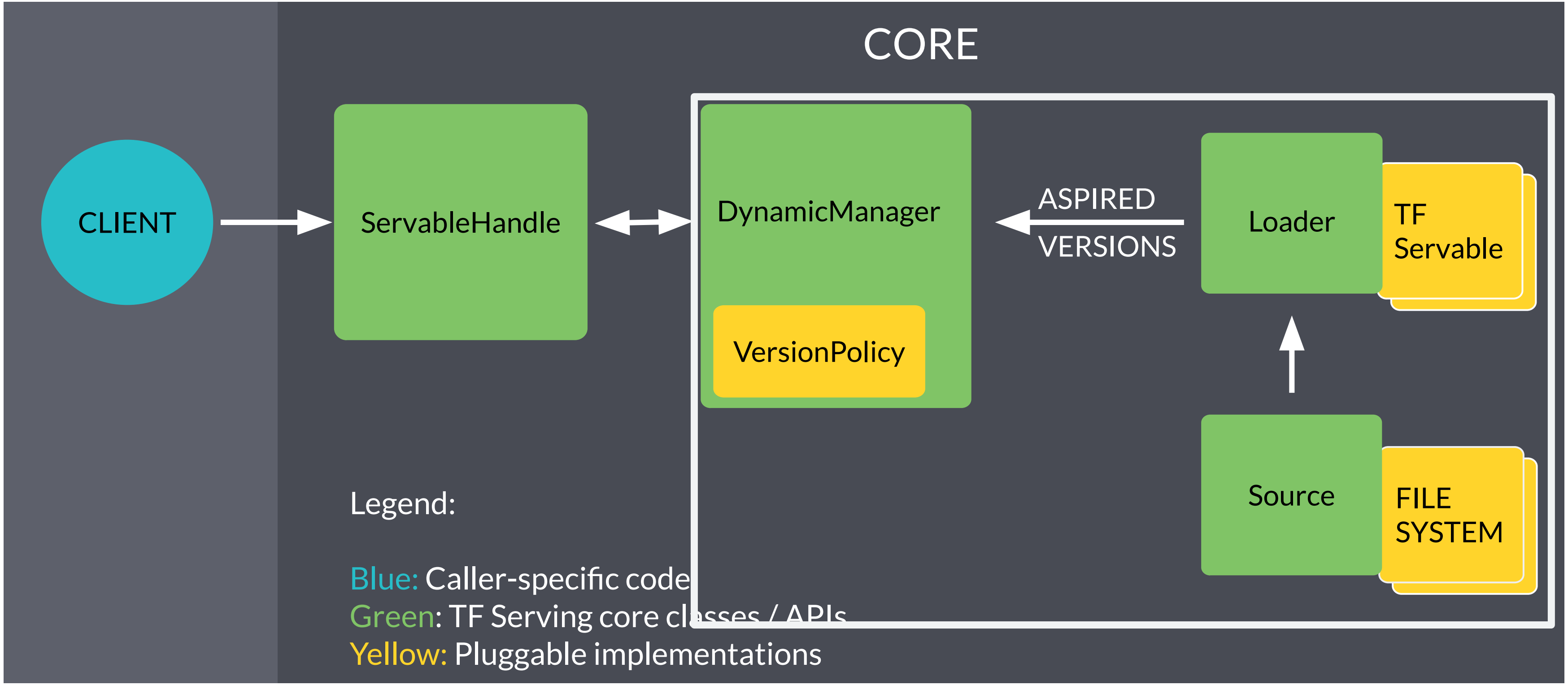


Legend:

Blue: Caller-specific code
Green: TF Serving core classes / APIs
Yellow: Pluggable implementations

TensorFlow Serving Architecture



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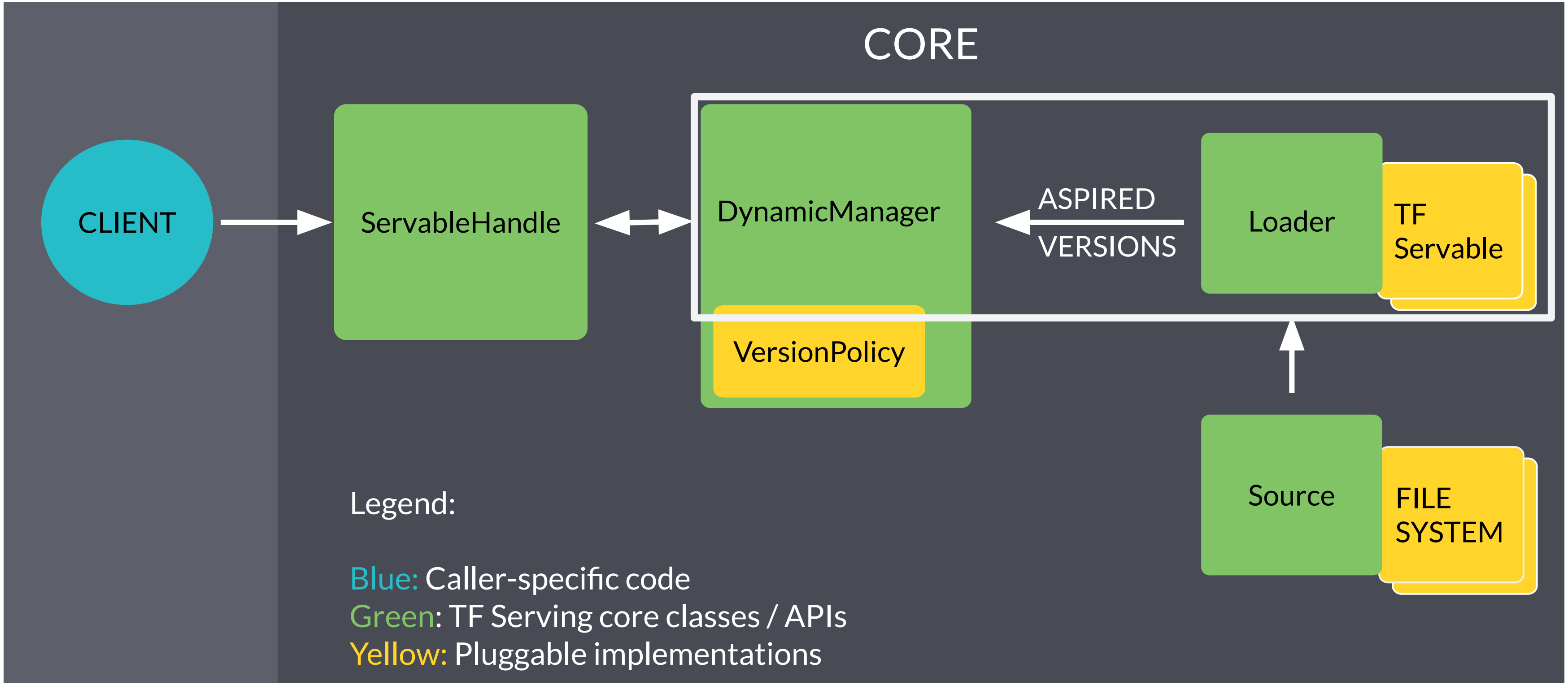

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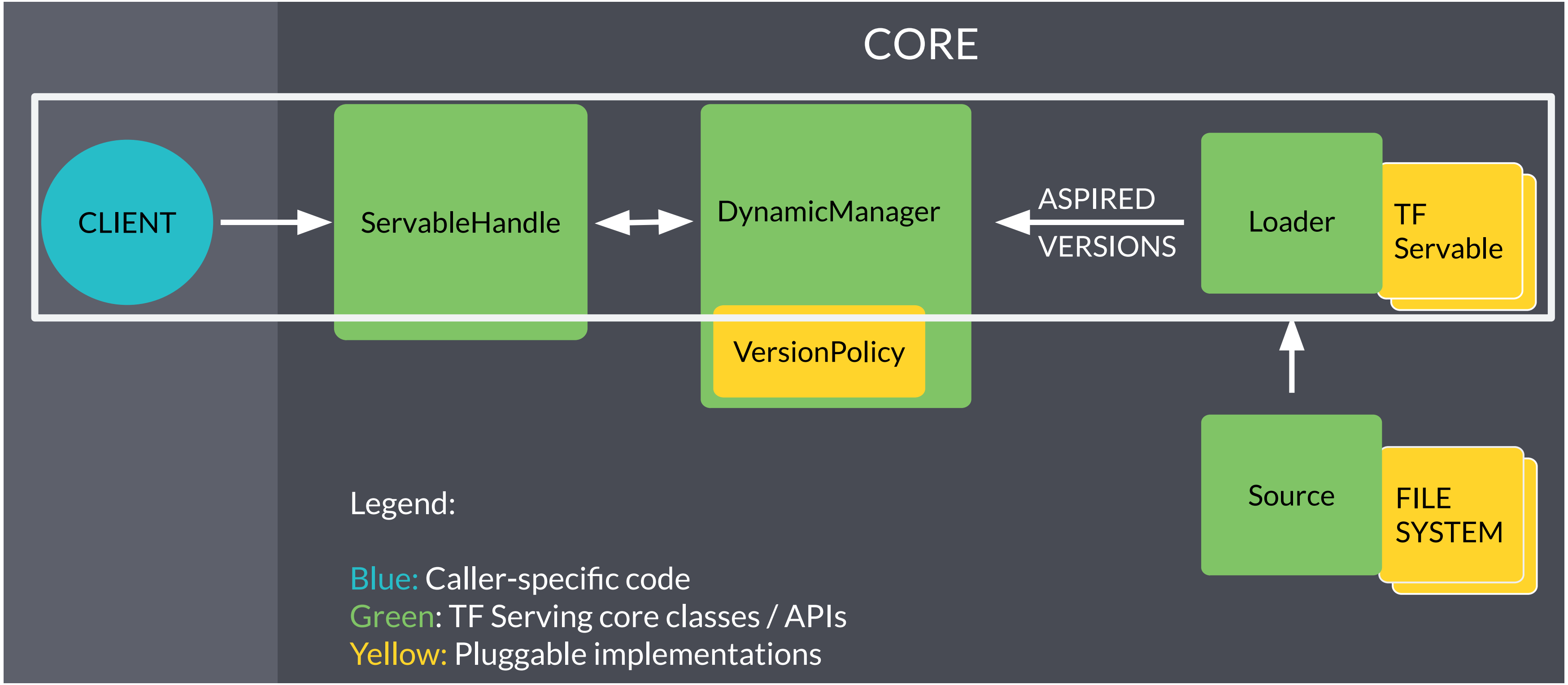


NVIDIA Triton Inference Server

NVIDIA
TRITON INFERENCE SERVER

- Simplifies deployment of AI models at scale in production.
- Open source inference serving software
- Deploy trained models from any framework:
    - TensorFlow, TensorRT, PyTorch, ONNX Runtime, or a custom framework
- Models can be stored on:
    - Local storage, AWS S3, GCP, Any CPU-GPU Architecture (cloud, data centre or edge)

HTTP REST or gRPC endpoints are supported.

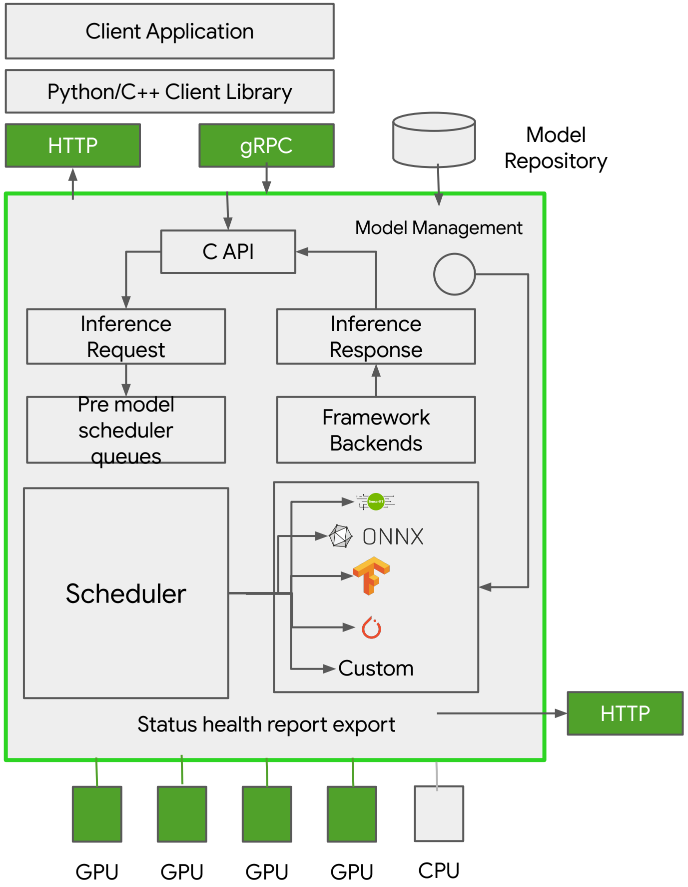
Architecture

Triton Inference Server Architecture supports:

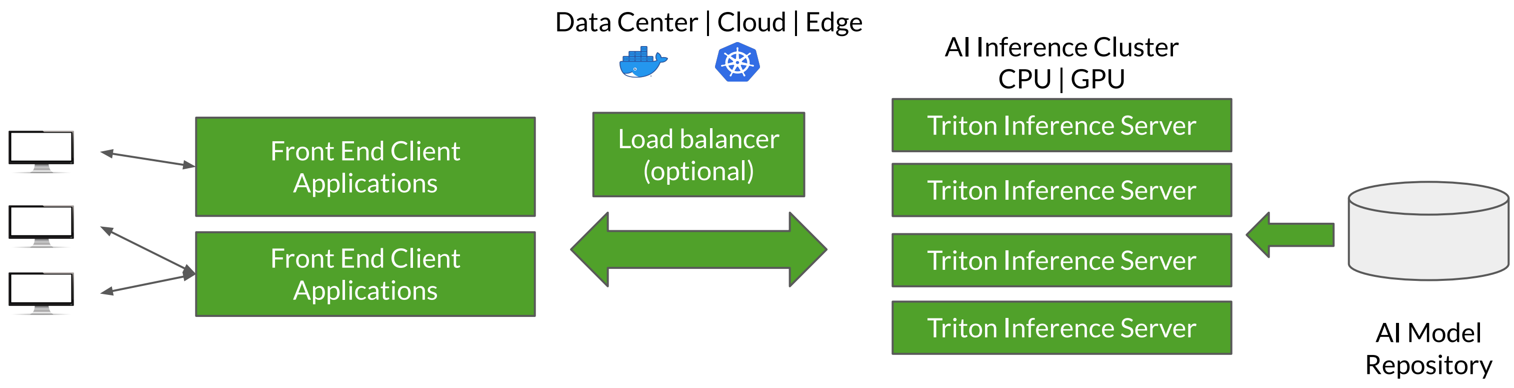
- Single GPU for multiple models from same or different frameworks
- Multi-GPU for same model
    - Can run instances of model on multiple GPUs for increased inference performance.

Supports model ensembles.

Client app can directly link to C API



Designed for Scalability



Can integrate with KubeFlow pipelines for end to end AI workflow

Torch Serve

- Model serving framework for PyTorch models.
- Initiative from AWS and Facebook

PyTorch

TorchServe

Batch and Real-time Inference

Supports REST Endpoints

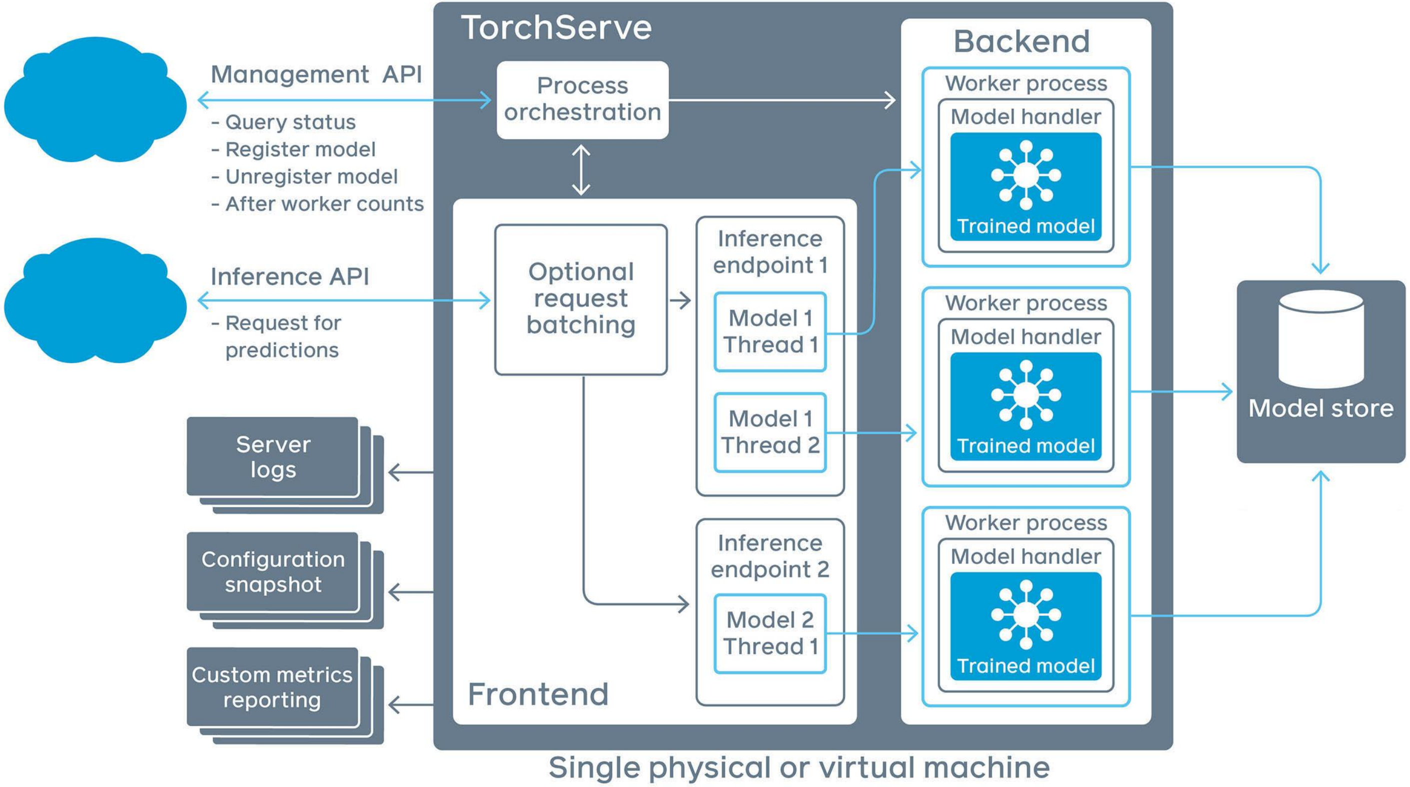
Default handlers for Image Classification, Object Detection, Image Segmentation, Text Classification

Multi-Model Serving

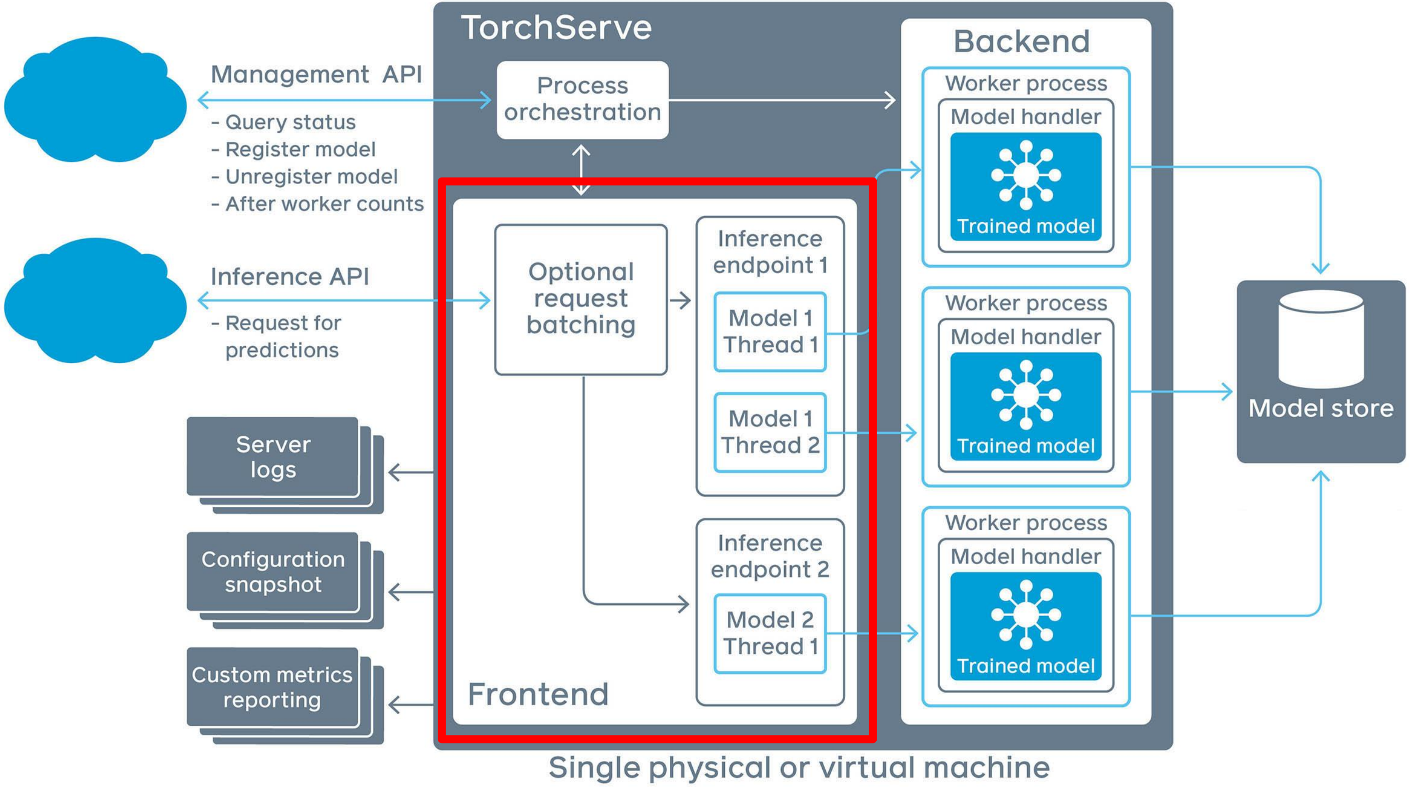
Monitor Detail Logs and Customized Metrics

A/B Testing

TorchServe Architecture



TorchServe Architecture



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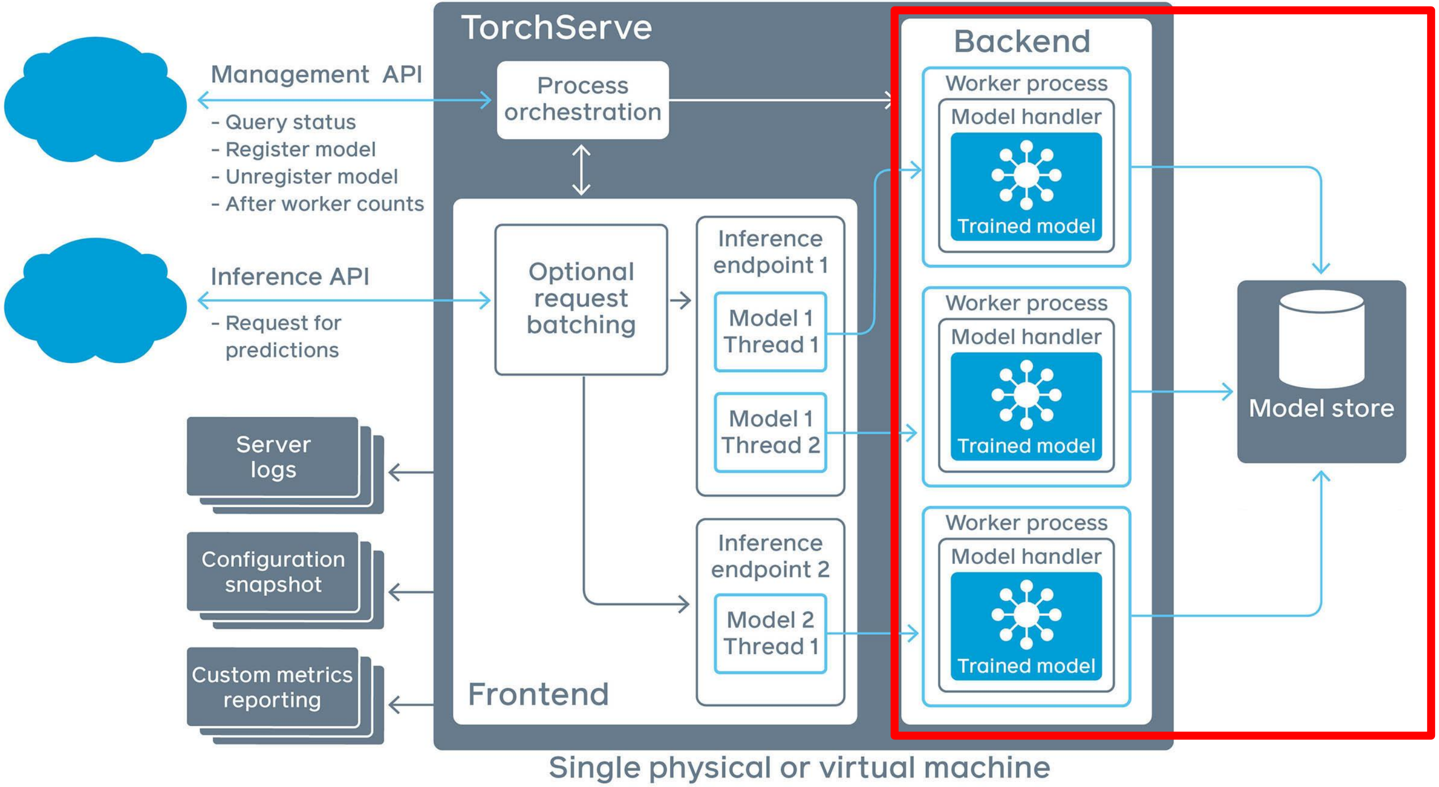

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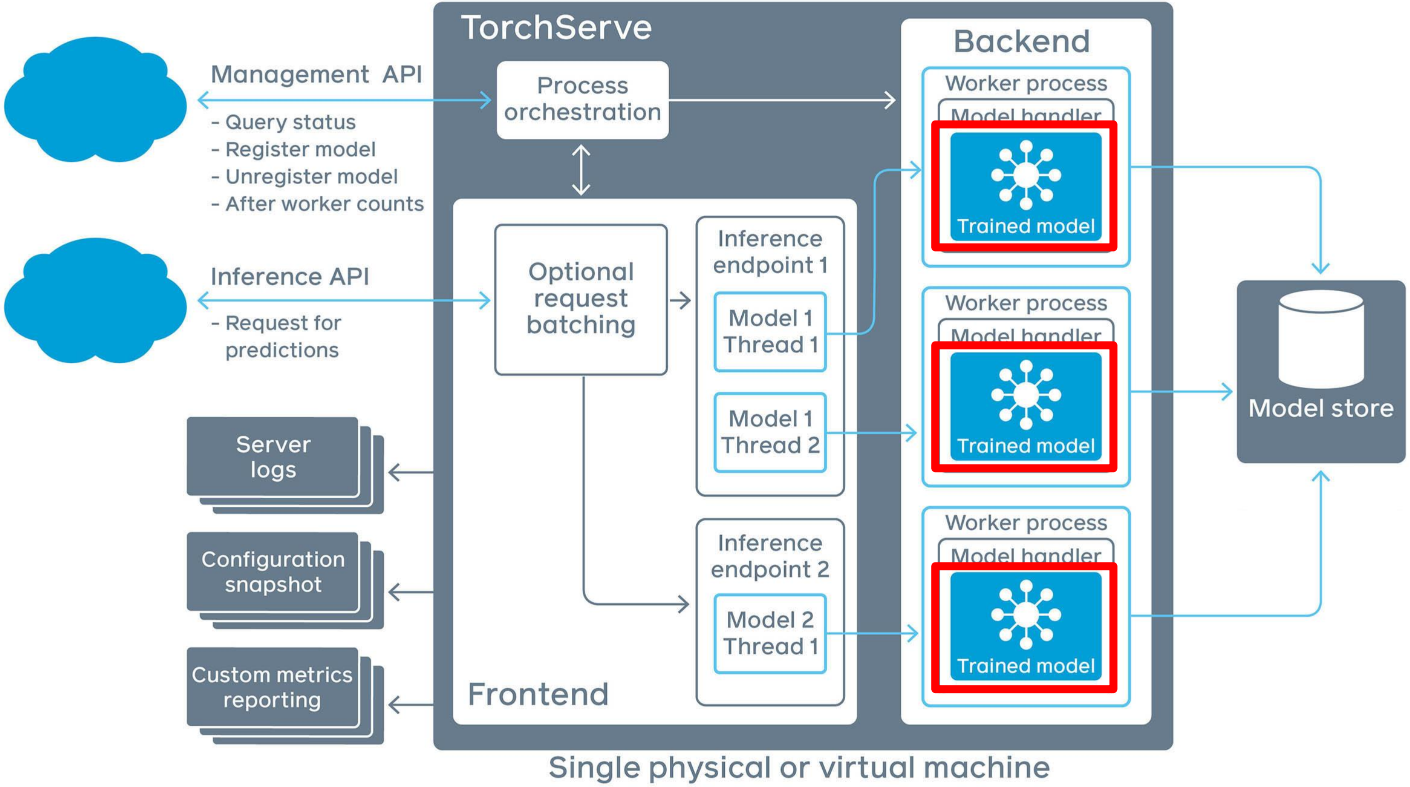

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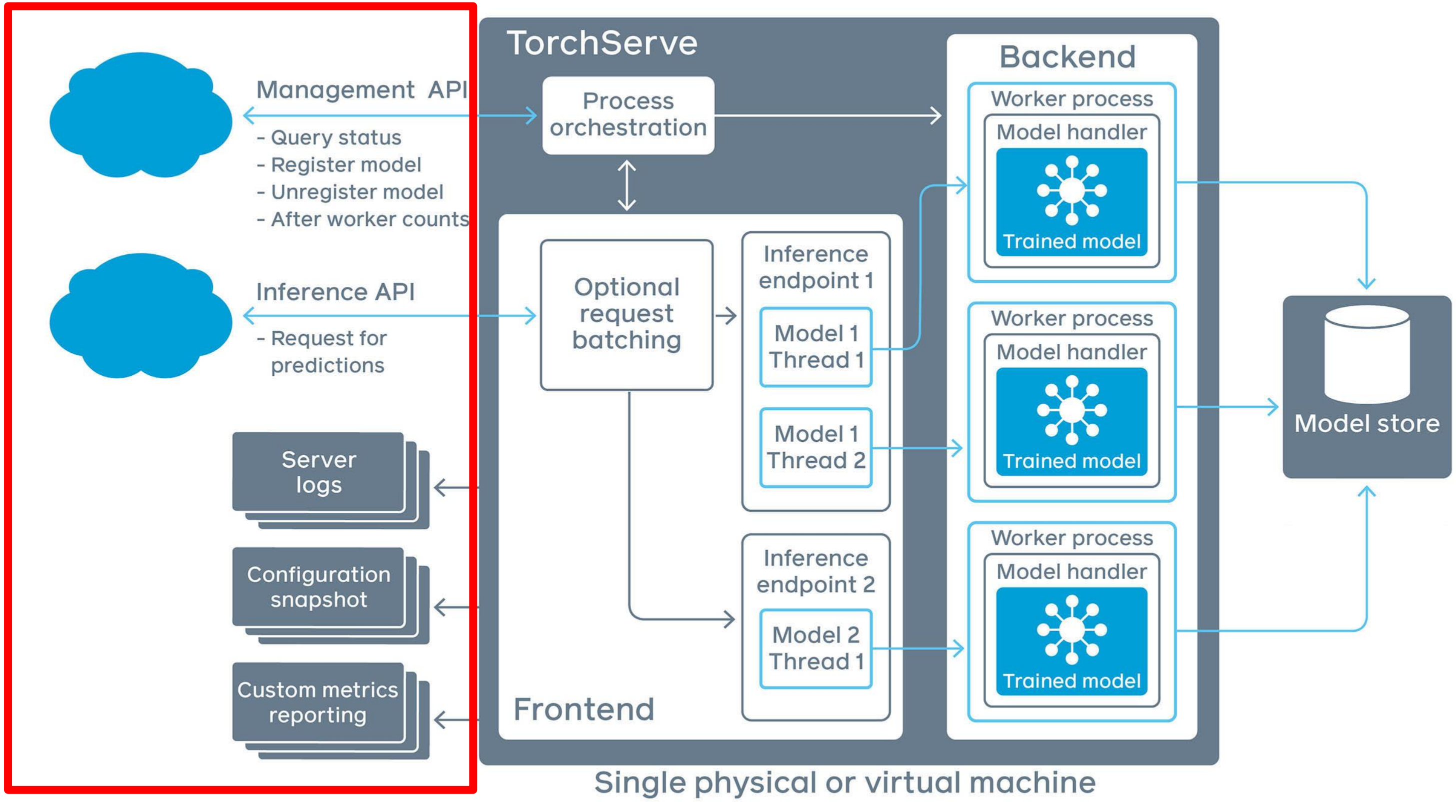
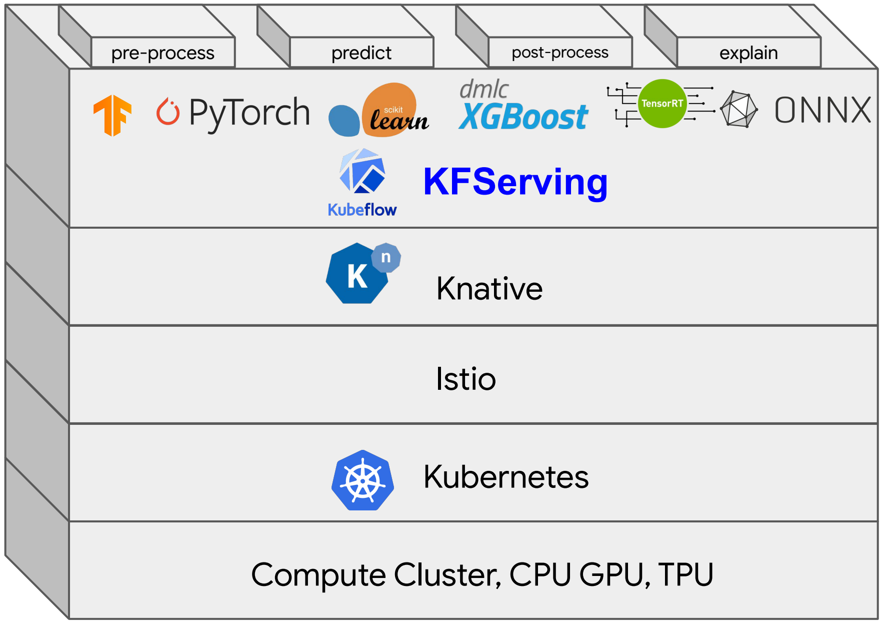


KFServing

Kubeflow

- Enables serverless inferencing on Kubernetes.
- Provides high abstraction interfaces for common ML frameworks like TensorFlow, PyTorch, scikit-learn etc.

KF Serving

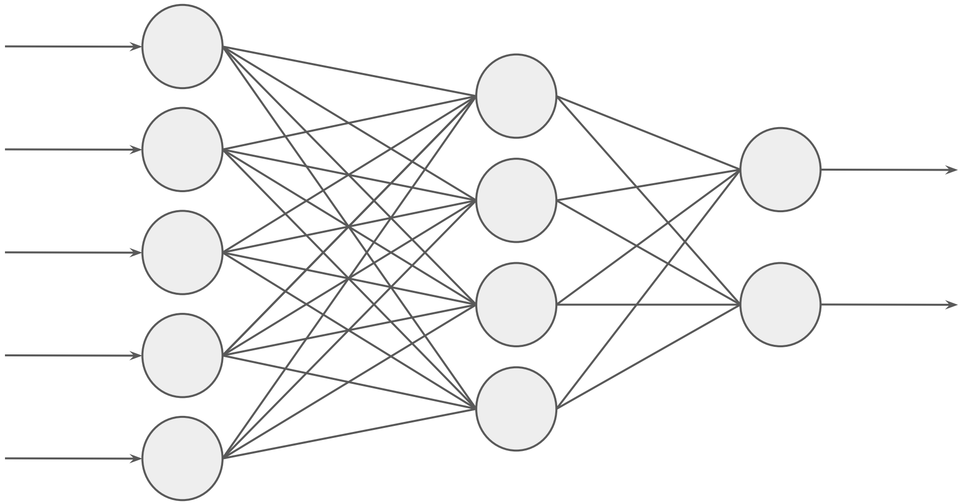


DeepLearning.AI

Scaling Infrastructure

Model Serving: Patterns and Infrastructure

Why is Scaling Important?



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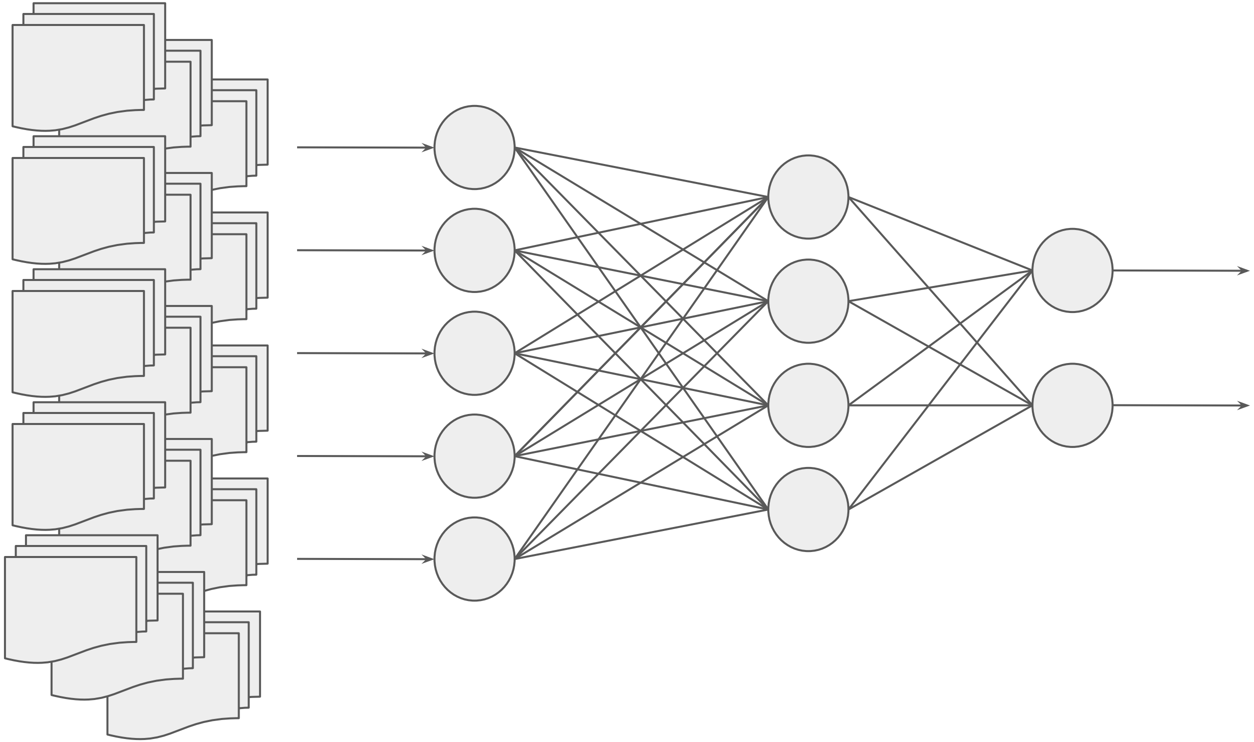

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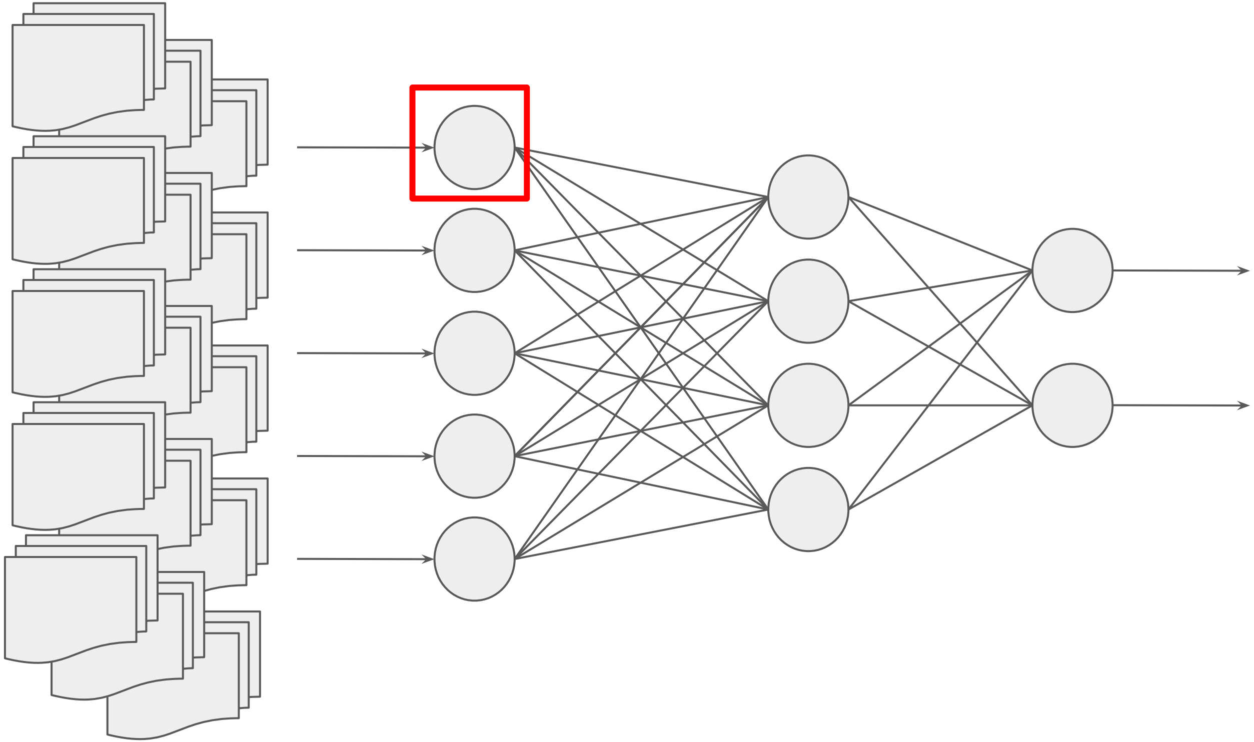

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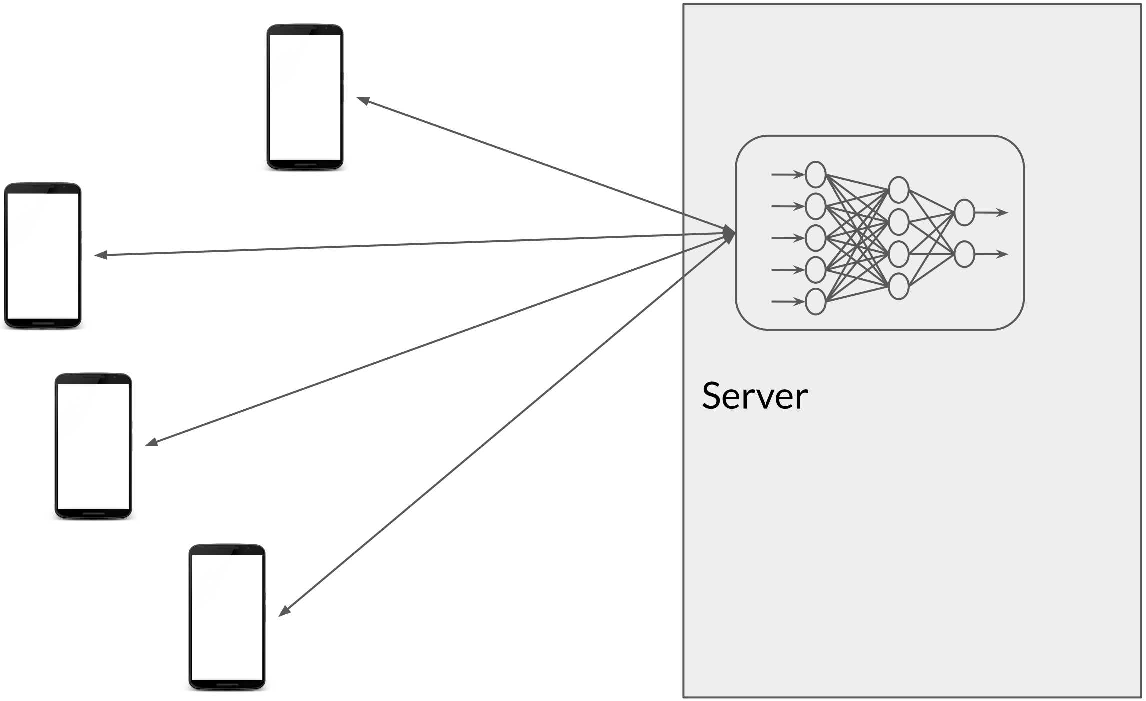
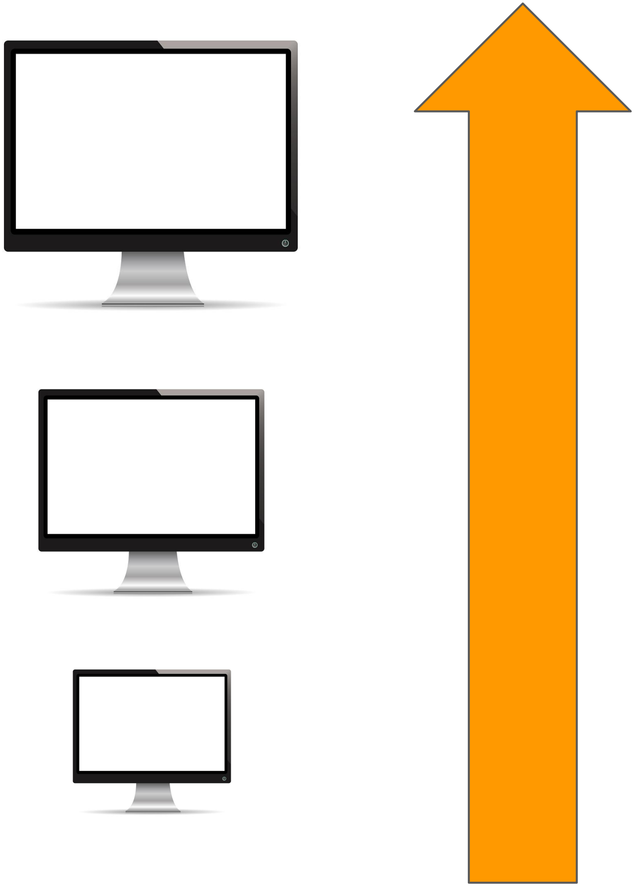
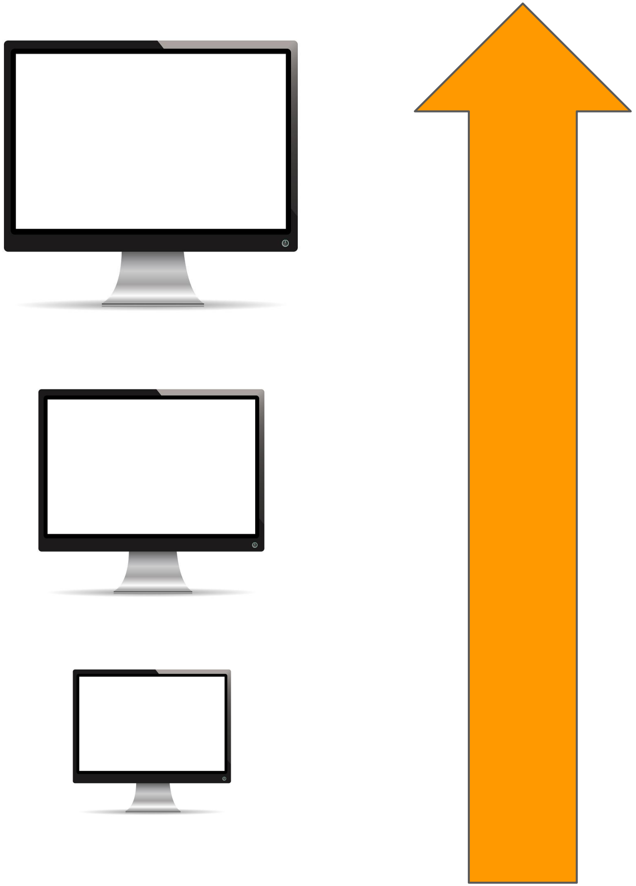
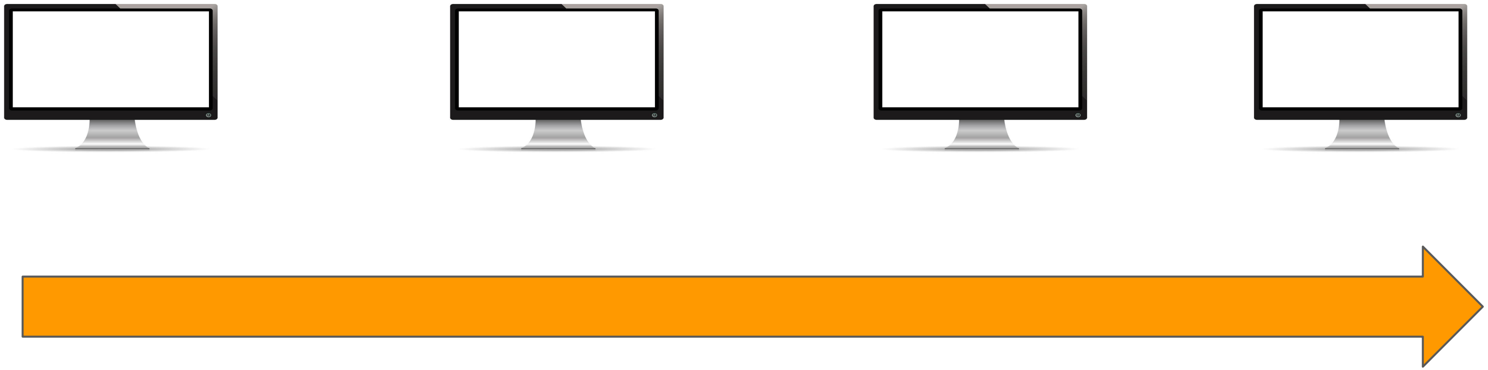
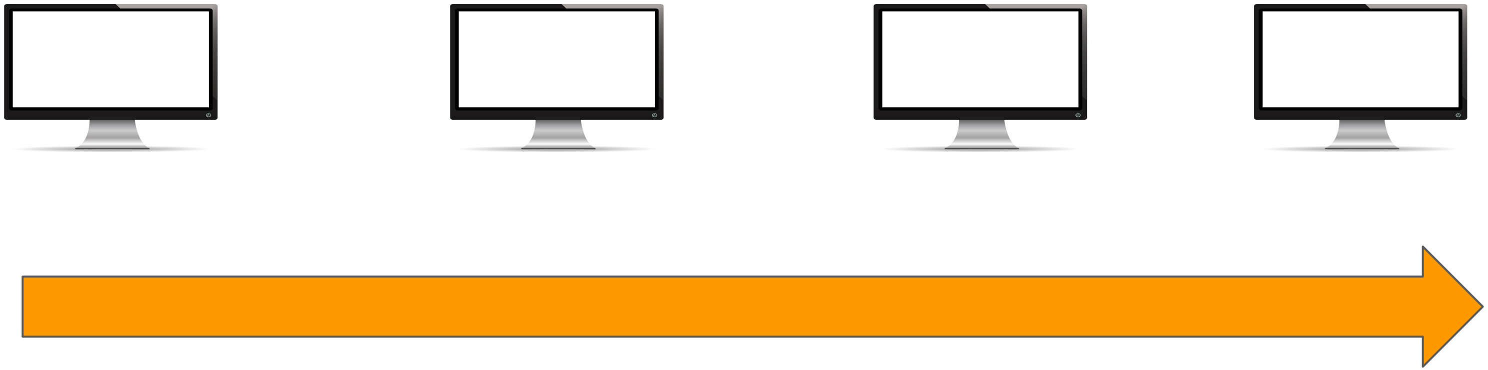






- Increased Power
- Upgrading
- More RAM
- Faster Storage
- Adding or upgrading GPU/TPU





- More CPUs/GPUs instead of bigger ones
- Scale up as needed
- Scale back down to minimums

Why Horizontal Over Vertical Scaling

Benefit of elasticity	• Shrink or grow no of nodes based on load, throughput, latency requirements.
Application never goes offline	• No need for taking existing servers offline for scaling
No limit on hardware capacity	• Add more nodes any time at increased cost

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Why Horizontal Over Vertical Scaling

Whatch out for 3 things:
- can I manually scale?
- can I auto scale?
- how agressive is the sytem at spinning up/ down based on needs

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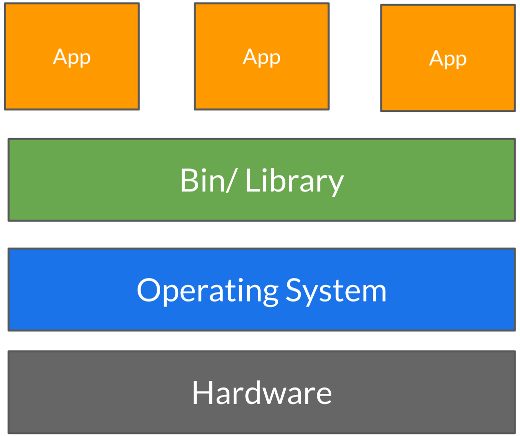
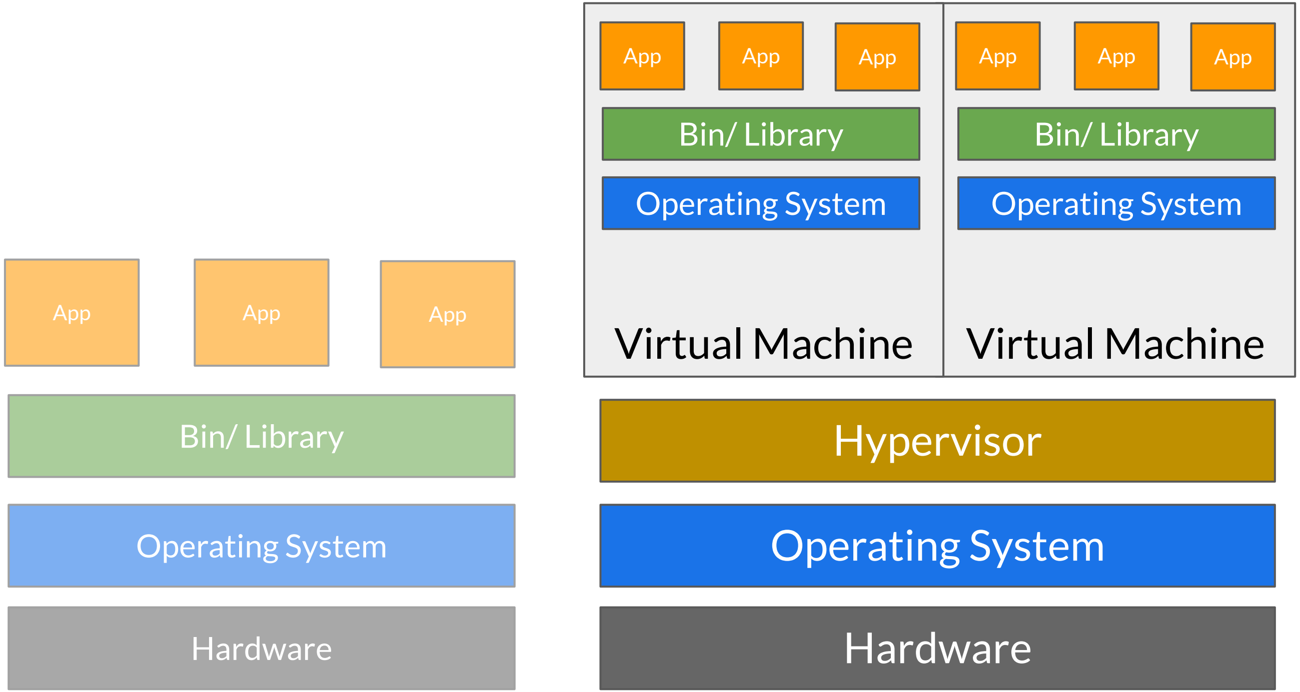
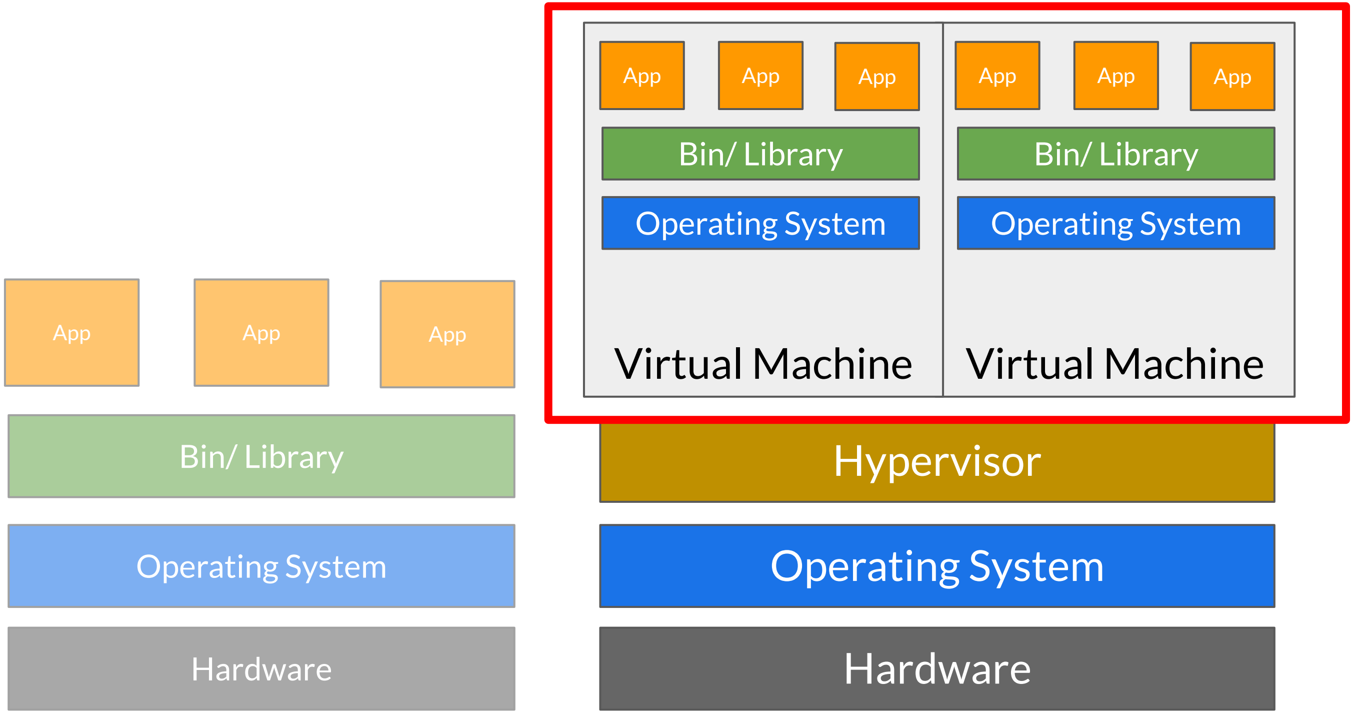
Typical System Architecture



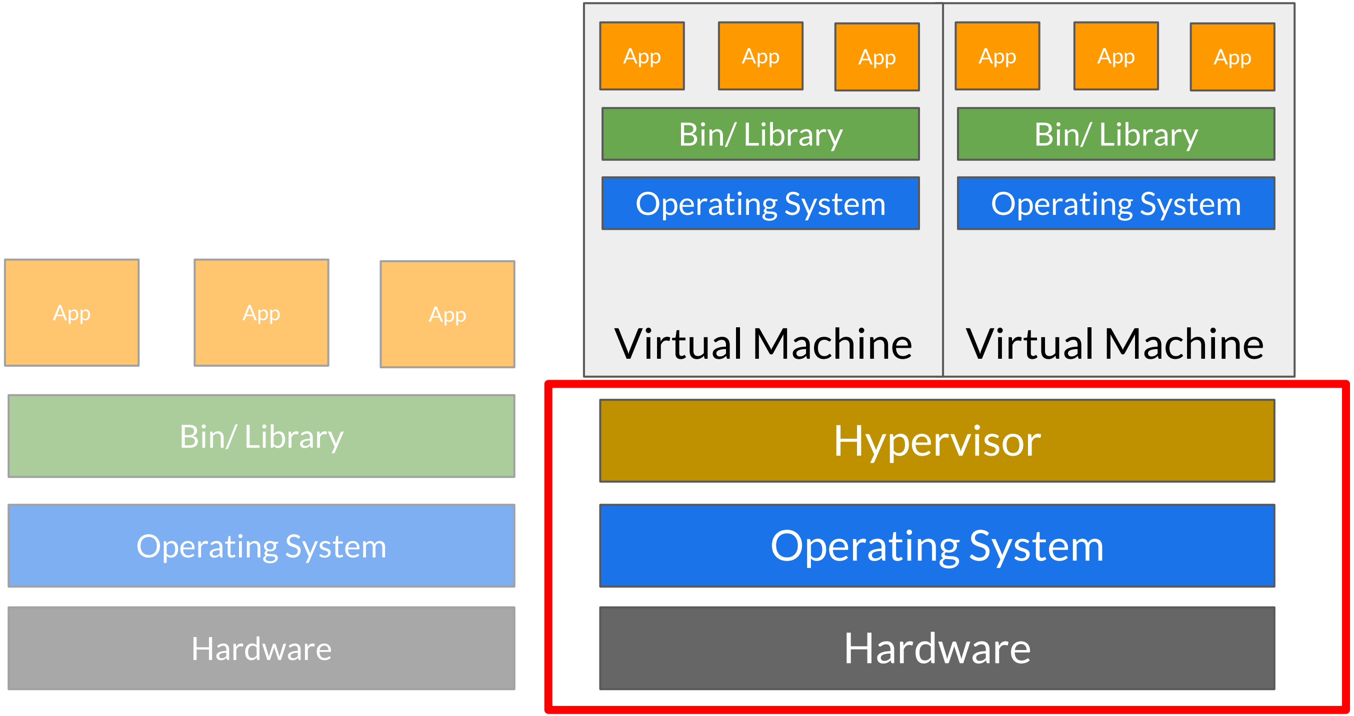
Virtual Machine (VM) Architecture



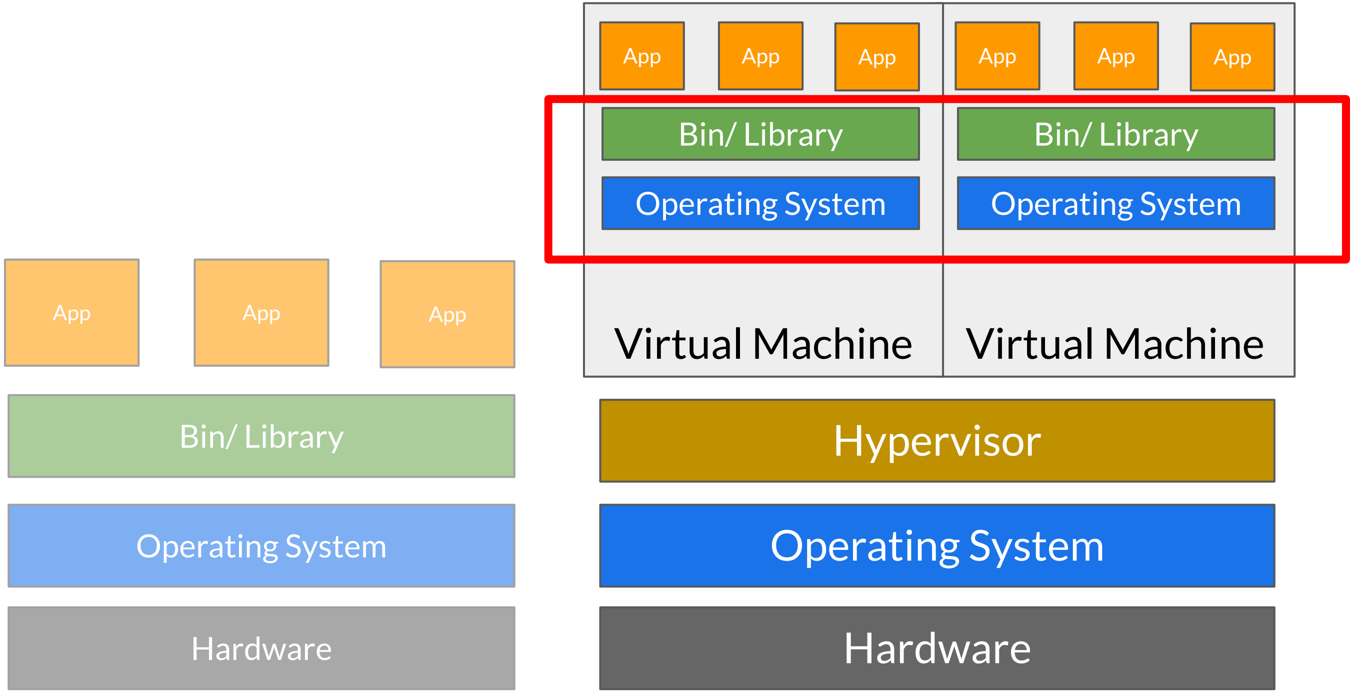
VM Management



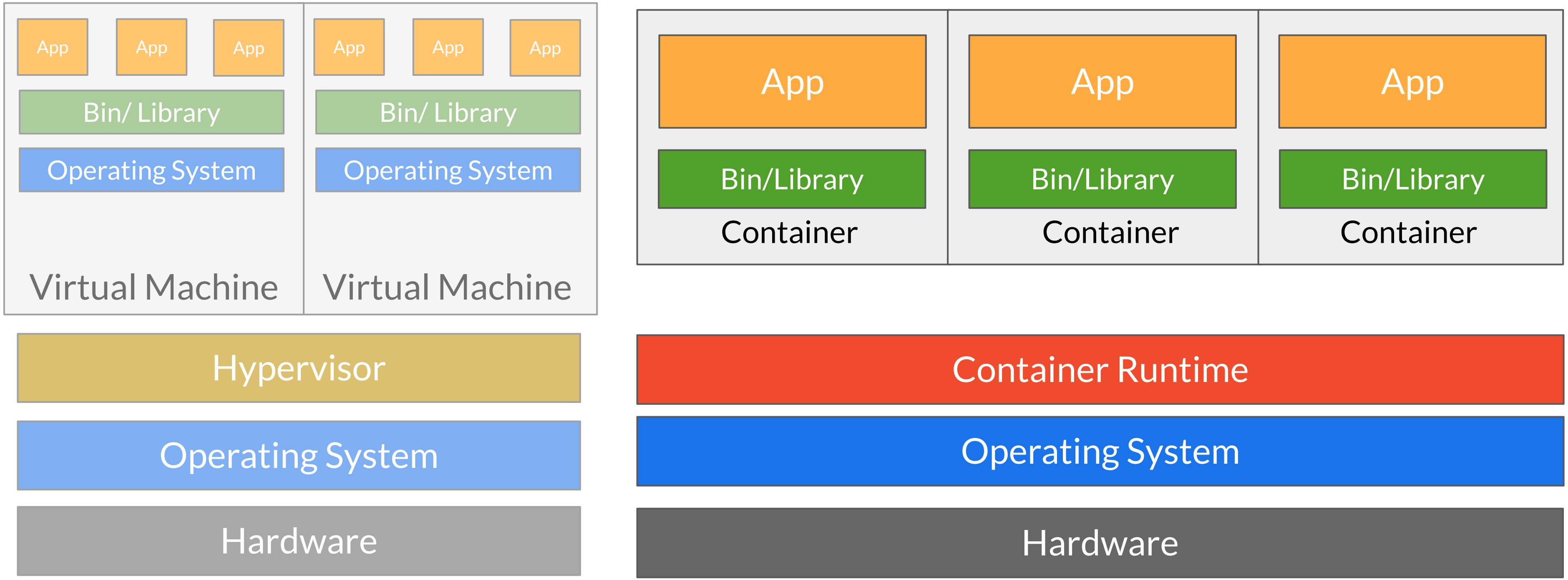
Hypervisor and Scaling



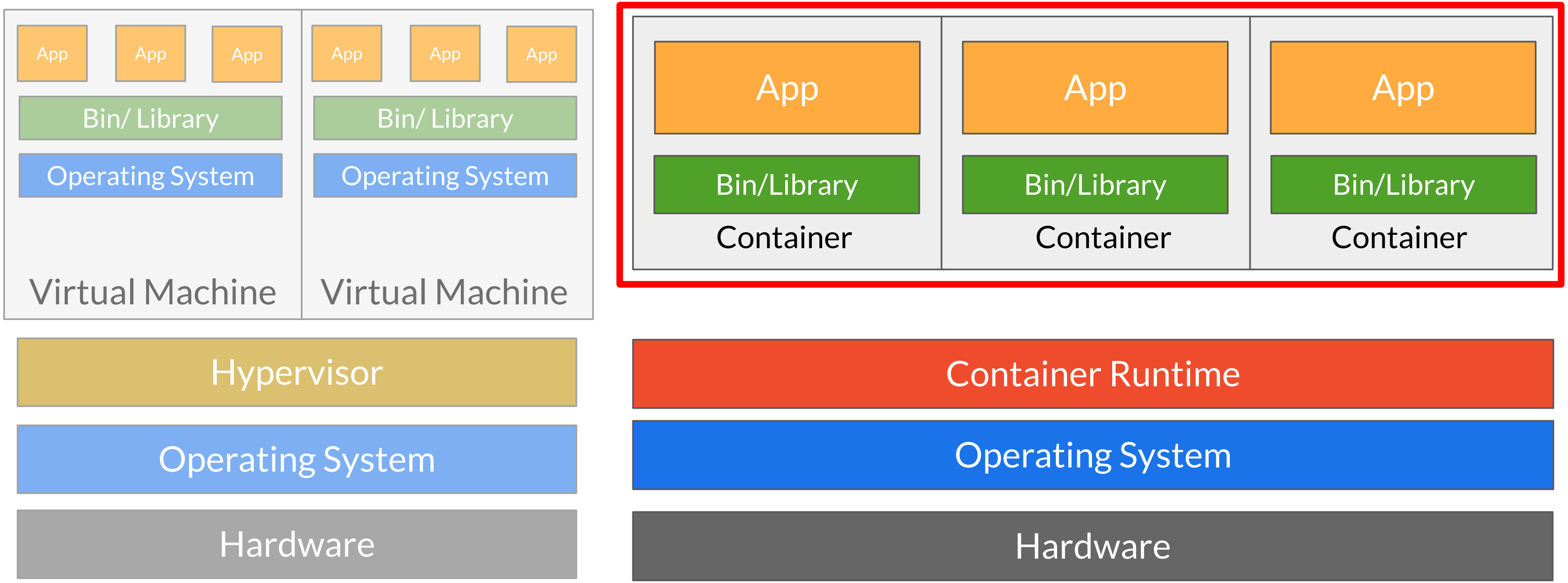
VM Limitations



Building Containers



Containers Advantages



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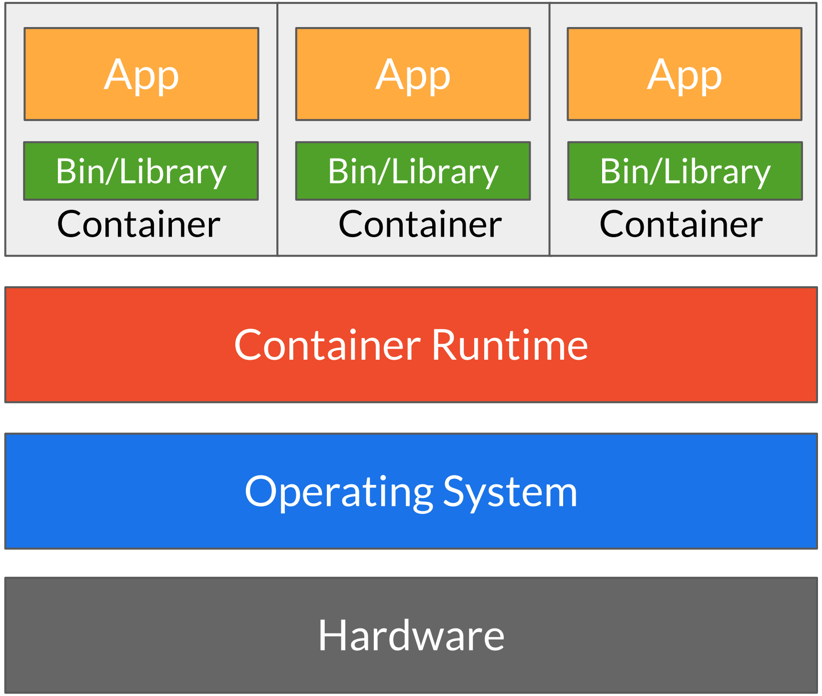
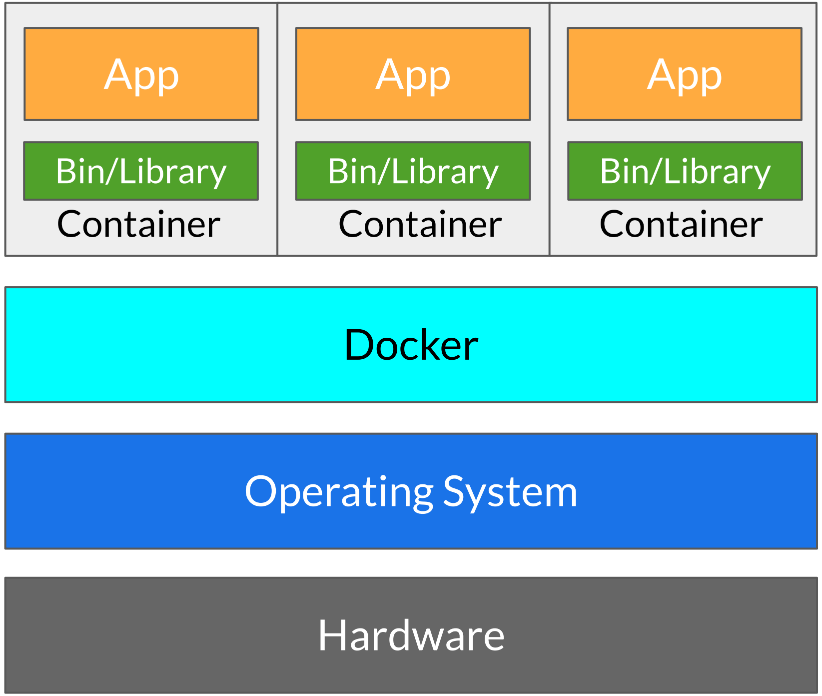


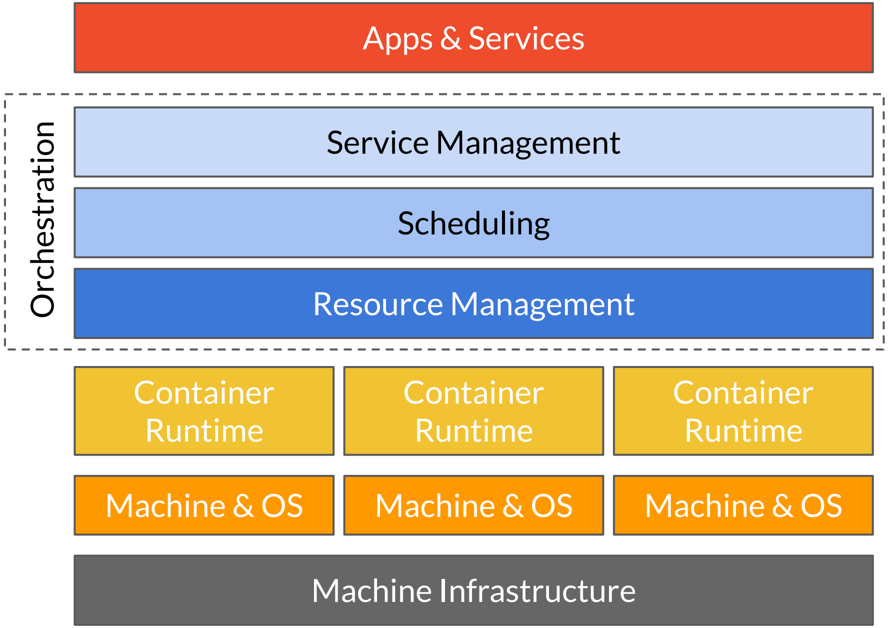
- Less OS requirements - more apps!
- Abstraction
- Easy deployment based on container runtime

Docker: Container Runtime



- Open source container technology
- Most popular container runtime
- Started as container technology for Linux
- Available for Windows applications as well.
- Can be used in data centres, personal machines or public cloud.
- Docker partners with major cloud services for containerization.

Enter Container Orchestration



- Manages life cycle of containers in production environments
- Manages scaling of containers
- Ensures reliability of containers
- Distributes resources between containers.
- Monitors health of containers

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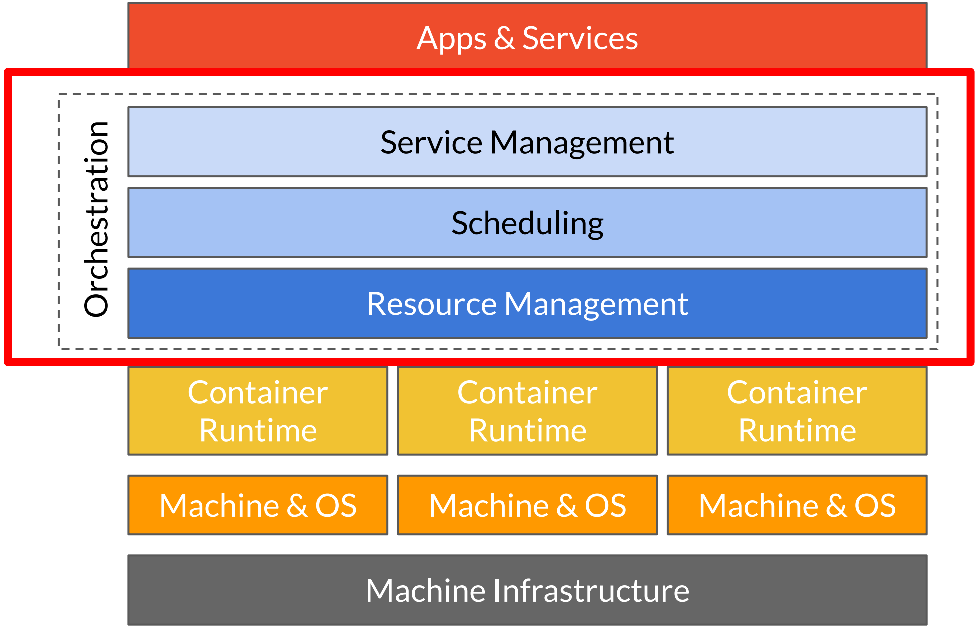

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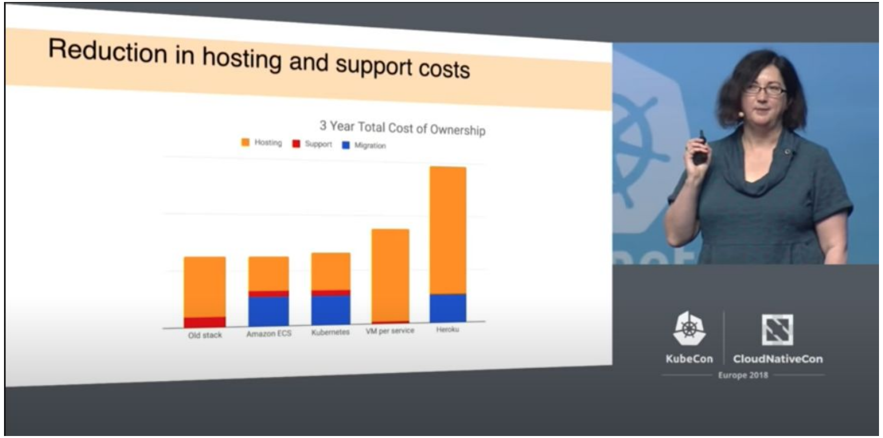
Popular Container Orchestration Tools

Kubernetes

Docker Swarm

Kubernetes


Reduction in hosting and support costs
3 Year Total Cost of Ownership
Hosting
Support
Migration
Old stack
Amazon ECS
Kubernetes
VM per service
Heroku
KubeCon
CloudNativeCon
Europe 2018

ML Workflows on Kubernetes - KubeFlow

- Dedicated to making deployments of machine learning (ML) workflows on Kubernetes simple, portable and scalable.
- Anywhere you are running Kubernetes, you should be able to run Kubeflow.
- Can be run on premise or on Kubernetes engine on cloud offerings AWS, GCP, Azure etc.,

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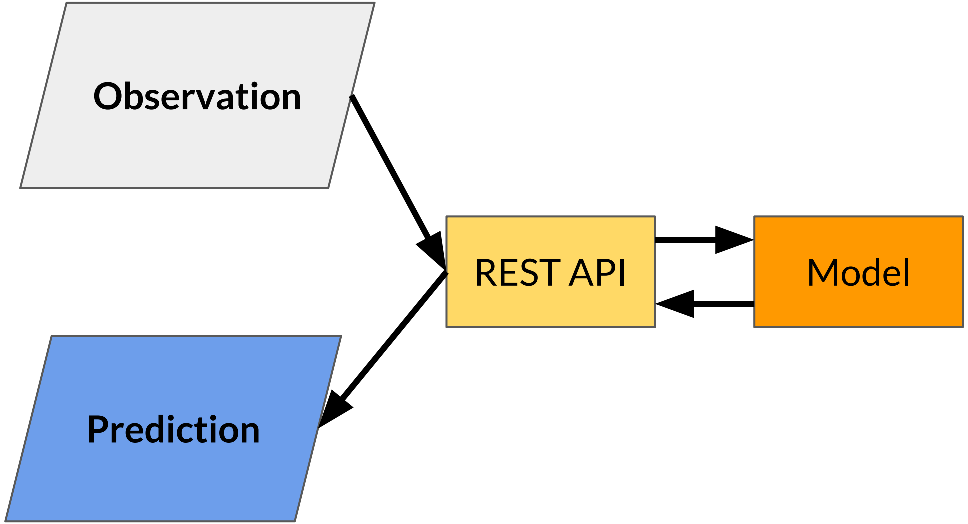
Online Inference

Model Serving: Patterns and Infrastructure

Online Inference



- Process of generating machine learning predictions in real time upon request.
- Predictions are generated on a single observation of data at runtime.
- Can be generated at any time of the day on demand

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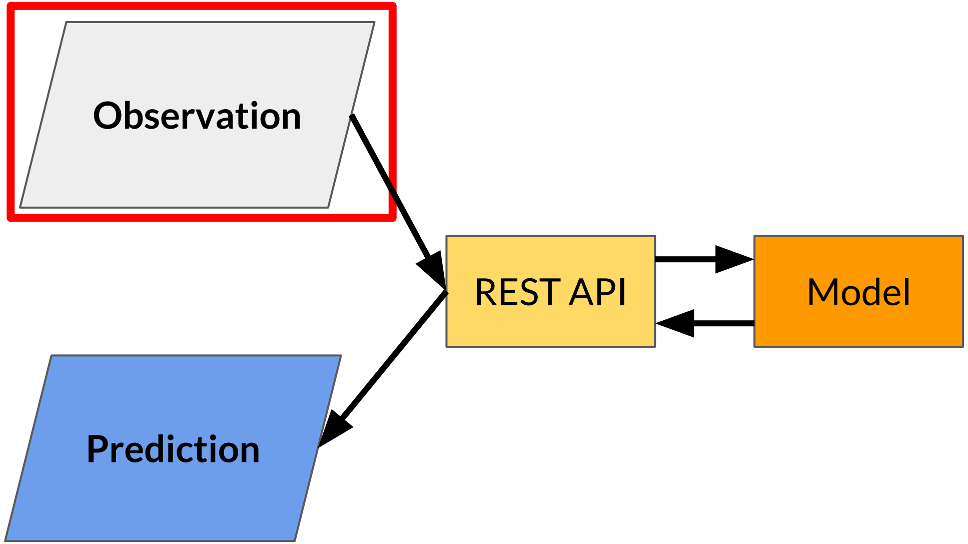

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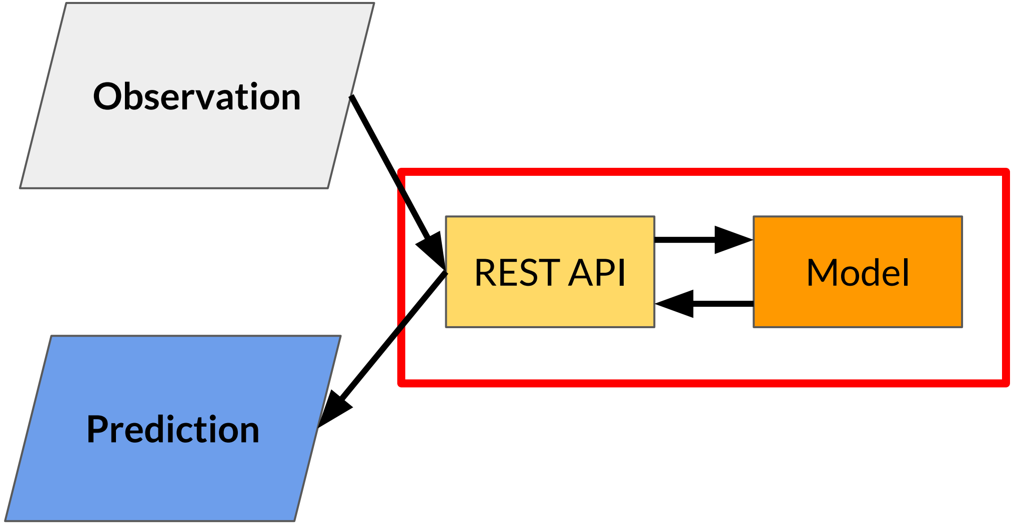

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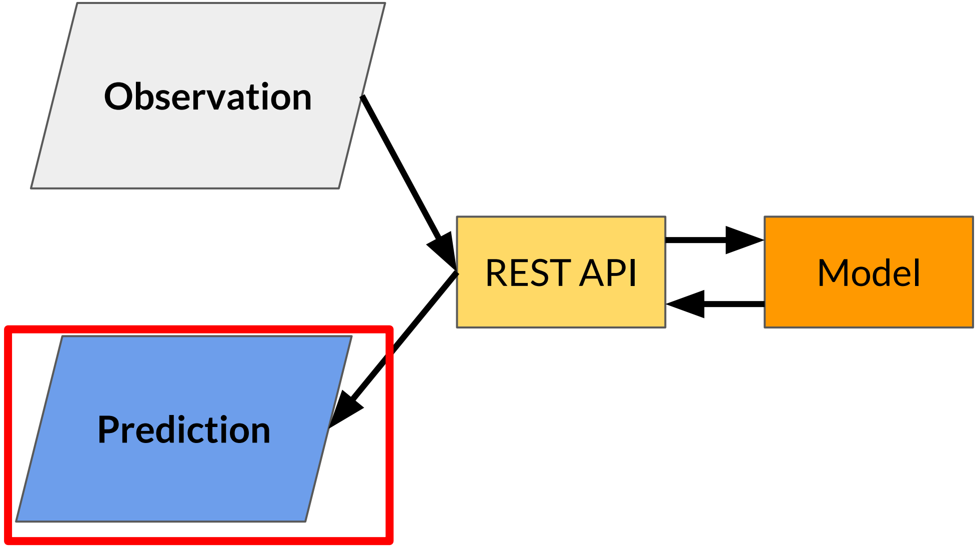

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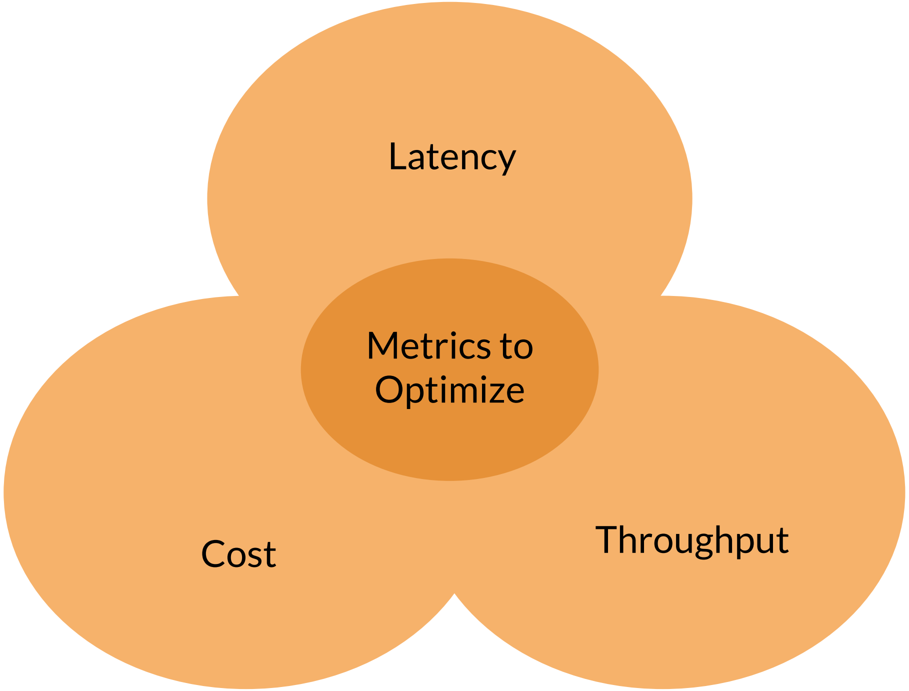
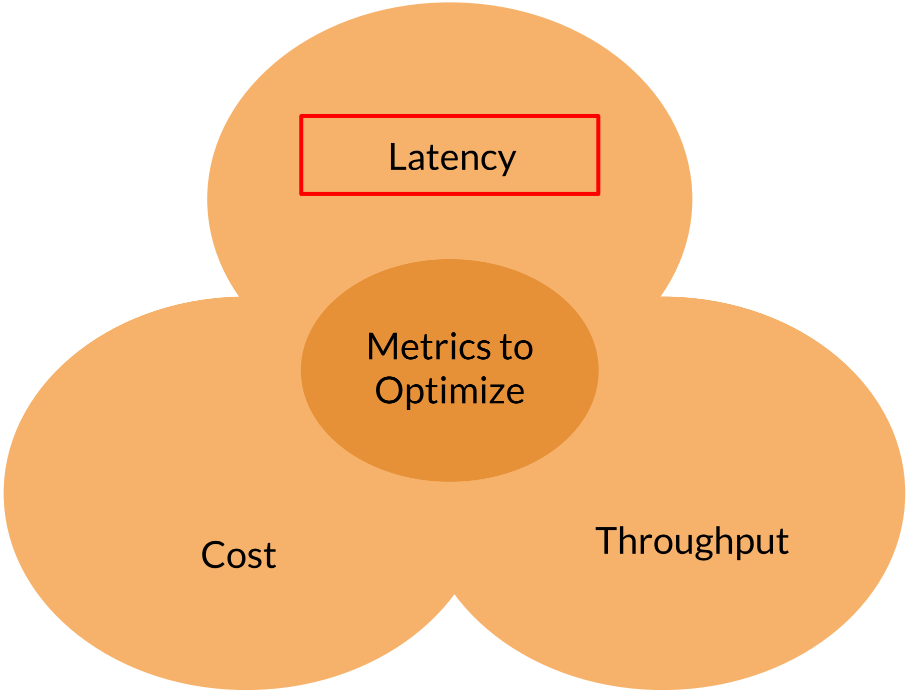
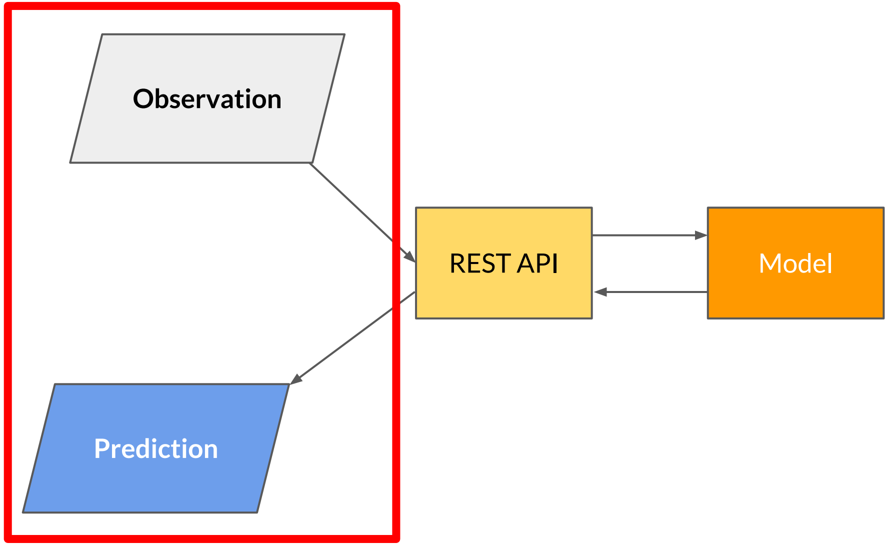
- Can be generated at any time of the day on demand

Optimising ML Inference



Optimising ML Inference





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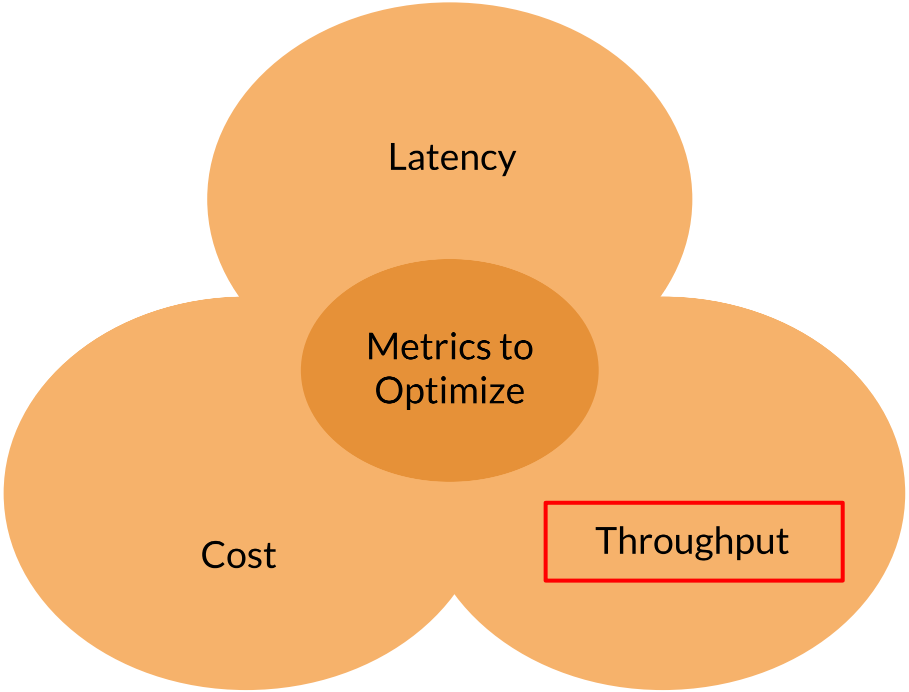
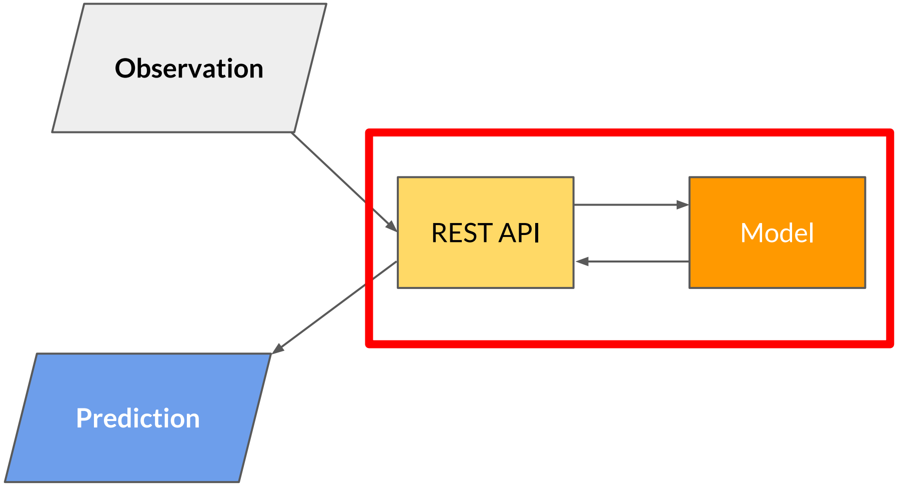
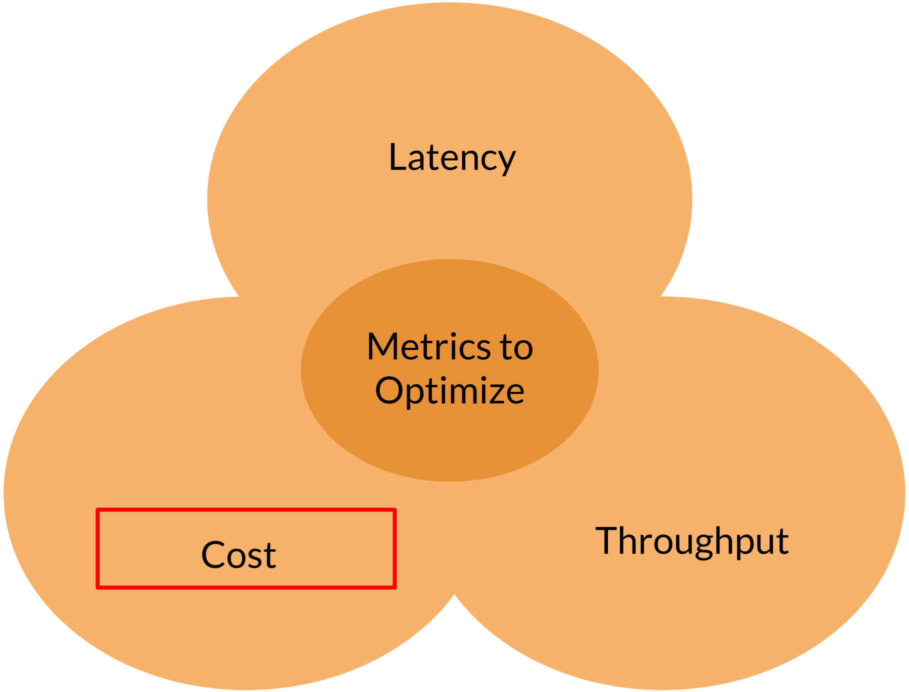
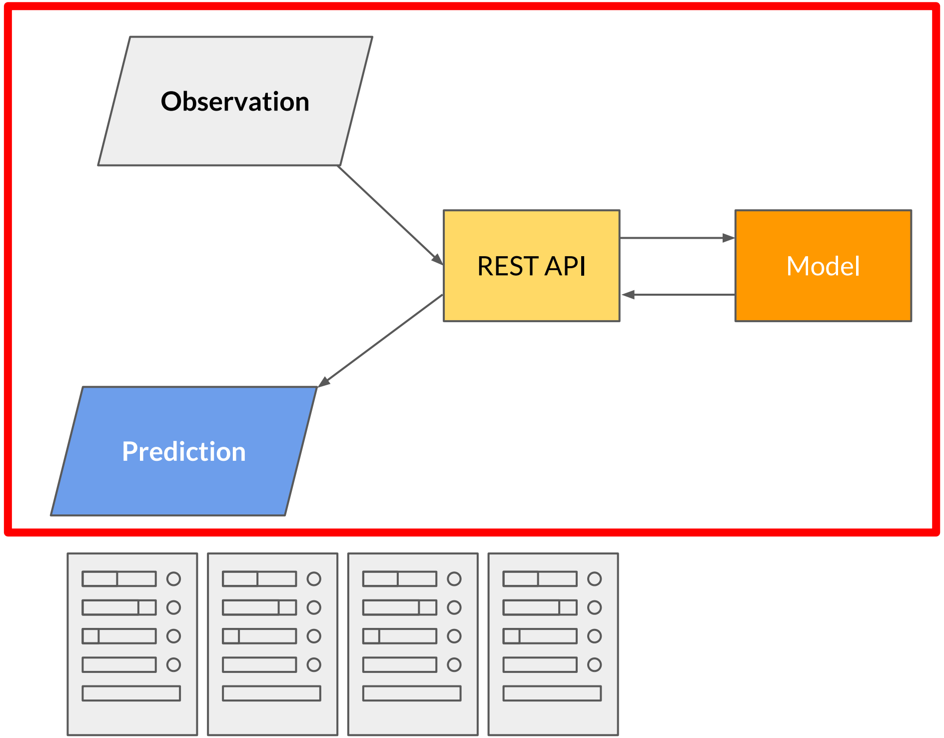


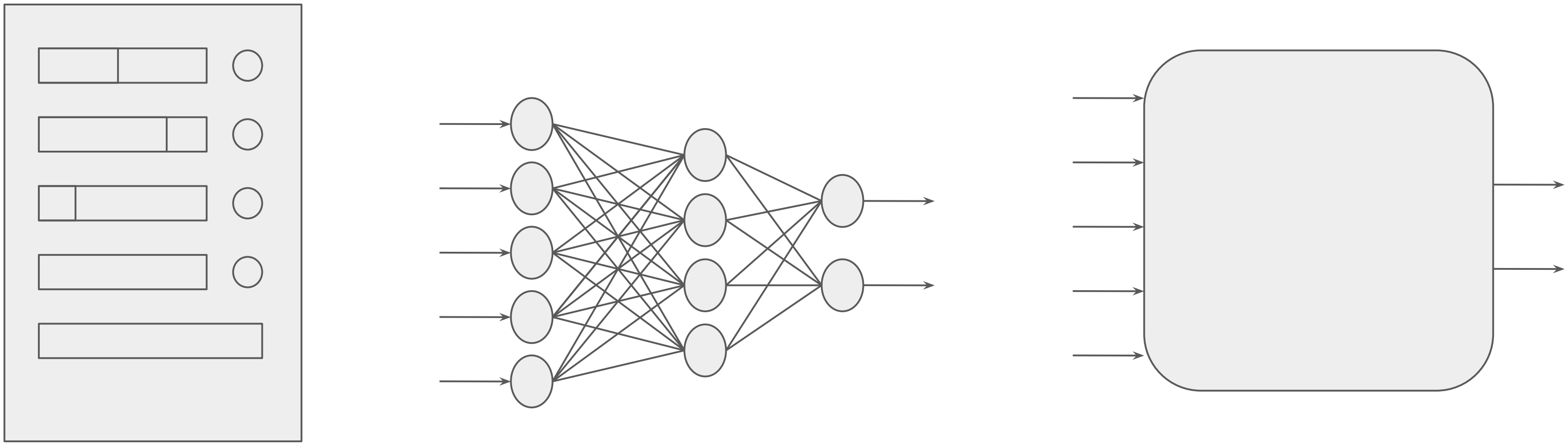


Optimising ML Inference

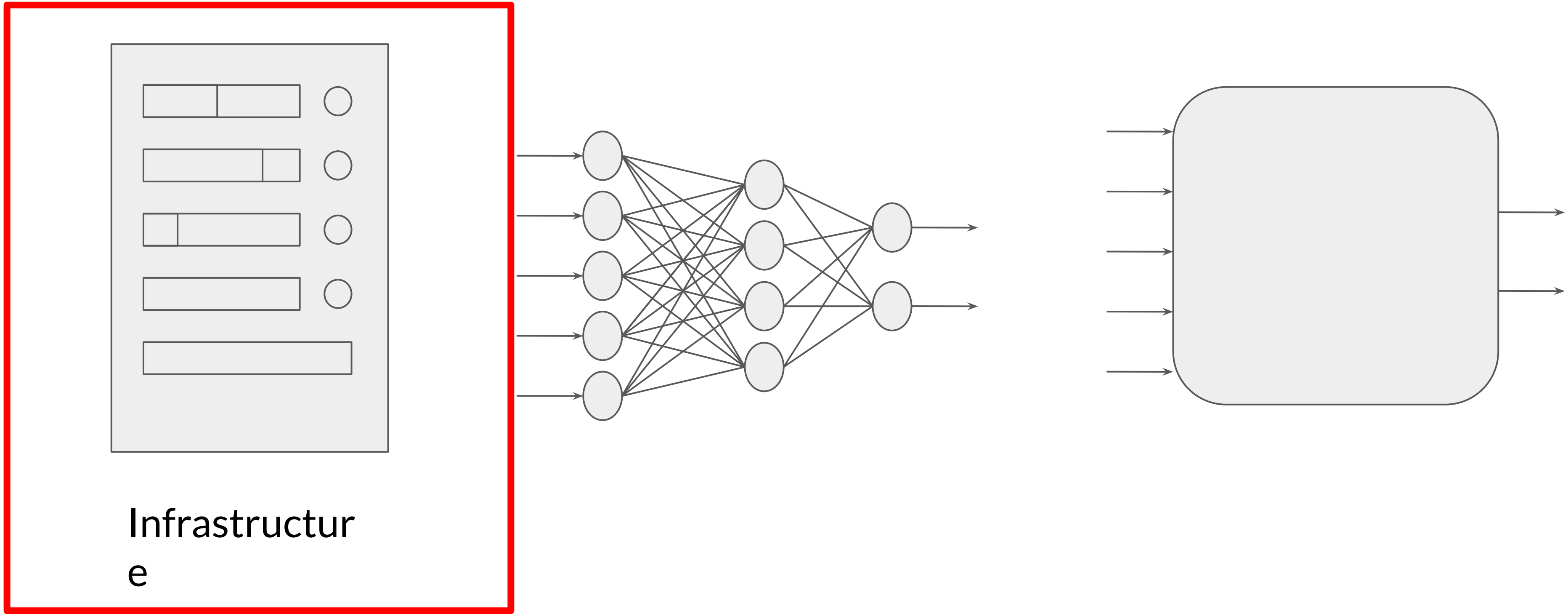




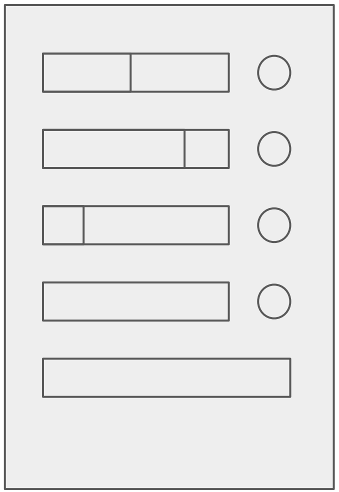
Inference Optimization

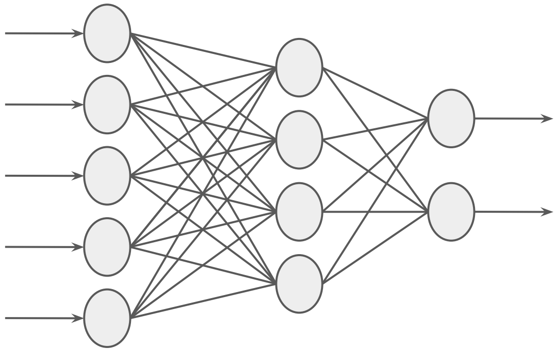


Inference Optimization: Infrastructure



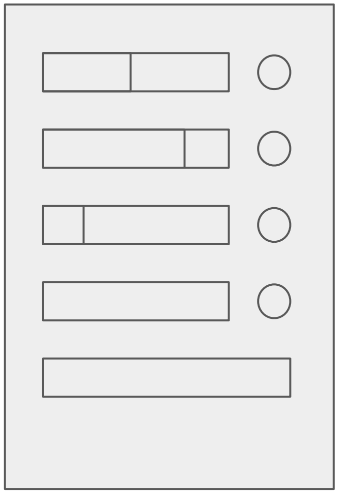
Inference Optimization: Model Architecture

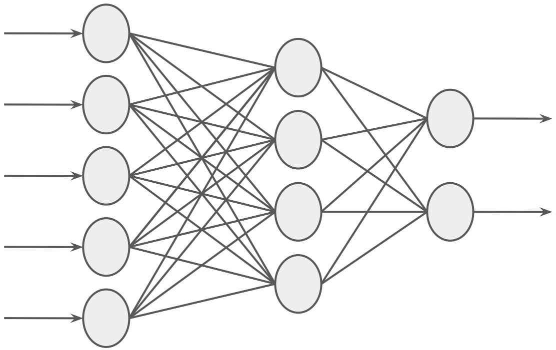




Model Architecture

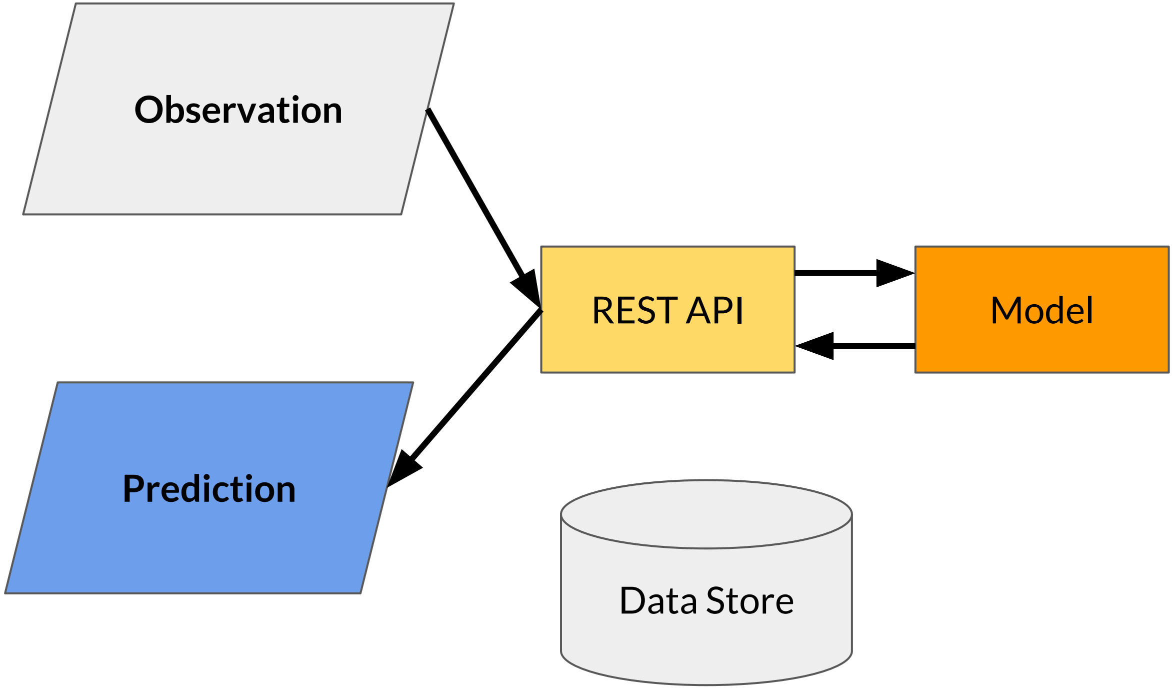
Inference Optimization: Model Compilation





Model Compilation

Additional Optimizations



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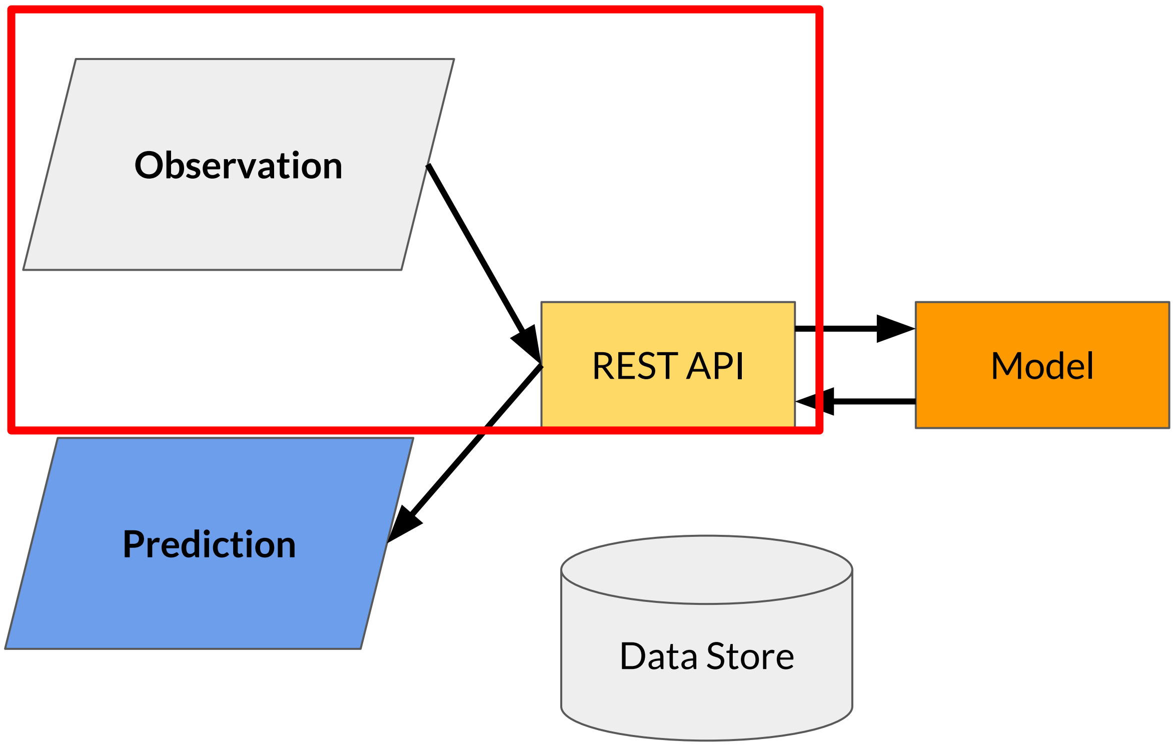

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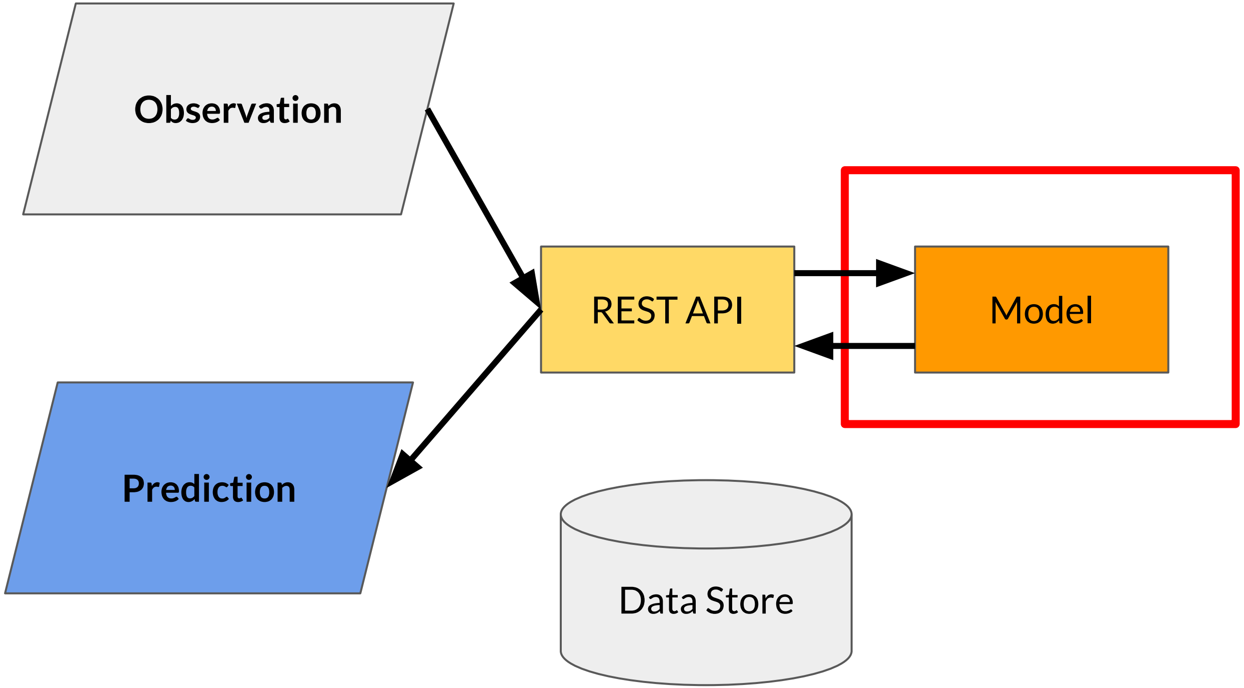

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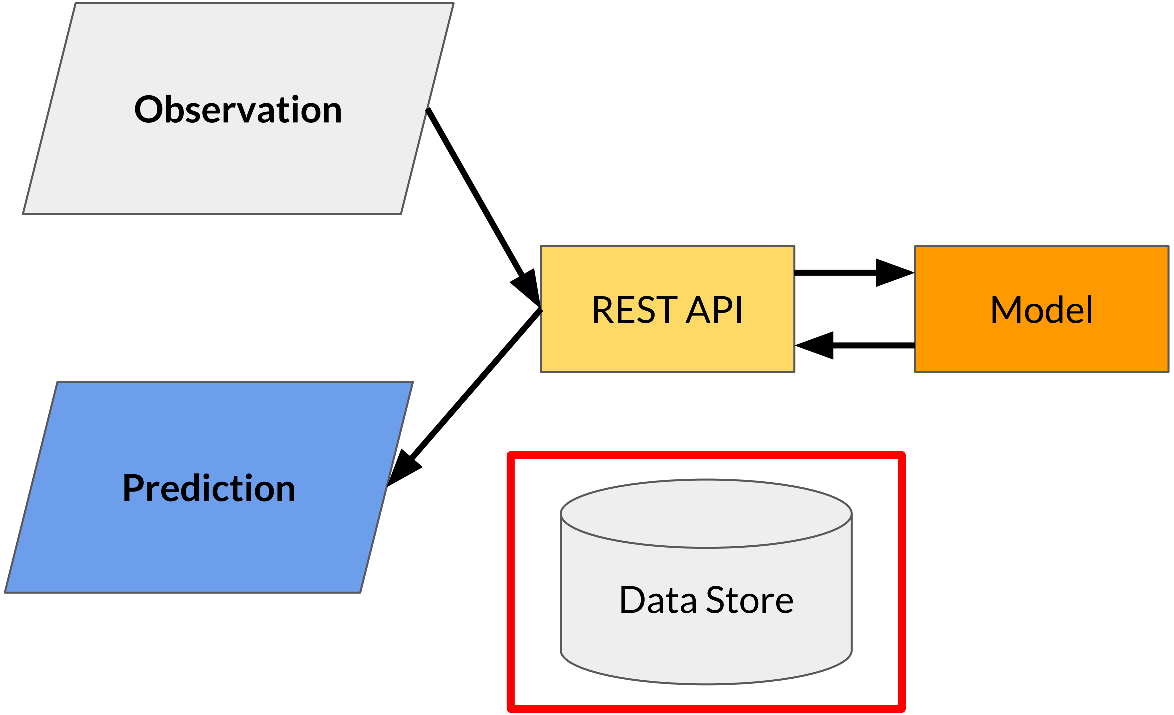

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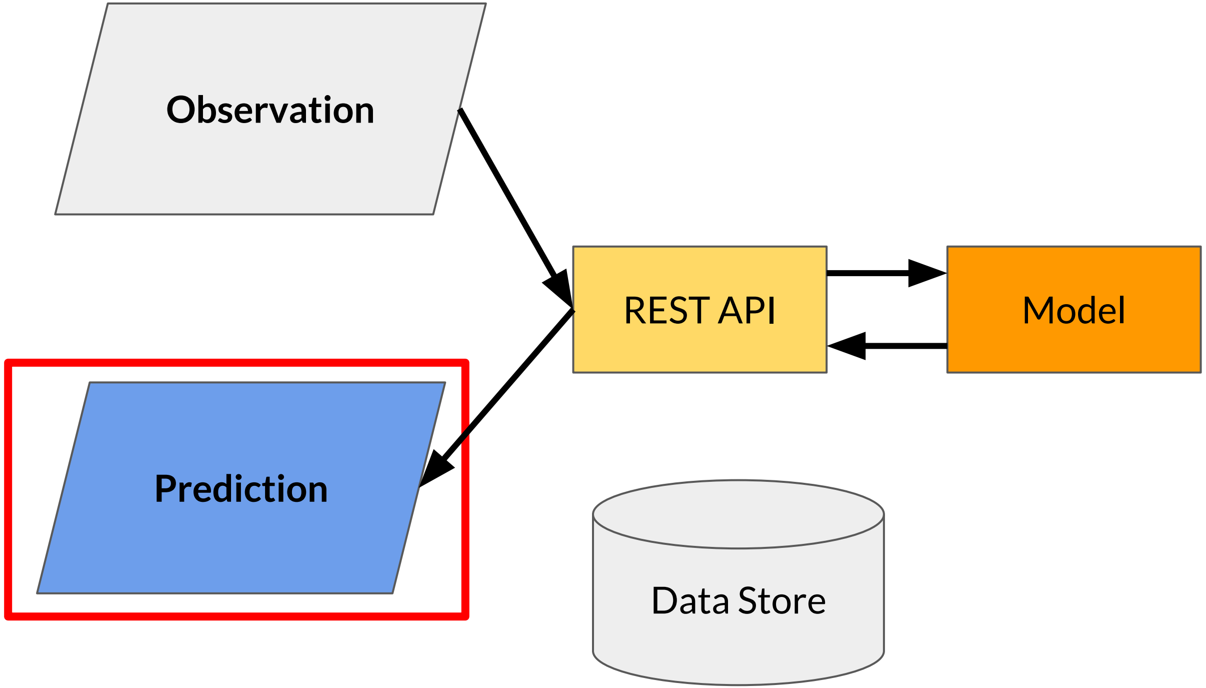

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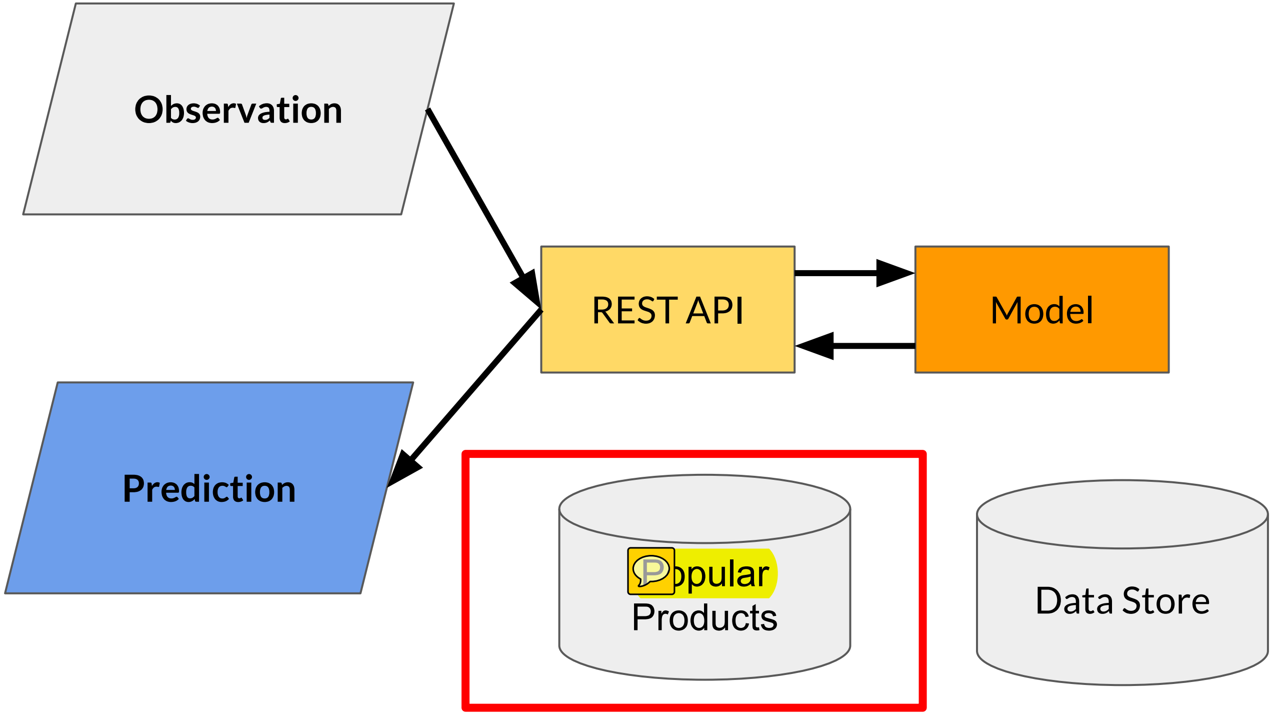


NoSQL Databases Caching and Feature Lookup

Amazon DynamoDB

Single digit milliseconds read latency, in memory cache available

Cloud Memorystore

In memory cache,
Sub milliseconds read latency

Google Cloud Bigtable

Scaleable, handles dynamically changing data, Milliseconds read latency

Google Cloud Datastore

Scaleable, can handle slowly changing data, Milliseconds read latency

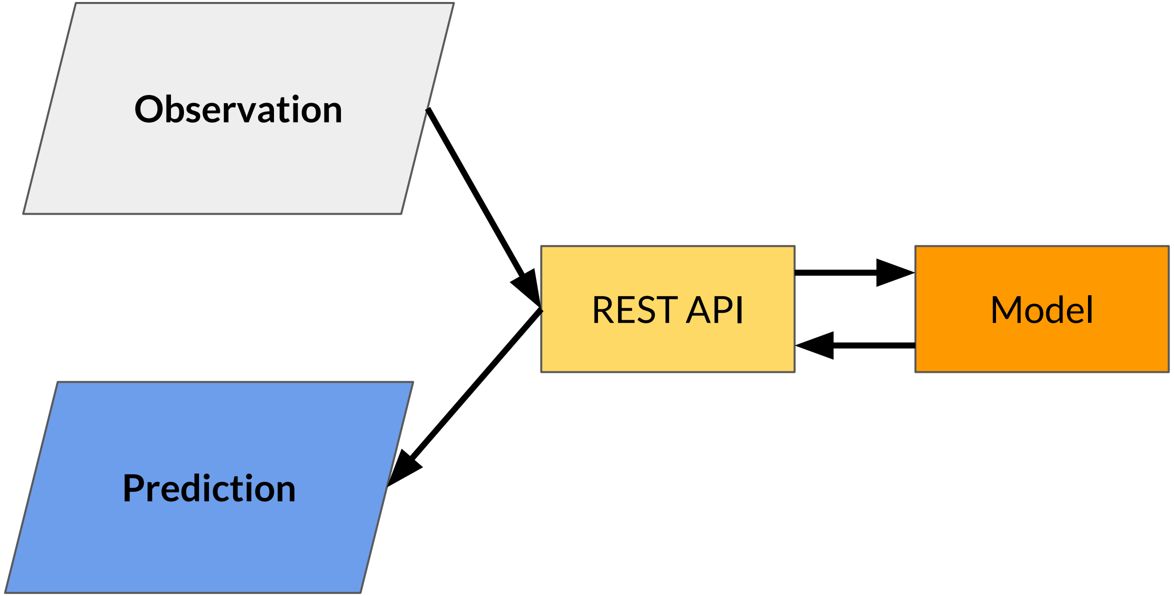
These resources are expensive
Carefully choose caching requirements based on your needs.

DeepLearning.AI

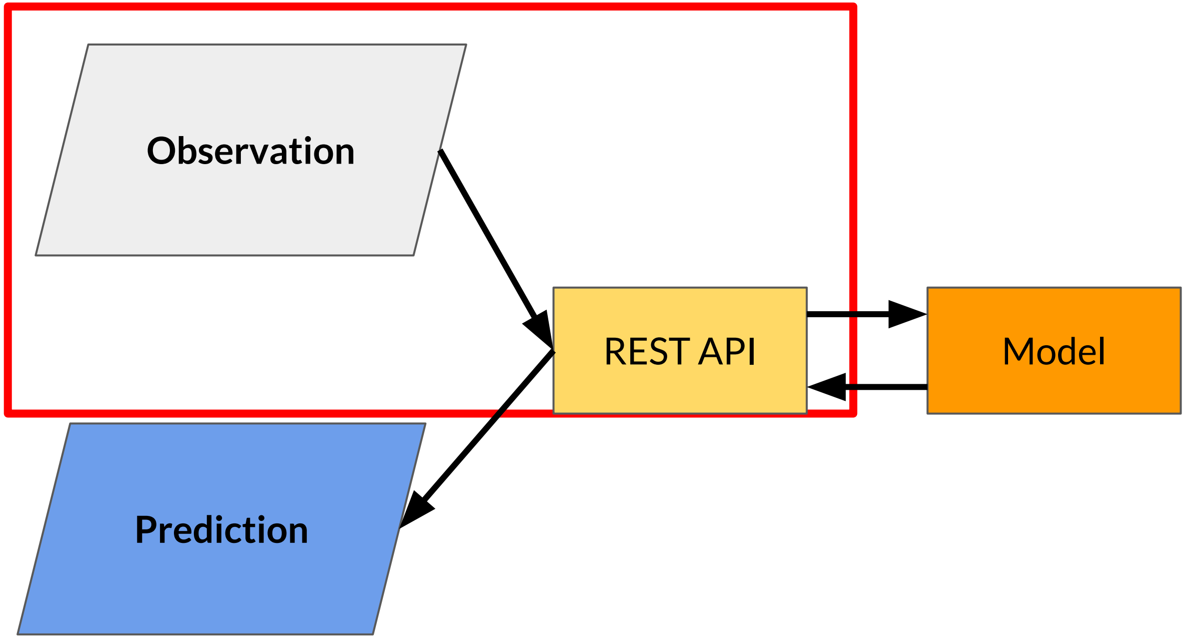
Data Preprocessing

Model Serving: Patterns and Infrastructure

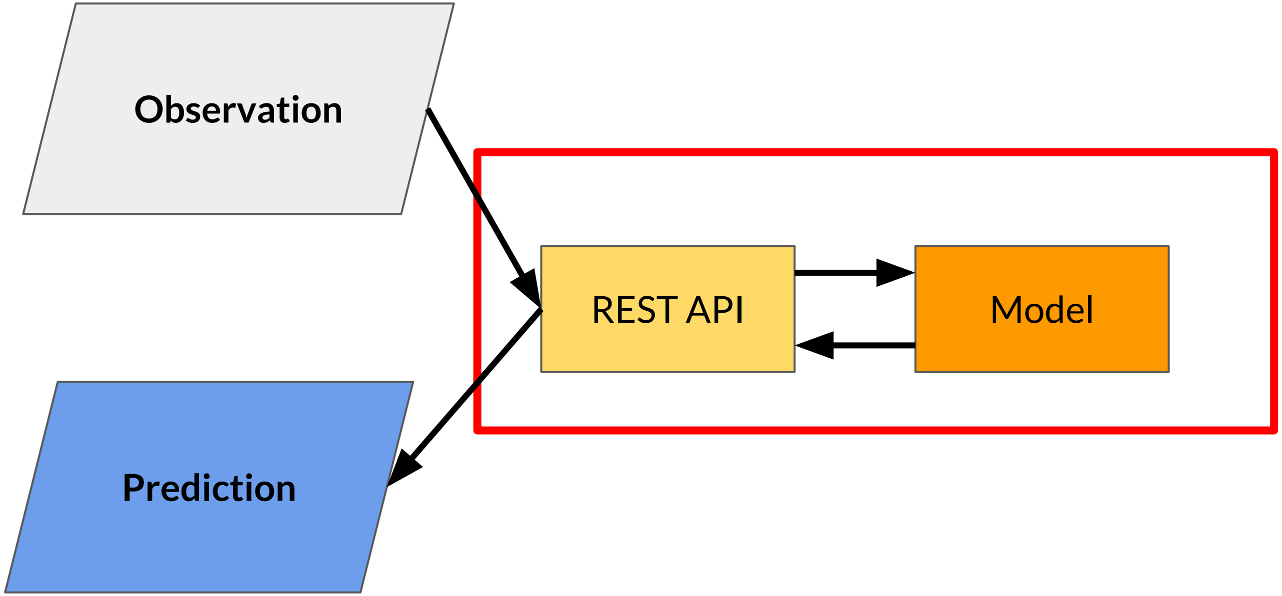
Data Preprocessing and Inference



Data Preprocessing and Inference



Data Preprocessing and Inference



Preprocessing Operations Needed Before Inference

Data Cleansing

- Correcting invalid values in incoming data

Feature Tuning

- Normalization
- Clipping outliers
- Imputing Missing Values

Feature Construction

- Combine inputs
- Feature crossing
- Polynomial expansion

Representation Transformation

- Change data format for the model
- One-hot encoding
- Vectorization

Feature Selection

- Apply same feature selection done during training on incoming data and features fetched from cache

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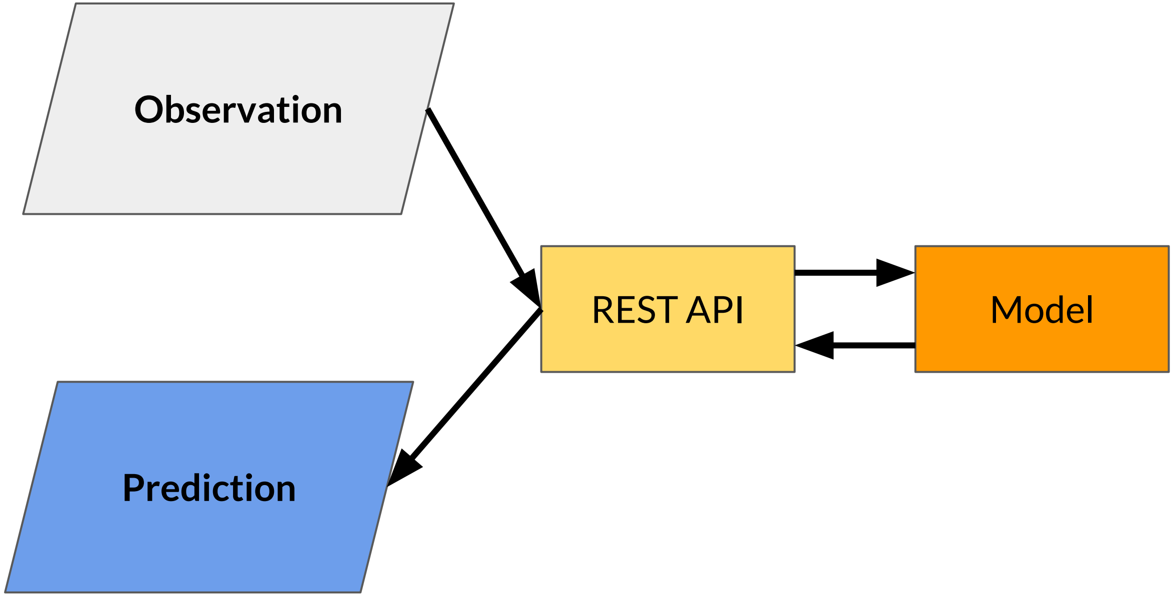
Processing After Obtaining Predictions



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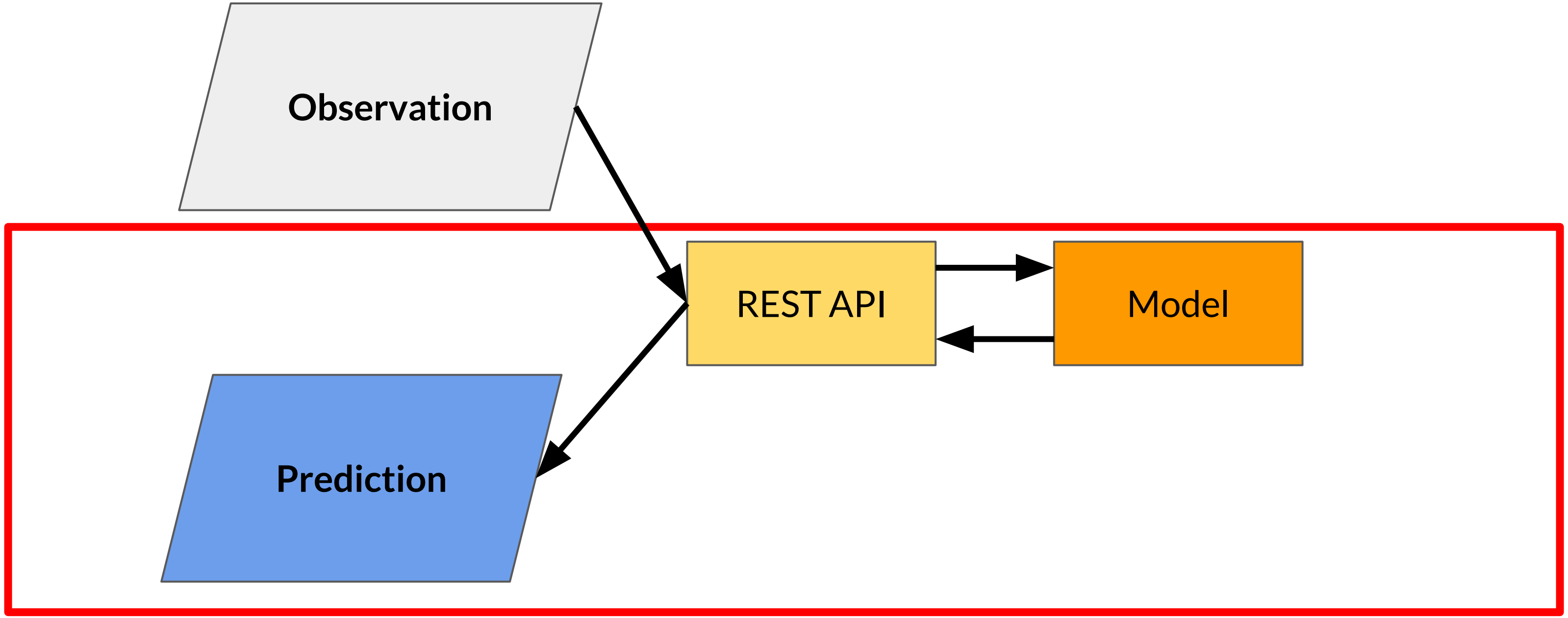
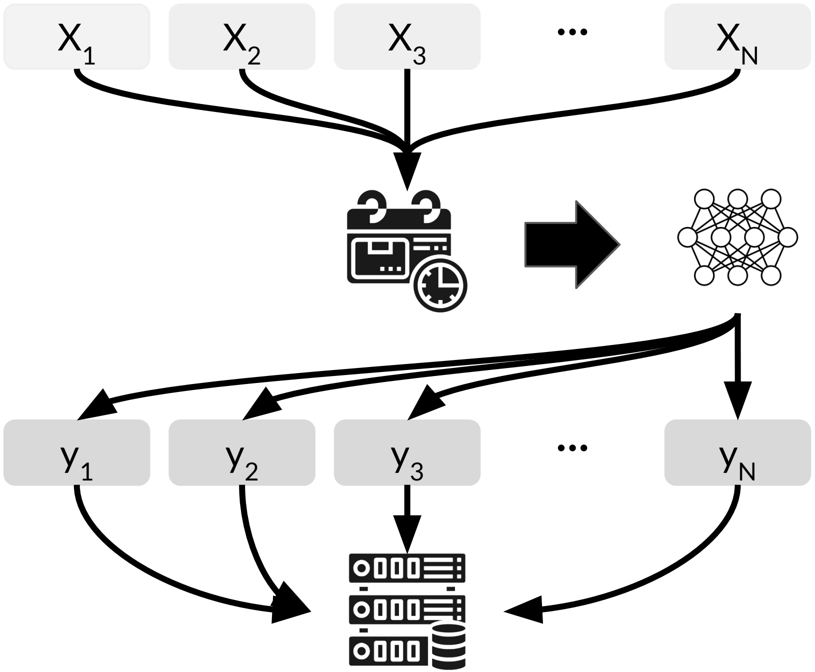


DeepLearning.AI

Batch Inference

Model Serving: Patterns and Infrastructure

Batch Inference



Generating predictions on batch of a observations

Batch jobs are often generated on some recurring schedule

Predictions are stored and made available to developers or end users

Advantages of Batch Inference

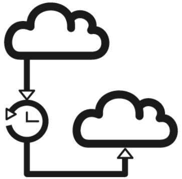
Complex machine learning models for improved accuracy

Caching not required

Reduced cost of ML system

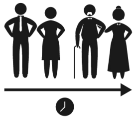
- Longer data retrieval
- Not a problem as predictions are not in real time

Limitations of Batch Inference



Long Update Latency

Predictions based on older data



Recommendations from same age bracket

Recommendations from same geolocation

Limitations of Batch Inference

Important Metrics to Optimize

Most important metric to optimize while performing batch predictions:

Throughput

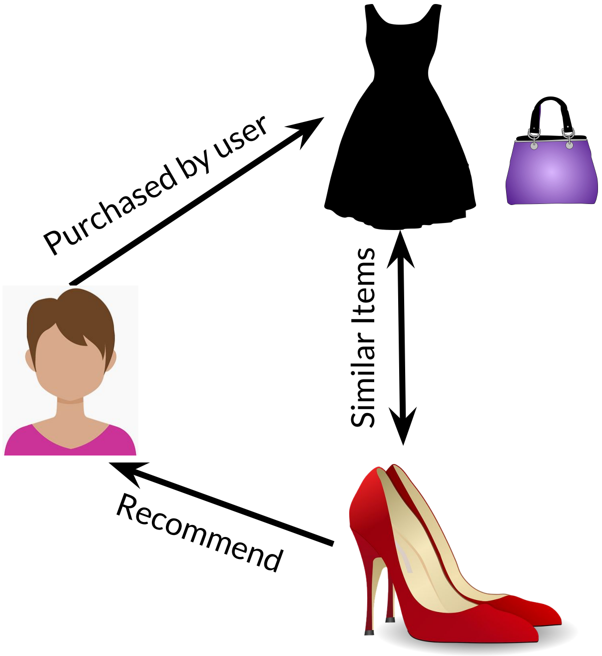
- Prediction service should be able to handle large volumes of inferences at a time.
- Predictions need not be available immediately.
- Latency can be compromised.

Limitations of Batch Inference

How to Increase Throughput?

- Use hardware accelerators like GPU's, TPU's.
- Increase number of servers/workers
    - Load several instances of model on multiple workers to increase throughput

Use Case - Product Recommendations

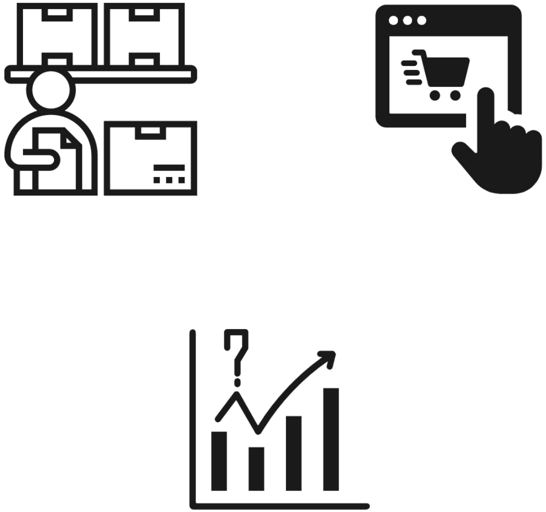


- E-commerce sites: new recommendations on a recurring schedule
- Cache these for easy retrieval
- Enables use of more predictors to train more complex models.
    - Helps personalization to a greater degree, but with delayed data

Use Case - Sentiment Analysis

- User sentiment based on customer reviews
- No need for realtime prediction for this problem
- CNN, RNN, or LSTM all work for this problem
- These models are more complex, but more accurate for the problem
- More cost effective to use them with batch prediction

Use Case - Demand Forecasting



- Estimate the demand for products for inventory and ordering optimization
- Predict future based on historical data (time series)
- Many models available as this is a batch predictions problem

DeepLearning.AI

Batch Inference

Using ML Models with Distributed Batch and Stream Processing Systems

Data Processing - Batch and Streaming

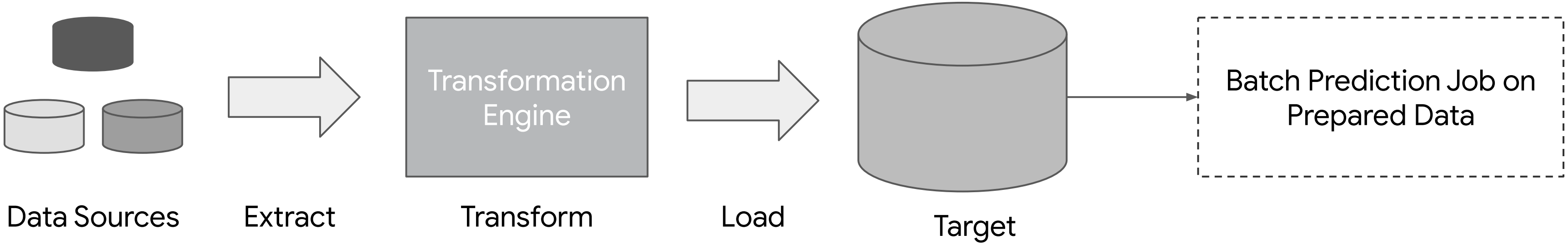
- Data can be of different types based on the source.
- **Batch Data**
    - Batch processing can be done on data available in huge volumes in data lakes, from csv files, log files etc.,
- **Streaming Data**
    - Real-time streaming data, like data from sensors.

ETL on Data

- Before data is used for making batch predictions:
  - It has to be extracted from multiple sources like log files, streaming sources, APIs, apps etc.,
  - Transformed
  - Loaded into a database for prediction

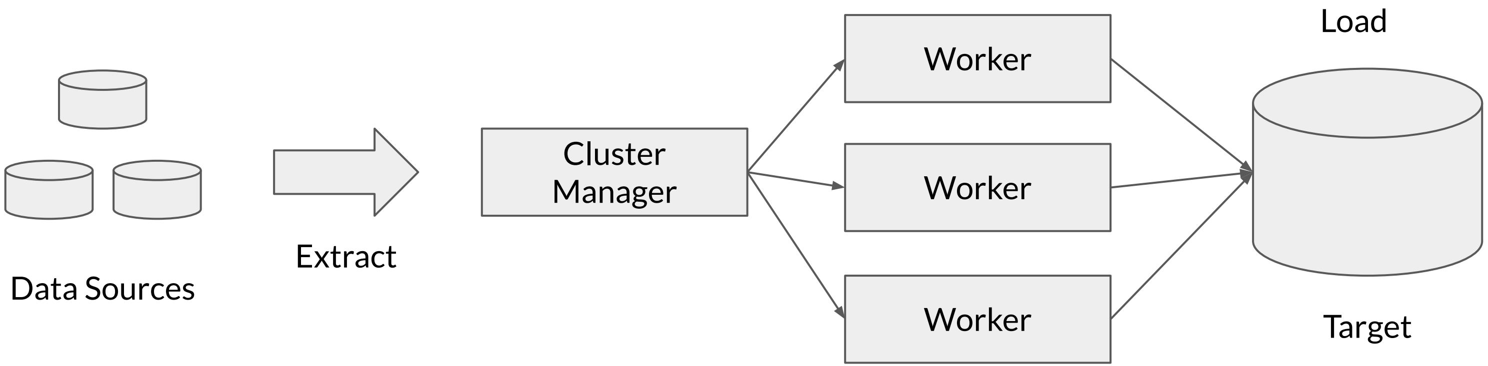
This is done using ETL Pipelines

ETL Pipelines



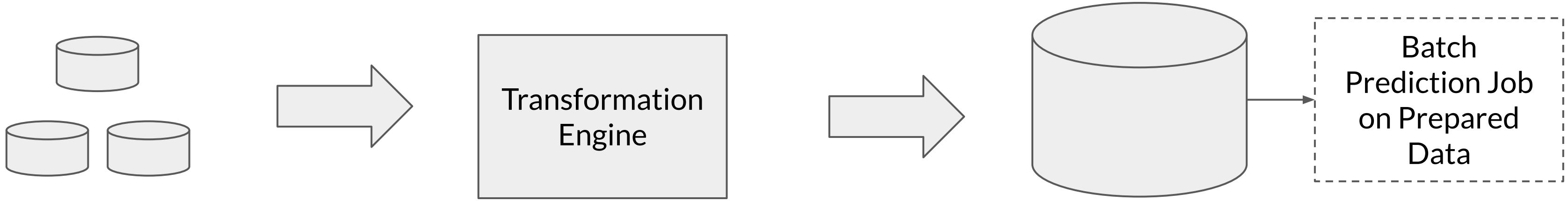
- Set of processes for
  - extracting data from data sources
  - Transforming data
  - Loading into an output destination like data warehouse
- From there data can be consumed for training or making predictions using ML models,

Distributed Processing



- ETL can be performed huge volumes of data in distributed manner.
- Data is split into chunks and parallely processed by multiple workers.
- The results of the ETL workflow are stored in a database.
- Results in lower latency and higher throughput of data processing.

ETL Pipeline components Batch Processing



Data Sources

- CSV Files
- XML
- JSON
- APIs
- Data Lake (like cloud storage)

Transform

Load

Cloud DataFlow + beam

Apache Spark

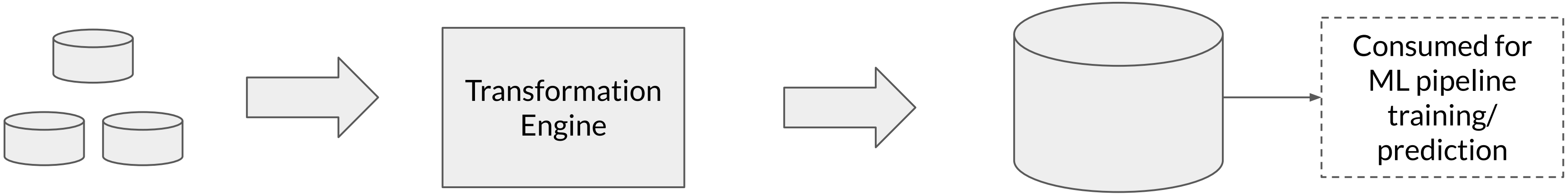
Target

- Data Warehouse

  Eg: BigQuery
- Data Mart
- Data Lake

  Eg: Cloud Storage

ETL Pipeline Components Stream Processing



Streaming Data Sources

Transform

Load

Target

Kafka

Pub Sub

Cloud DataFlow + beam

Spark Streaming

Kafka

- Streaming data for another pipeline
- Data Warehouse
  Eg: BigQuery
- Data Mart
- Data Lake
  Eg: Cloud Storage