Prediction Systems

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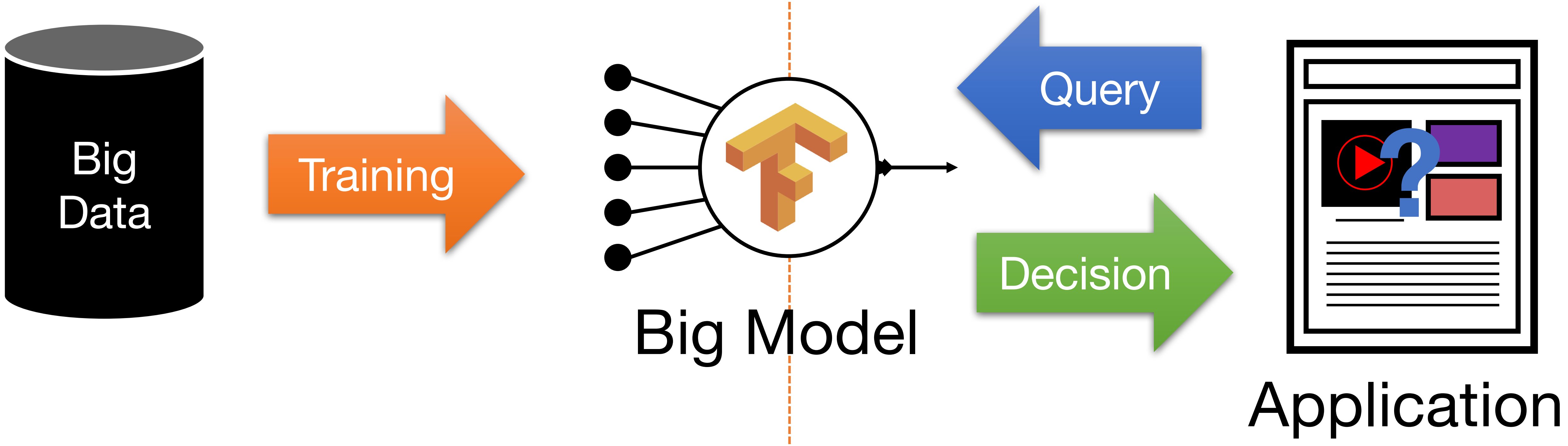
UCB RISE Lab Seminar
10/3/2015

Learning

Timescale: minutes to days
Systems: offline and batch optimized
Heavily studied ... major focus of the ***AMPLab***

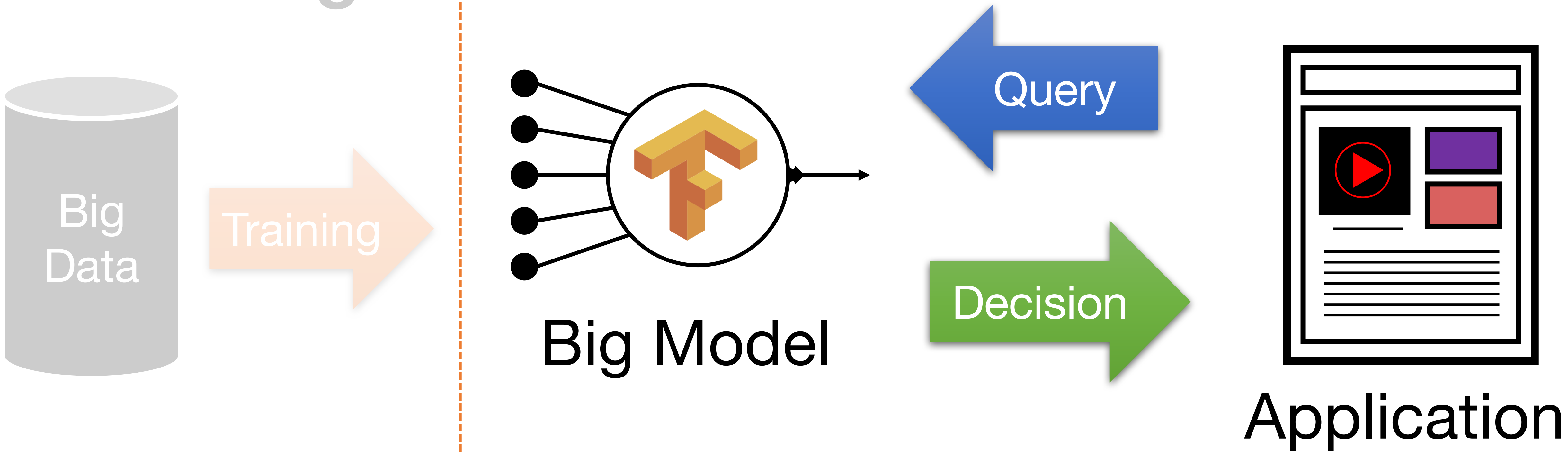
Learning

Inference



Learning

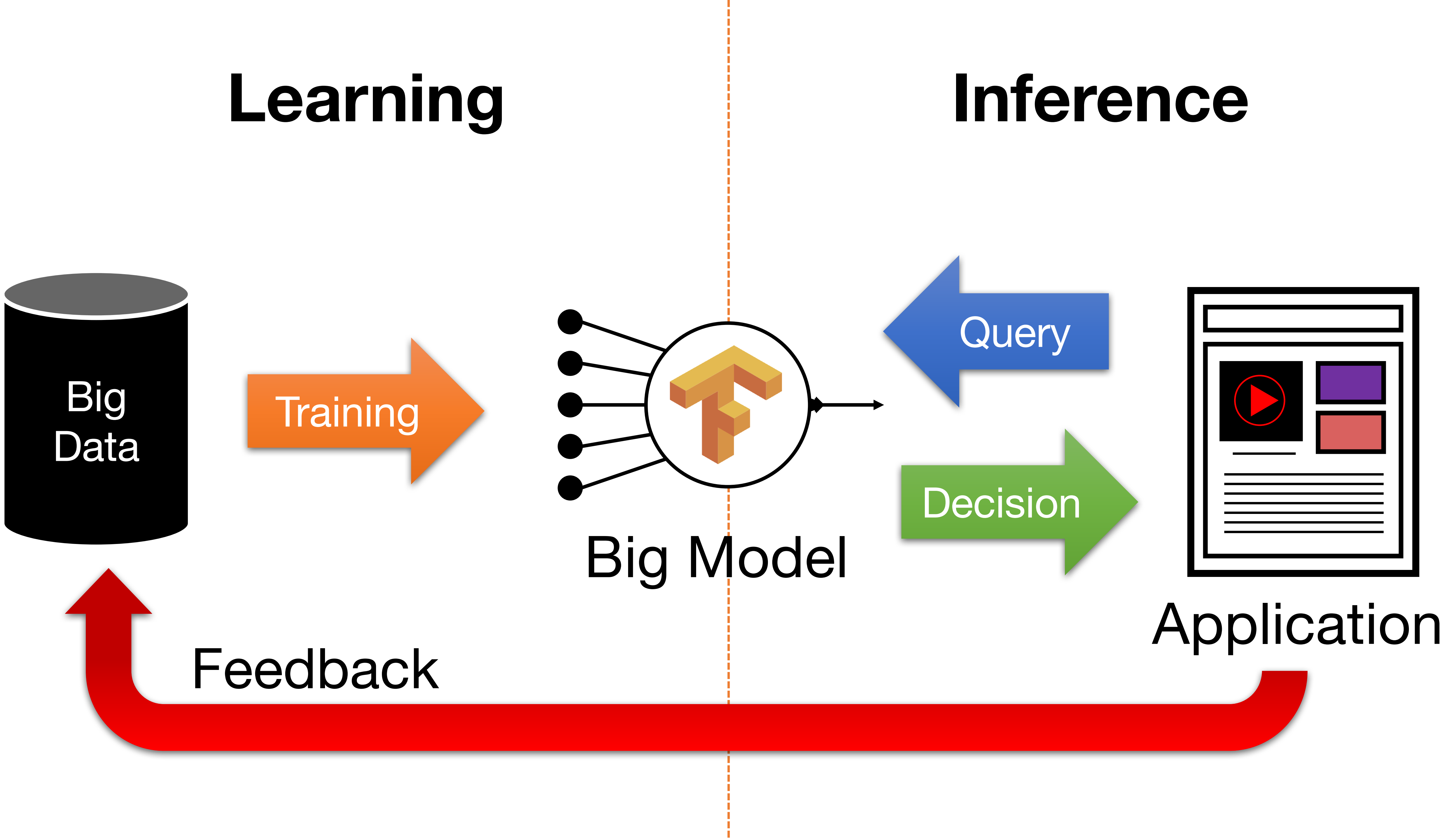
Inference



Timescale: ~20 milliseconds

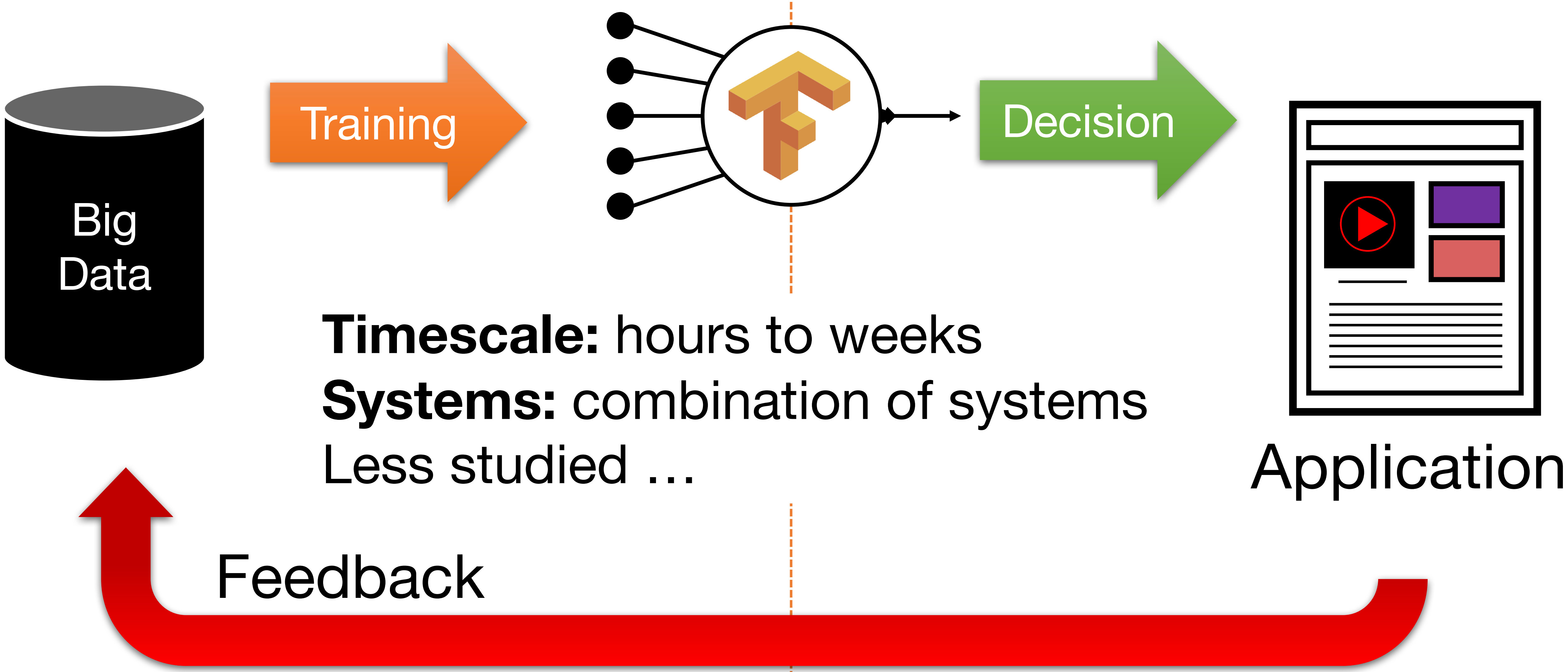
Systems: *online* and *latency* optimized

Less studied …


Learning
Inference
Big Data
Training
Big Model
Query
Decision
Application
Feedback

Learning

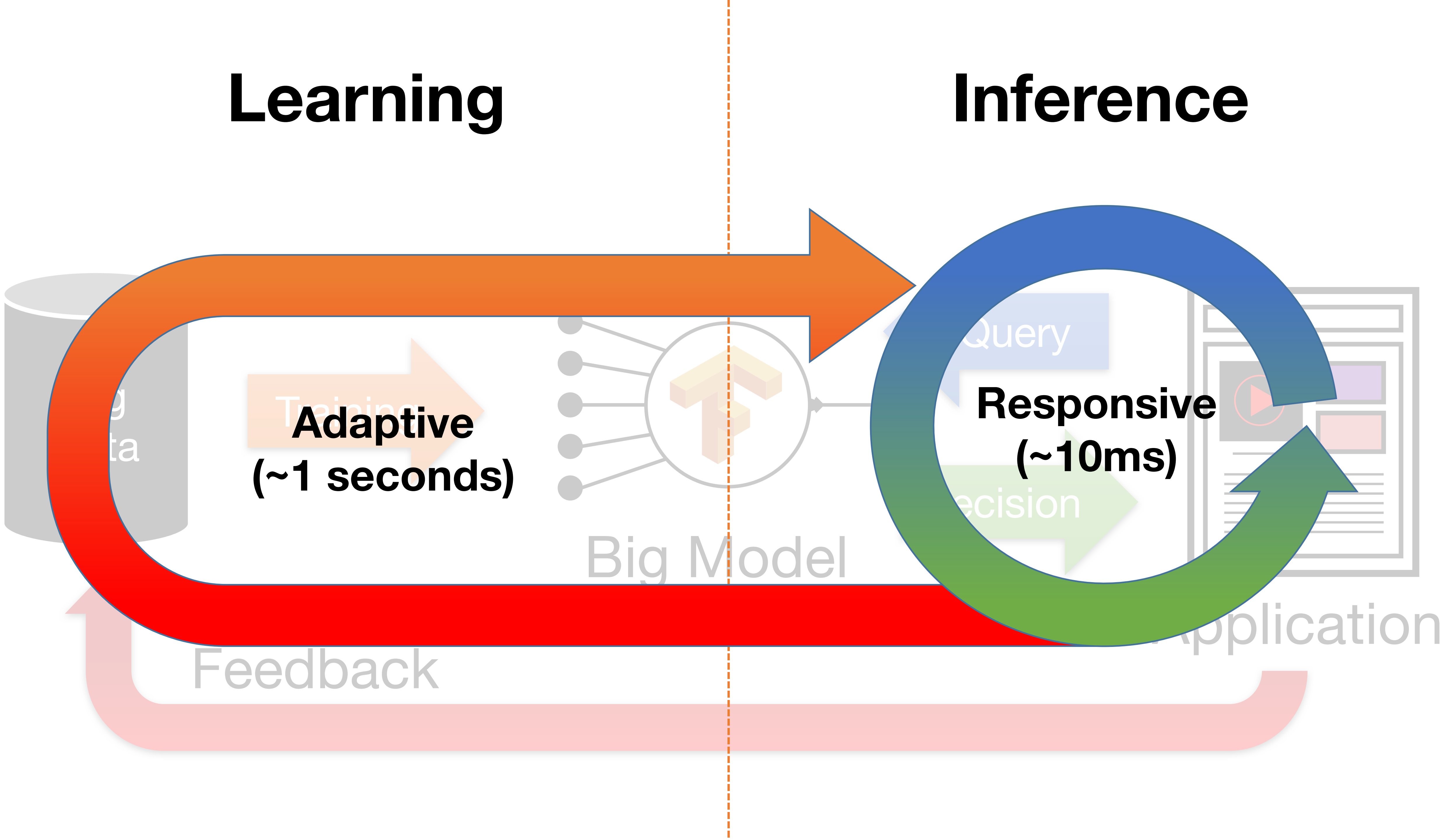
Inference



Timescale: hours to weeks

Systems: combination of systems

Less studied …



Learning
Inference
Adaptive
(~1 seconds)
Responsive
(~10ms)
Big Model
Query
ecision
Feedback
pplication

Prediction Serving Challenges

- Complexity of deploying new models
  - New applications or products (***0 → 1 models***).
  - New data, features, model family: (***N → N+1 models***).
  - *Why is it hard*: Frameworks not designed for low-latency serving, frameworks have ***different APIs, different resource requirements, and different costs***.
- System Performance
  - Need to ensure ***low-latency predictions, scalable throughput***. Deploying a new model can't degrade system performance.
- Model or Statistical Performance
  - Model Selection: Which models to use?
  - When to deploy a new model?
  - How to adapt to feedback?
  - *At a meta-level: what are the right metrics for measuring model performance?*

LASER: A Scalable Response Prediction Platform for Online Advertising

Agarwal et al. 2014

Linkedin

LASER Overview

- Top-down system design enforced by company organizational structure
- Picked a model (logistic regression) and built the system based on that choice
- Force data-scientists to use this model, express features in specialized configuration language
- Result: ***System and model family are tightly coupled***

$$p_{ijt} = \frac{1}{1 + \exp(-s_{ijt})}$$

$$s_{ijt} = \omega + s_{ijt}^{1,c} + s_{ijt}^{2,c} + s_{ijt}^{2,\omega}$$

Addressing Deployment Complexity

- **Fixed Model Choice:** Can be hardcoded into system, no need for API to specify model
- **Configuration language**: specify feature construction in JSON-based configuration language
  - Restricts feature transformations to be built from component library
  - Allows for changes in pipeline without service restarts or code modification
  - Allows easy re-use of common features across an organization
  - Similar to PMML, PFA
- **Language details**
  - *Source*: translate data to numeric feature vectors
  - *Transformer*: Vector-to-vector transformations (transform, aggregate)
  - *Assembler*: Concatenates all feature pipelines together into single vector

Addressing System Performance

- **Precompute second-order interaction terms**
  - The LASER logistic regression model includes second order interaction terms between user and campaign features:

$$s_{ijt}^{2,c} = x_i' \boxed{A c_j} + \dots$$

- **Don't wait for delayed features**
  - Features can be delayed by slow DB lookup, expensive computation
  - *Solution: Substitute expected value for missing features and degrade accuracy, not latency*
  - *Solution: Cache precomputed scalar products in PRC, save overhead of re-computing features and dot products which are lazily evaluated*

Addressing Model Performance

- Decompose model into slowly-changing and quickly-changing components
  - Fast retraining of warm-start (quickly-changing) component of model without cost of full retraining

$$s_{ijt} = \boxed{\omega + s_{ijt}^{1,c} + s_{ijt}^{2,c}} + \boxed{s_{ijt}^{2,\omega}}$$

Warm Start
Trained Online

Cold Start
Trained Offline

- Explore/Exploit with Thompson Sampling
  - Sometimes serve ads with low empirical mean but high-variance
  - Draw sample from posterior distribution over parameters and use sample to predict CTR instead of mode
  - In practice, hold Θ_c fixed and sample from Θ_w

Some Takeaways from LASER

- System performance is paramount in the broader application context
  - Slow page load has much larger impact on revenue than poor ad-recommendation
- AUC/accuracy is not always the most useful model performance metric
- The more assumptions you can make about your tools (software, models) the more tricks you can play (config language, shared features, warm-start/cold-start decomposition)
  - Safe for LASER to make these assumptions because they are enforced through extra-technological methods
  - Similar to some of the design choices we saw in Borg last week

Clipper

A Low-Latency Online Prediction Serving System

Daniel Crankshaw,
Xin Wang
Giulio Zhou
Michael Franklin,
Joseph E. Gonzalez
Ion Stoica

Goals of Clipper

- **Design Choice: *General purpose, easy to use*** prediction serving system
  - Generalize to many ***different ML applications*** (contrast to LASER which was designed to address LinkedIn's ad-targeting needs)
  - Generalize to ***many frameworks/tools*** for a single application
    - Don't tie the hands of data scientists developing models
  - Make it simple for a ***data-scientist*** to deploy a new model into production
- Given these design choices, maximize system and model performance using ***model-agnostic*** techniques

Clipper **Generalizes** Models Across ML Frameworks

Fraud Detection

Content Rec.

NETFLIX

Personal Asst.

Robotic Control

Machine Translation

Clipper

theano

Dato Create

KeystoneML

Caffe

TensorFlow

scikit learn

dmlc mxnet

VW

KALDI

Clipper Architecture

Applications

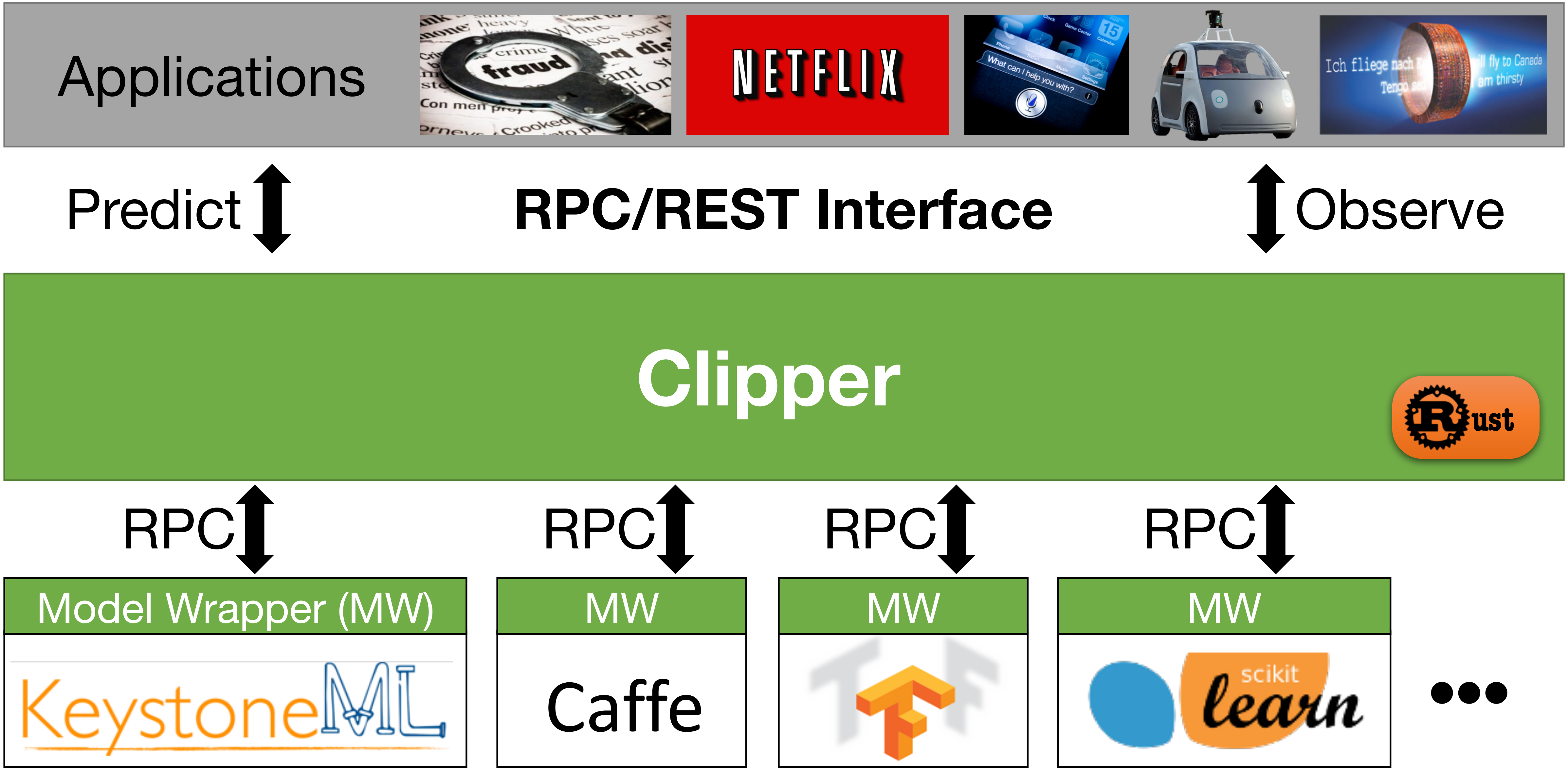
NETFLIX

Predict ↕ **RPC/REST Interface** ↕ Observe

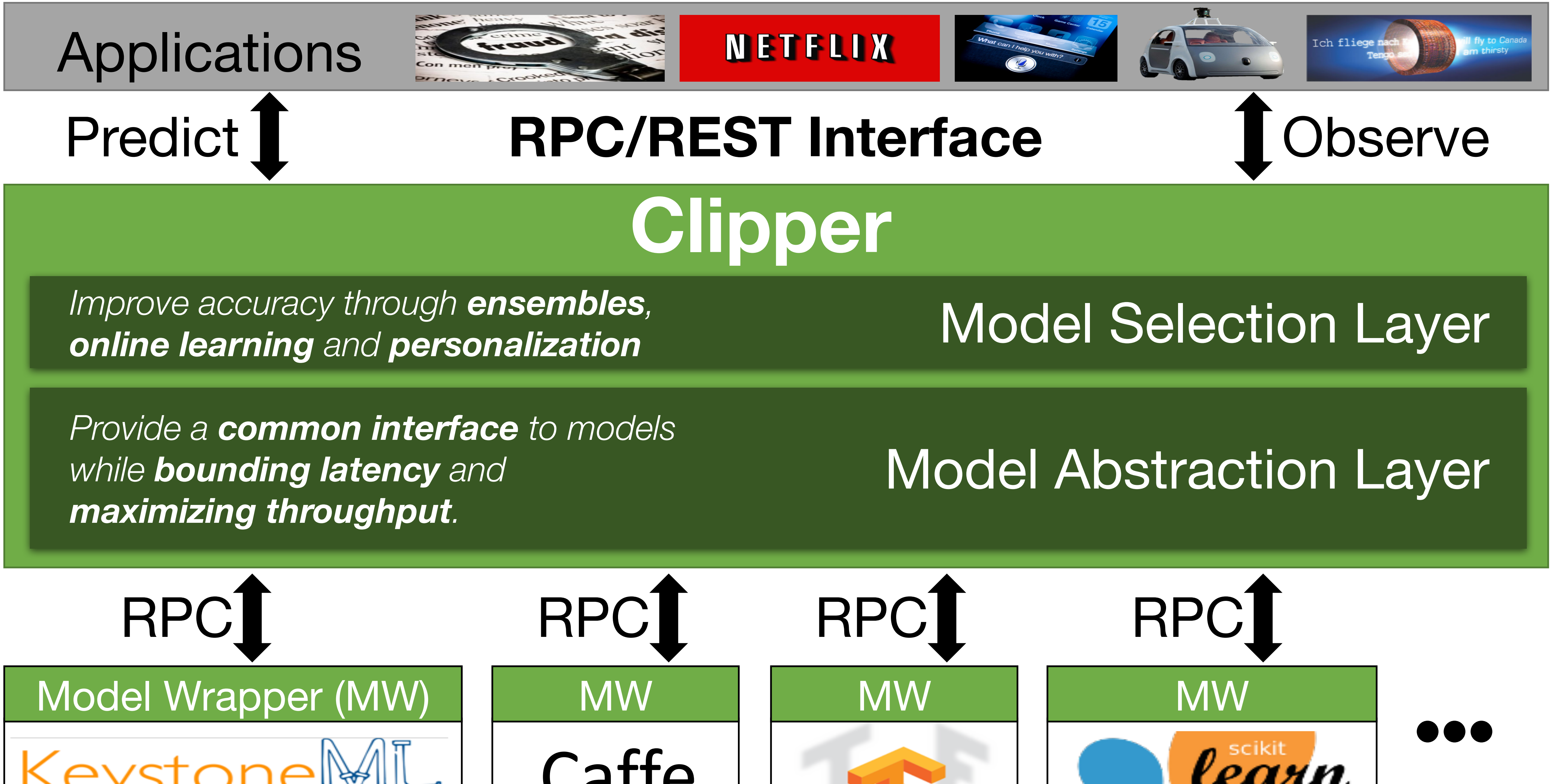
Clipper

theano
Dato Create
KeystoneML
Caffe
TensorFlow
scikit learn
dmlc mxnet
VW
KALDI

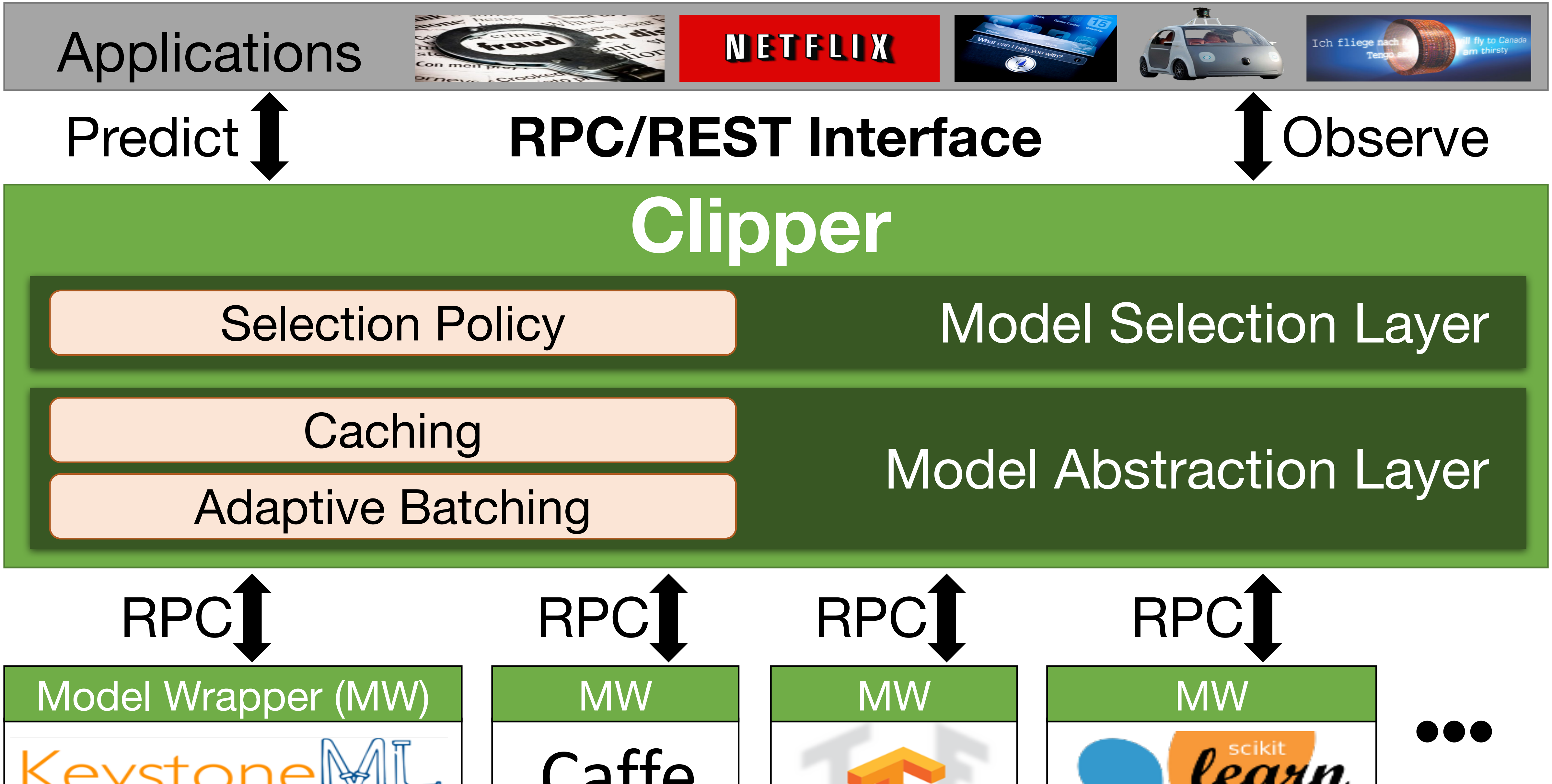
Clipper Architecture

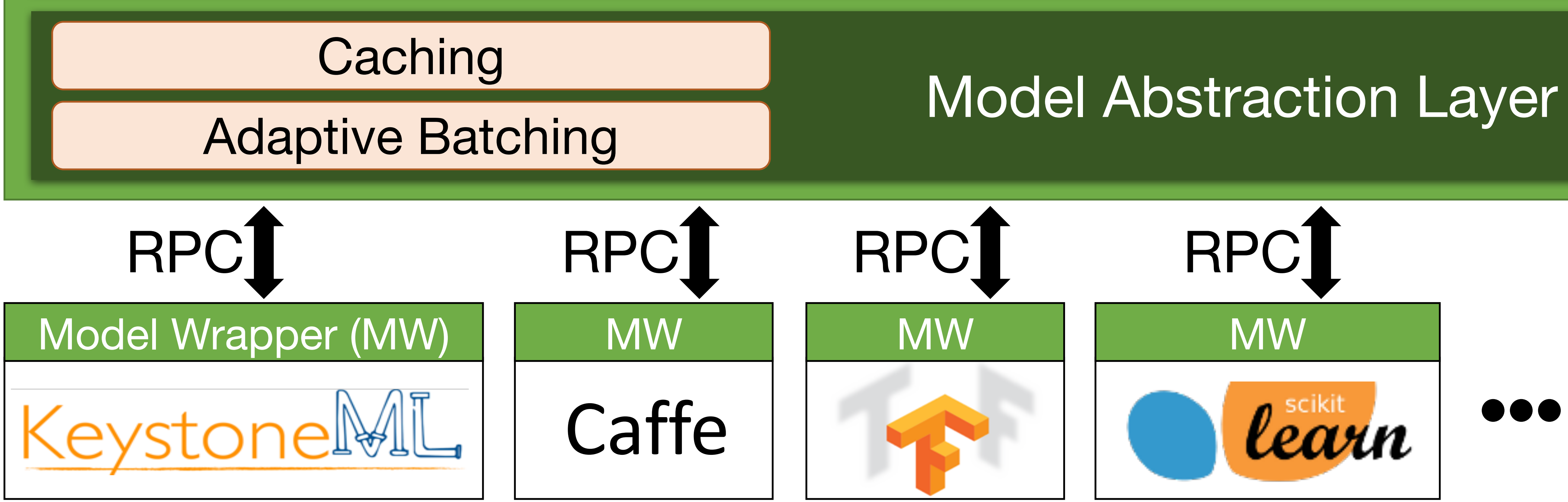


Clipper Architecture

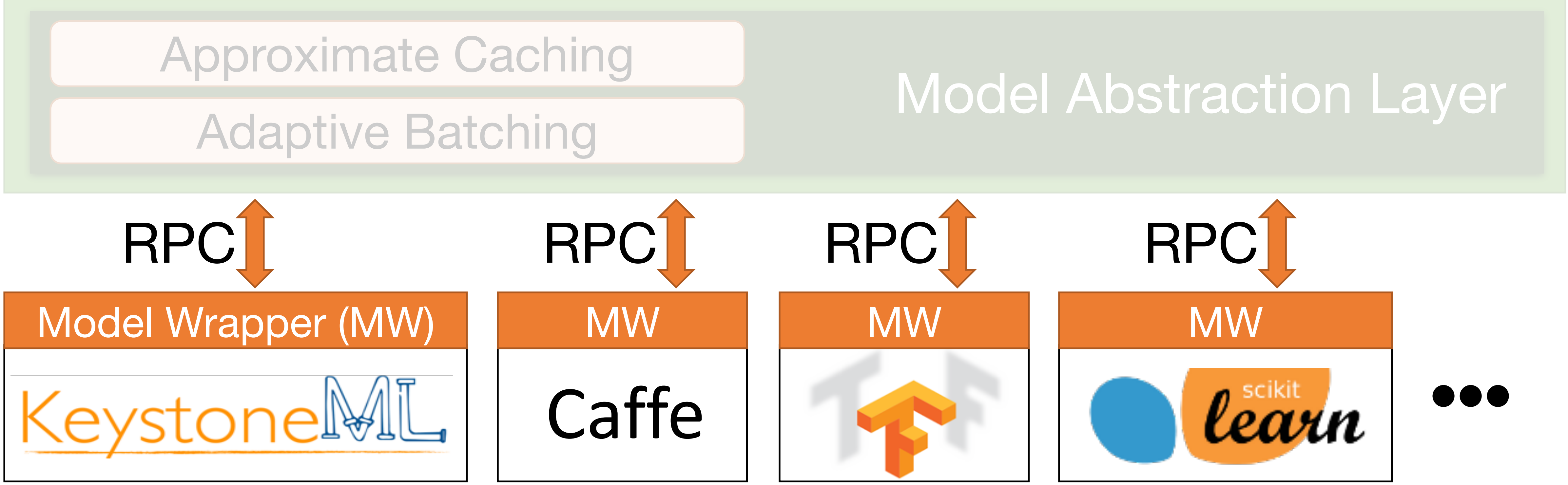


Clipper Architecture



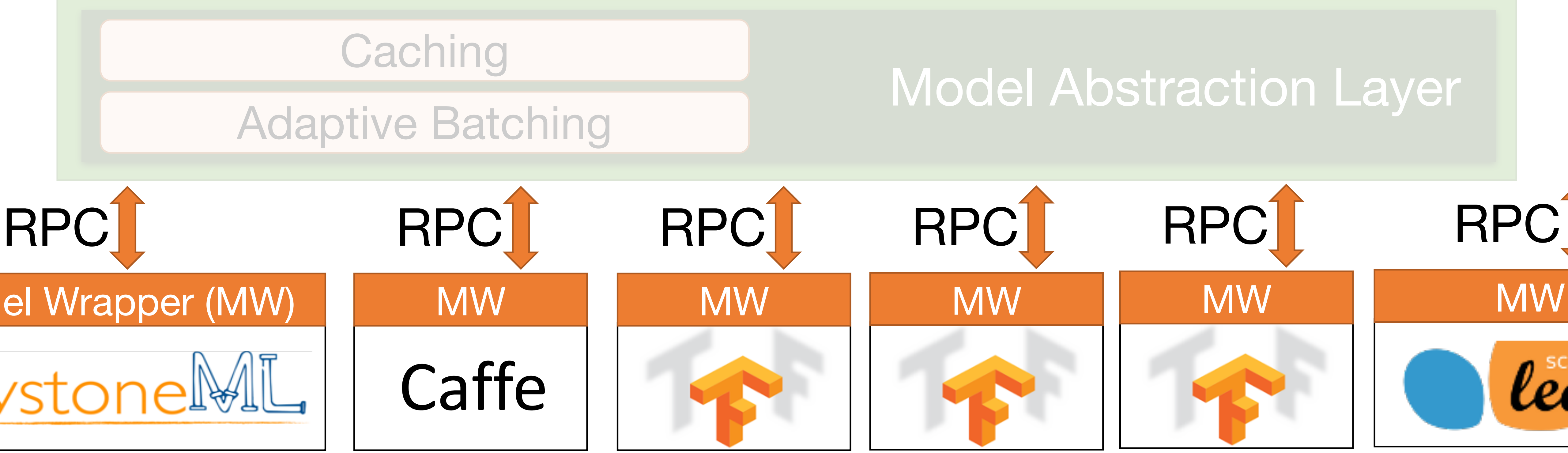


Caching
Adaptive Batching
Model Abstraction Layer
RPC
RPC
RPC
RPC
Model Wrapper (MW)
MW
MW
MW
KeystoneML
Caffe
scikit
learn



Common Interface → Simplifies Deployment:

- Evaluate models using original code & systems
- Models run in separate processes (Docker containers)
  - Resource isolation



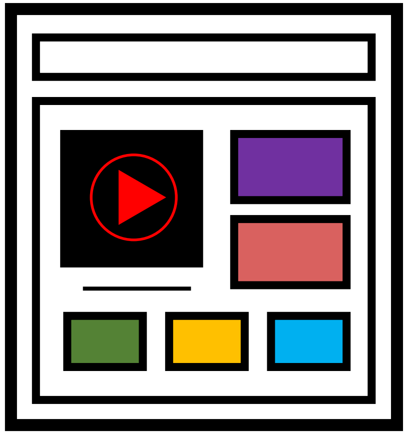
Common Interface → Simplifies Deployment:

- Evaluate models using original code & systems
- Models run in separate processes
  - Resource isolation
  - Scale-out

Problem: frameworks optimized for **batch processing** not **latency**

Adaptive Batching to Improve Throughput

- Why batching helps:



A single page load may generate many queries

Hardware Acceleration

GRPC

Helps amortize system overhead

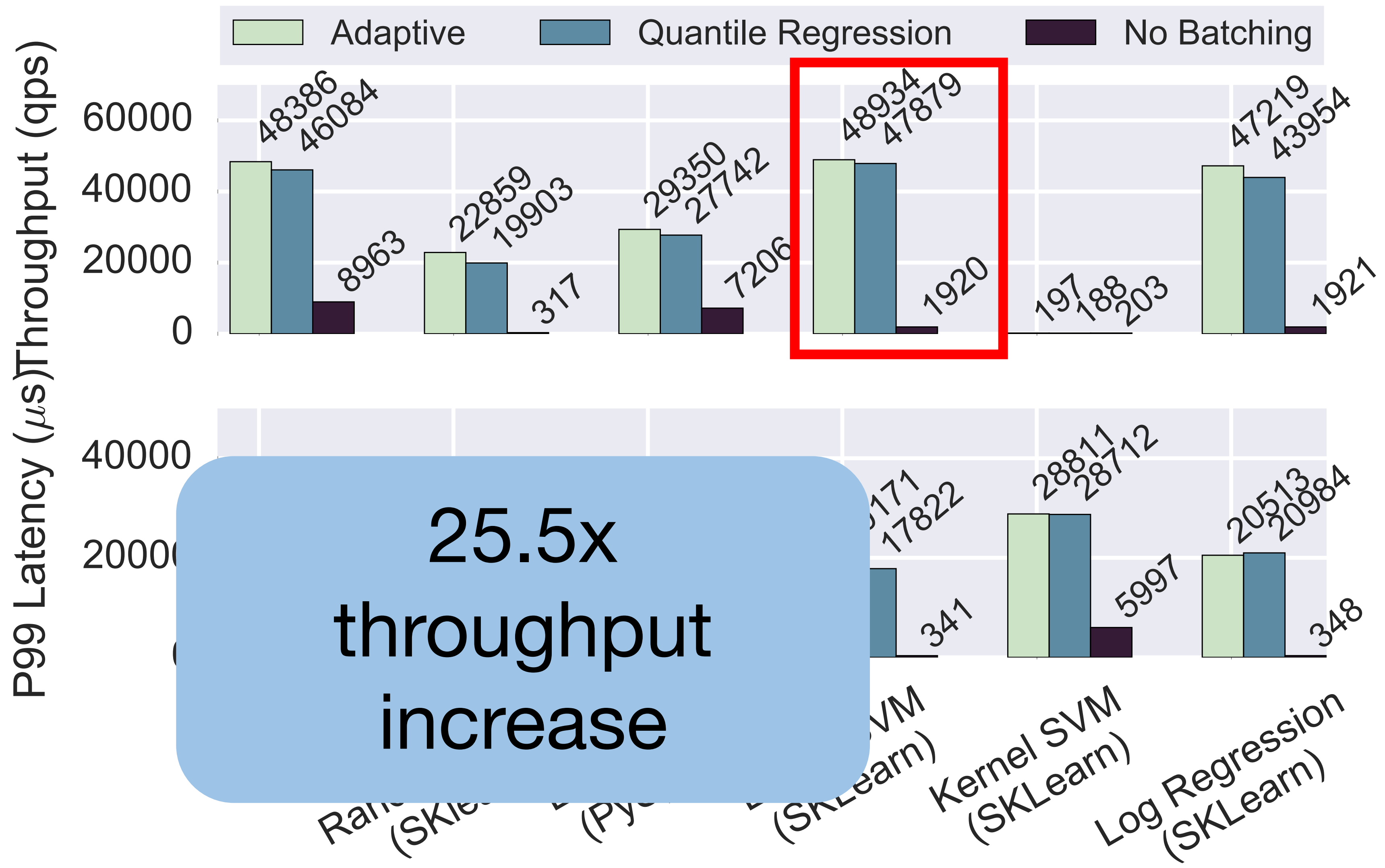
- Optimal batch depends on:
  - hardware configuration
  - model and framework
  - system load

Clipper Solution:

*be as **slow** as **allowed**…*

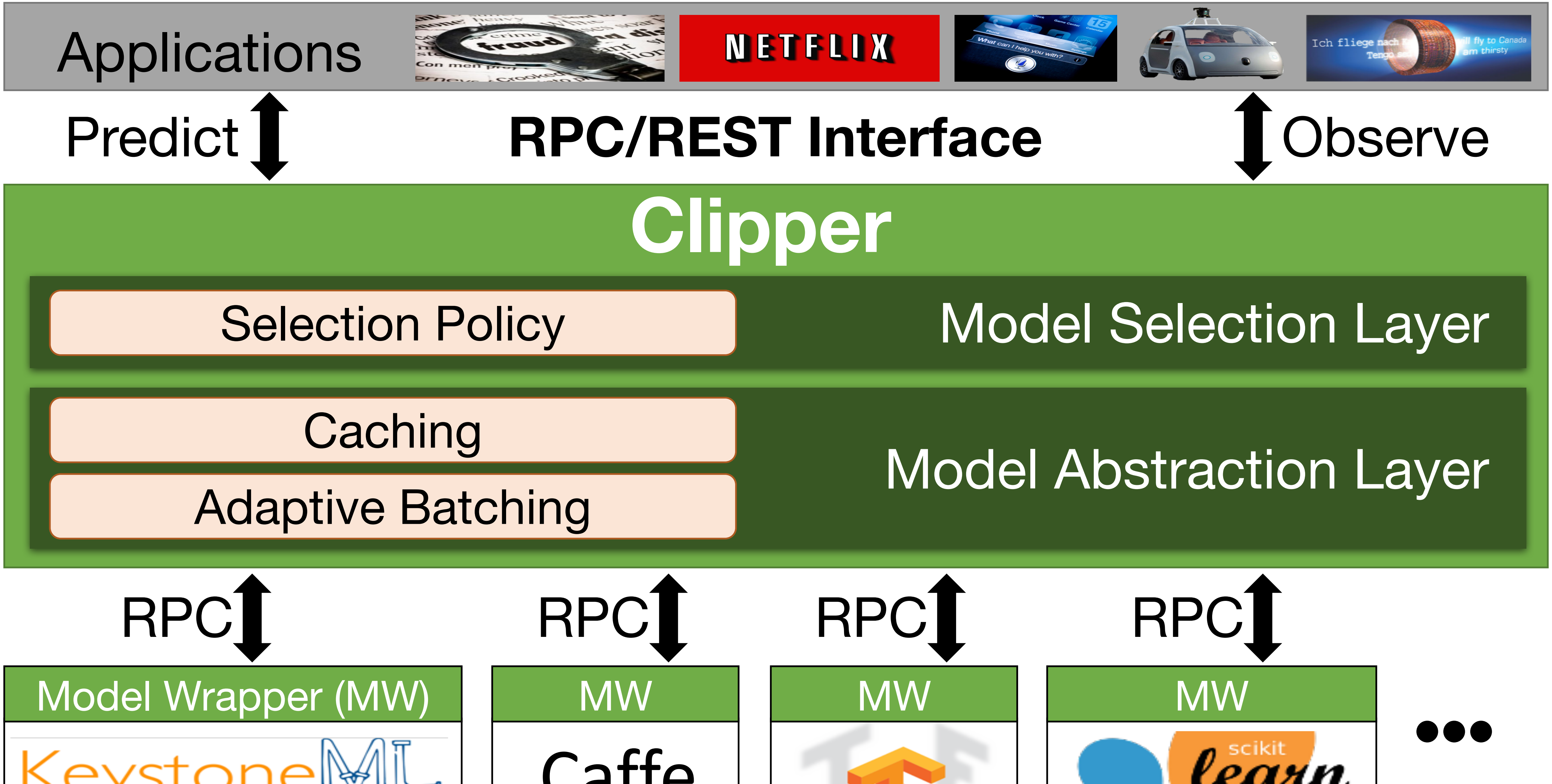
- Inc. batch size *until the latency objective is exceeded* (**Additive Increase**)
- If latency exceeds SLO cut batch size by a fraction (**Multiplicative Decrease**)

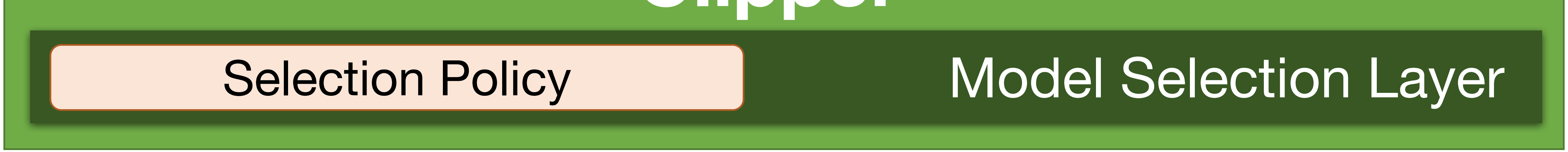
Adaptive Batching to Improve Throughput



25.5x throughput increase

Clipper Architecture



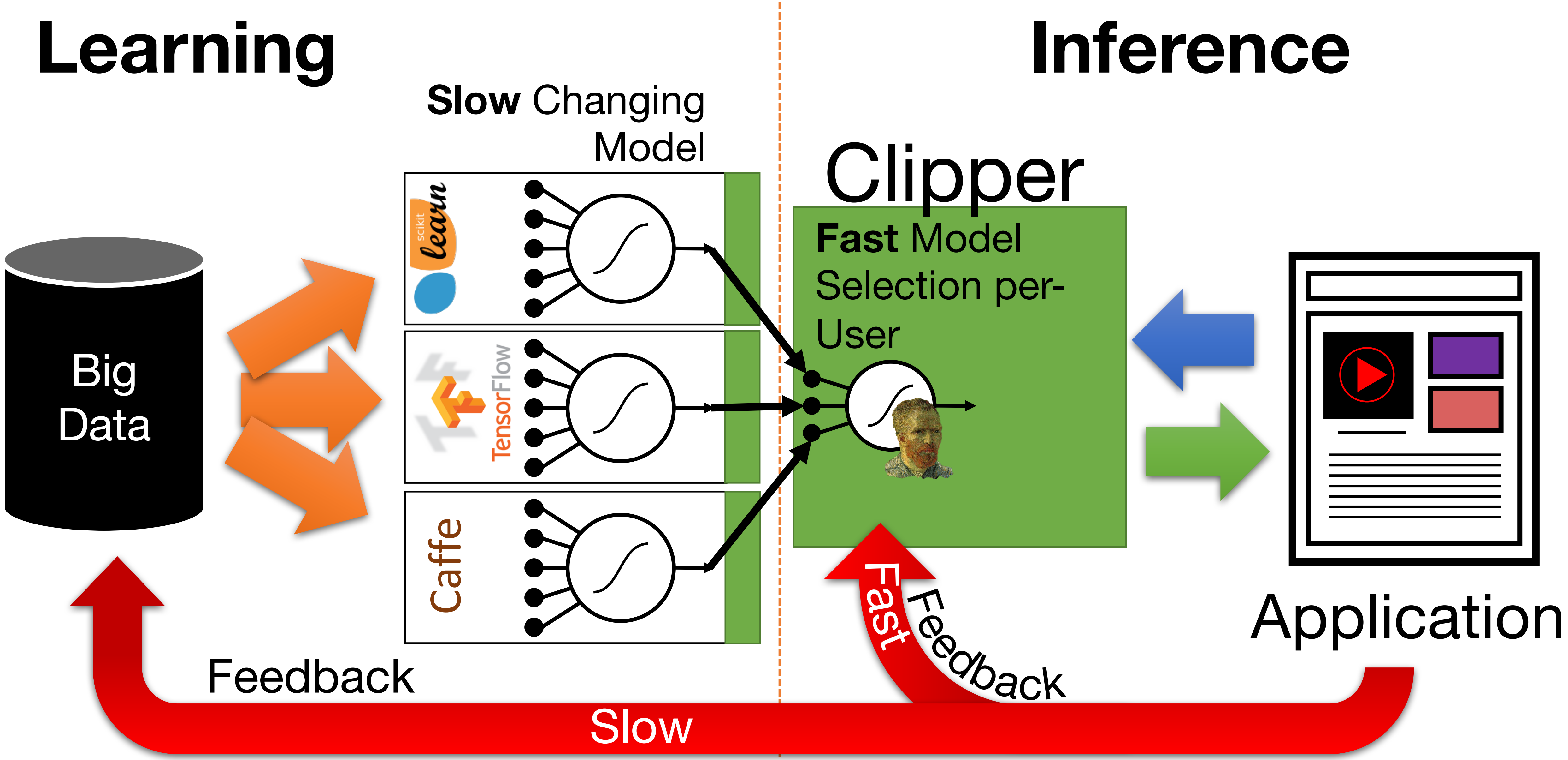


Goal:

*Maximize **accuracy** through **bandits** and **ensembles**, **online learning**, and **personalization***

Incorporate feedback in real-time to achieve:

- **robust predictions** by combining multiple models & frameworks
- **online learning** and **personalization** by selecting and personalizing **predictions** in response to feedback

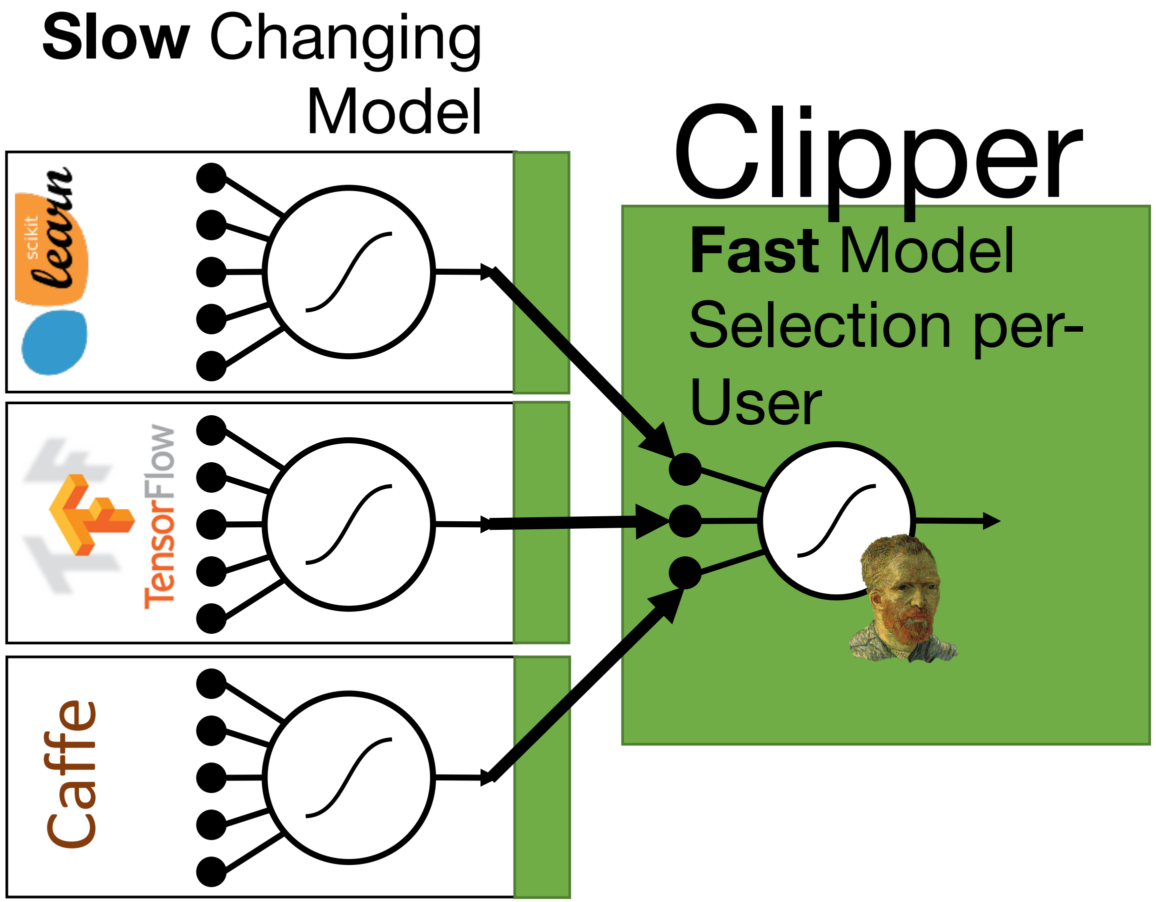


Learning
Inference
Slow Changing Model
Clipper
Fast Model Selection per-User
Big Data
scikit learn
TensorFlow
Caffe
Application
Feedback
Slow
Fast Feedback

Model Selection Policy

Improves prediction **accuracy** by:

- Incorporates real-time **feedback**
- Estimates **confidence** of predictions
- Determines how to **combine** multiple **predictions**
    - e.g., choose best, average, …
  - enables frameworks to **compete**



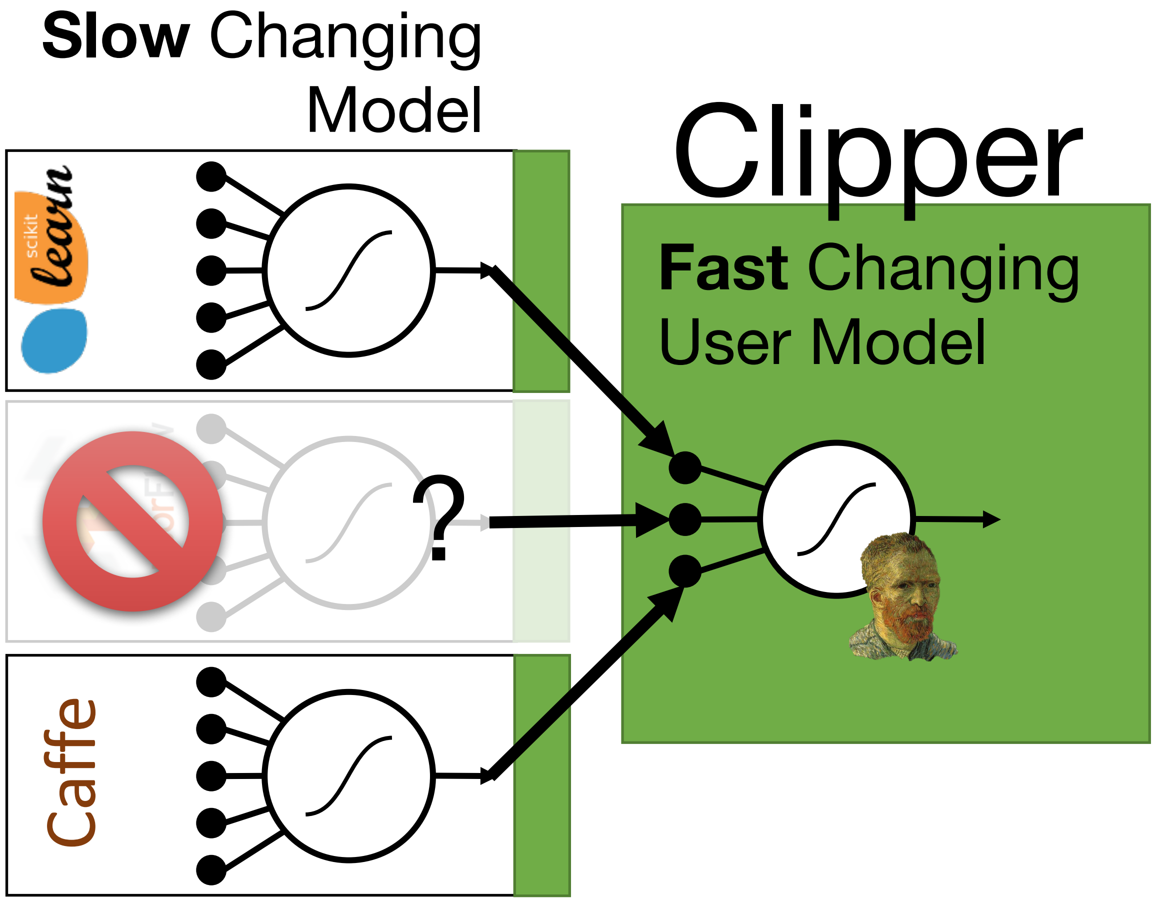
Cost of Ensembles

Increased Load

- *Solutions:*
  - **Caching** and **Batching**
  - **Model Selection** prioritizes frameworks for load-shedding

Stragglers

- e.g., framework fails to meet SLO
- *Solution:* **Anytime** predictions
  - Selection policy must select/combine from *available* predictions
  - e.g., built-in ensemble policy **substitutes expected value**



Limitations of Clipper

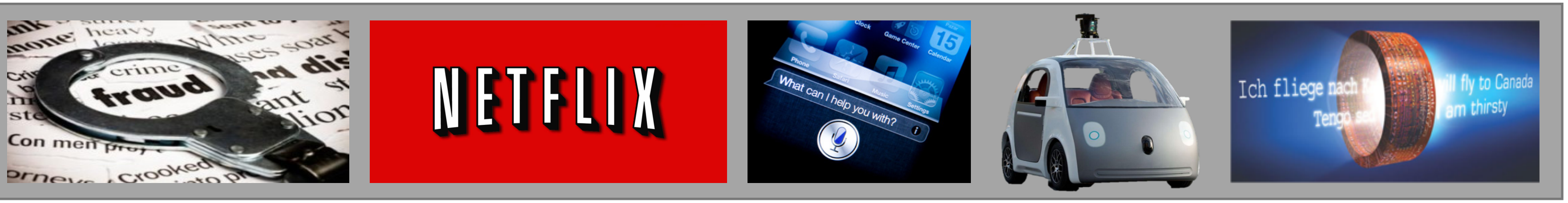
- Clipper does not address offline model retraining
- By treating deployed models as black boxes, Clipper forgoes the opportunity to optimize prediction execution of the models themselves or share computation between models
- Only performs coarse-grained tradeoffs of accuracy, robustness, and performance.

TensorFlow Serving

- Recently released open-source prediction-serving system from Google
- Companion to TensorFlow deep-learning ML framework
- Easy to deploy ***TensorFlow Models***
- System automatically manages the lifetime of deployed models
  - Watches for new versions, loads and transfers requests to new models automatically
- System does not address model performance, only system performance (through batching)

TensorFlow Serving Architecture

Applications



Predict

RPC/REST Interface

TensorFlow-Serving

Prediction Batching

RETIRED

V1 TensorFlow

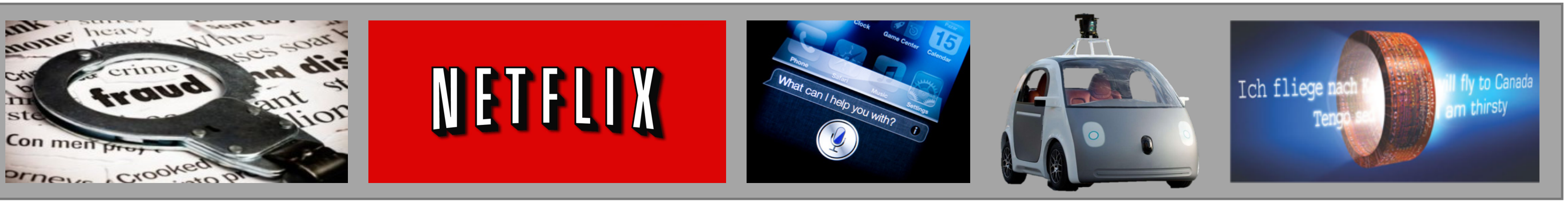
V2 TensorFlow

New model version trained

V3 TensorFlow

TensorFlow Serving Architecture

Applications



Predict ↕ **RPC/REST Interface**

TensorFlow-Serving

Prediction Batching

RETIRED

V1 TensorFlow

V2 TensorFlow

V3 TensorFlow

Other Prediction-Serving Systems

- **Turi**
  - Company co-founded by **Joey**, Carlos Guestrin, and others to serve predictions from models (primarily) trained in the GraphLab Create framework
  - Not open-source
  - Recently acquired by Apple
- **Oryx**
  - Developed by Cloudera for serving Apache Spark Models
  - Implementation of Lambda Architecture with Spark and Spark Streaming to incrementally maintain models
  - Open source
- **PredictionIO**
  - Open-source Apache Incubating project, the company behind the project was recently acquired by Salesforce
  - Built on Apache Spark, Hbase, Spray, ElasticSearch