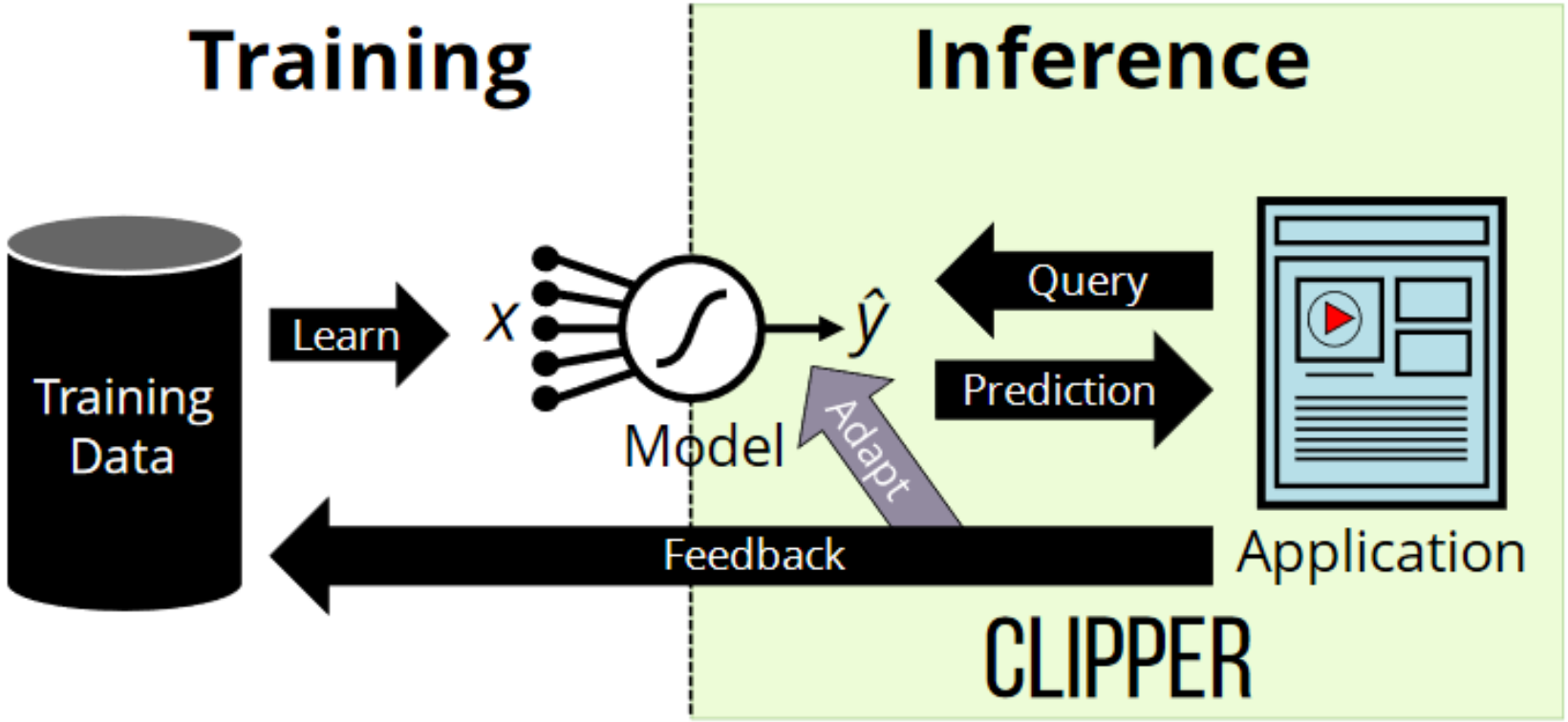
Clipper: A Low-Latency Online Prediction Serving System

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

**UC Berkeley* *†The University of Chicago*

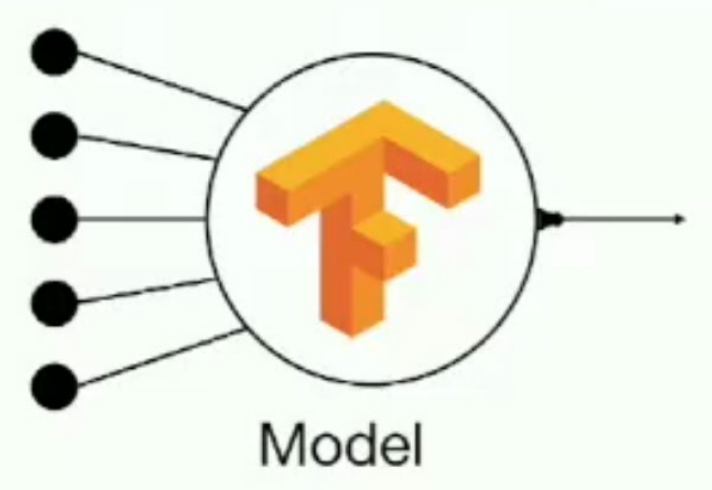
Machine Learning Lifecycle



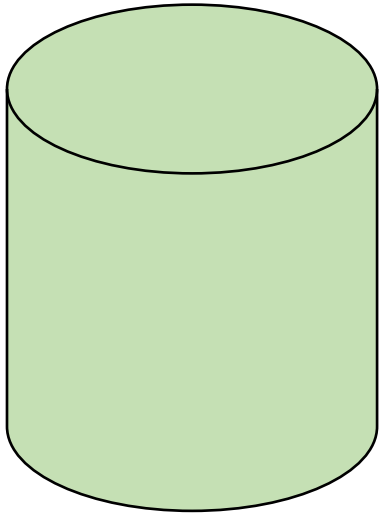
One-off Systems

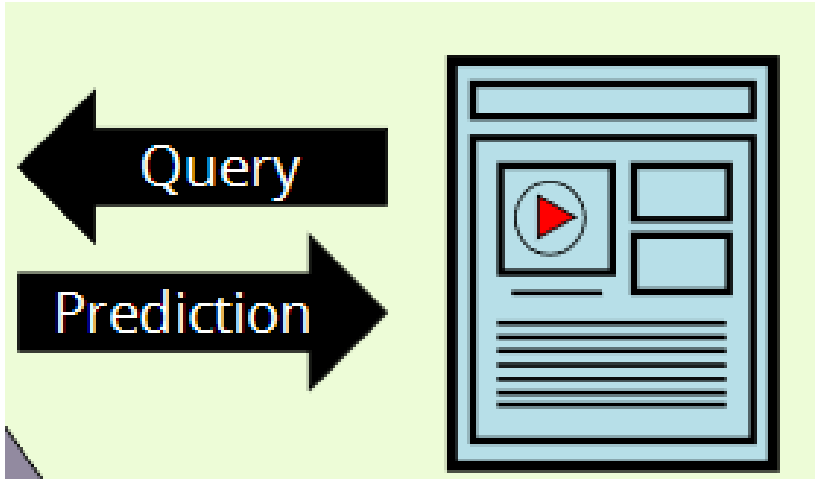
- Large companies invest a lot into building one-off systems to serve complex models
- Model and framework are tightly coupled to the application
- Can't easily change or update the model

Offline Scoring



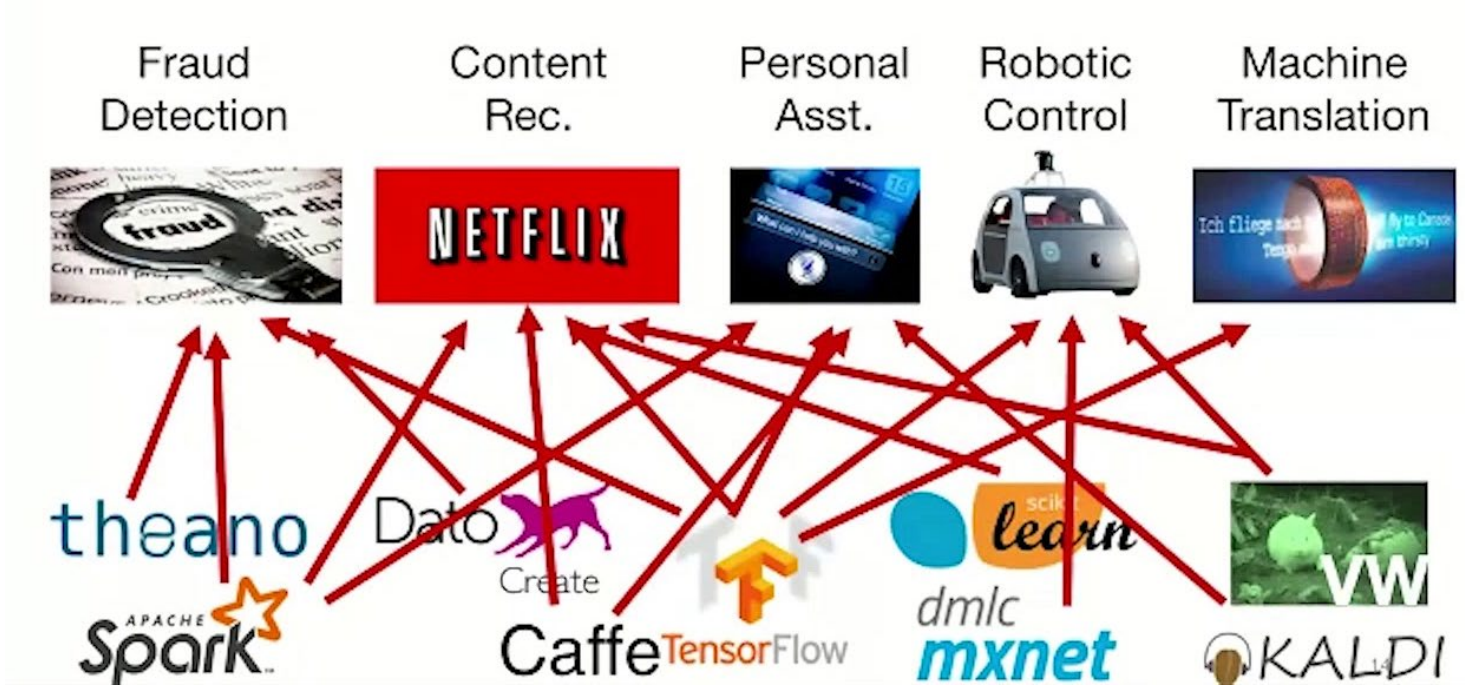
Data Store



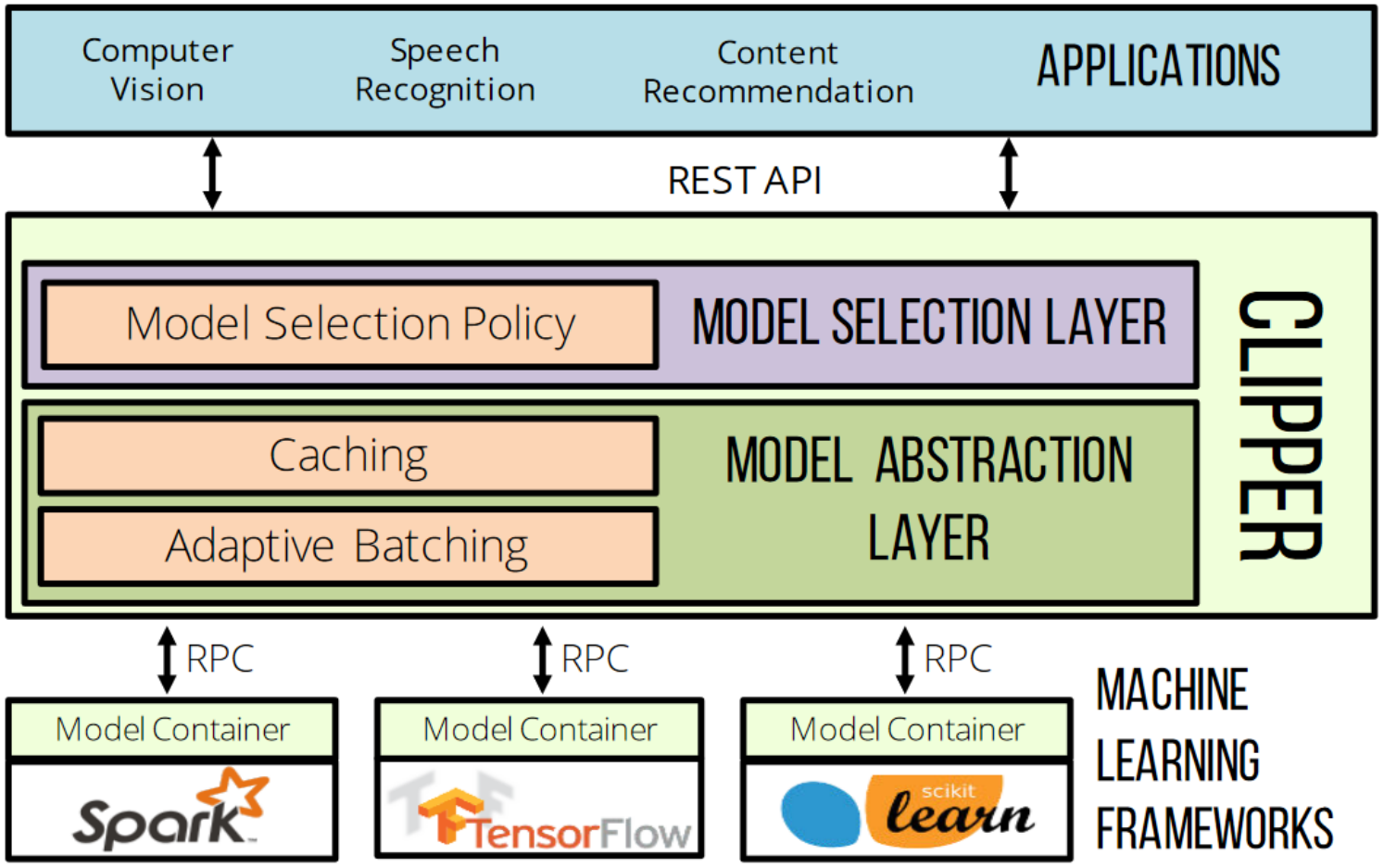


Clipper's Goals

- Support high throughput and low latency serving
- Support many frameworks for many different applications



Clipper


Computer Vision
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Content Recommendation
APPLICATIONS
REST API
Model Selection Policy
MODEL SELECTION LAYER
Caching
Adaptive Batching
MODEL ABSTRACTION LAYER
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Model Container
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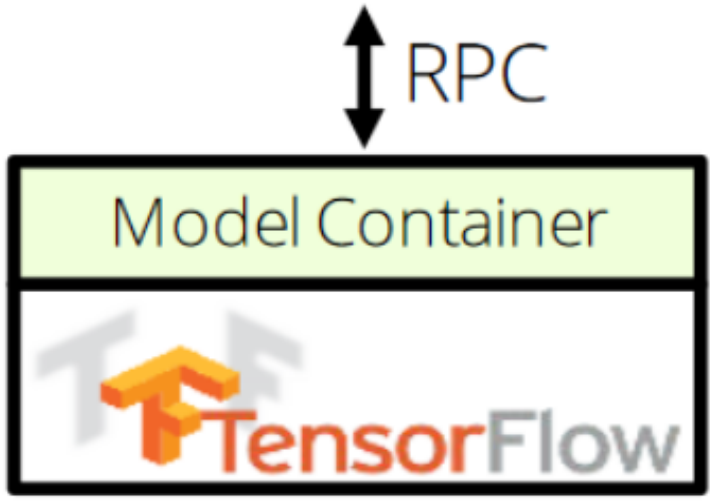
Spark
TensorFlow
scikit learn
MACHINE LEARNING FRAMEWORKS

Model Container



Model API

```
class ModelContainer:
  def __init__():
    """ Initialize the model """

  def predict_batch(inputs: list[X]) -> list[Y]:
    """ Compute predictions for a batch of inputs """
```

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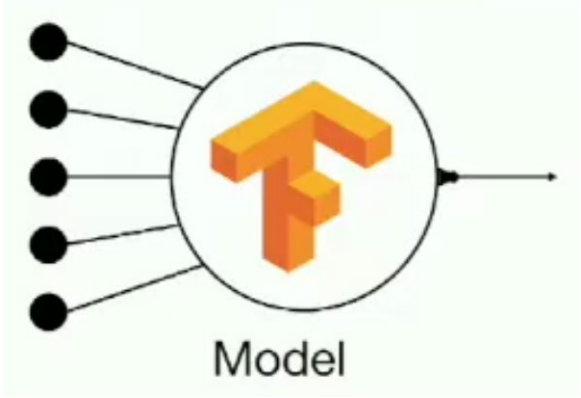
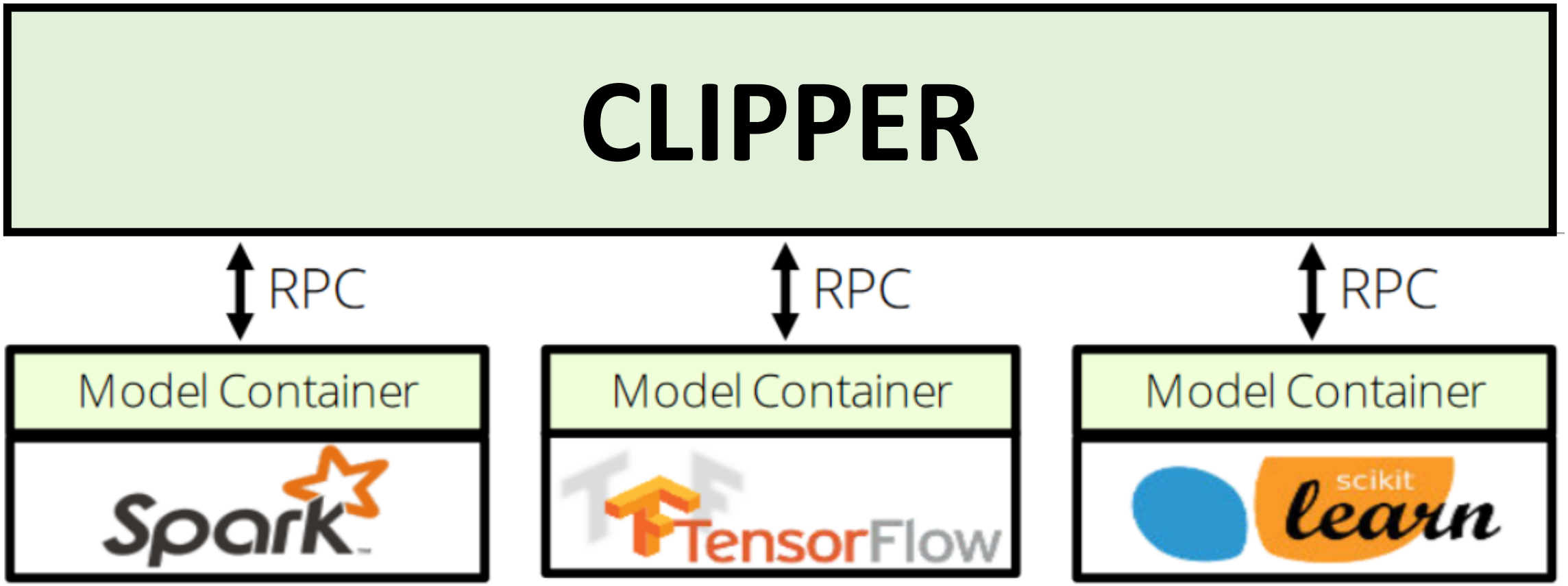


TensorFlow


CLIPPER
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learn

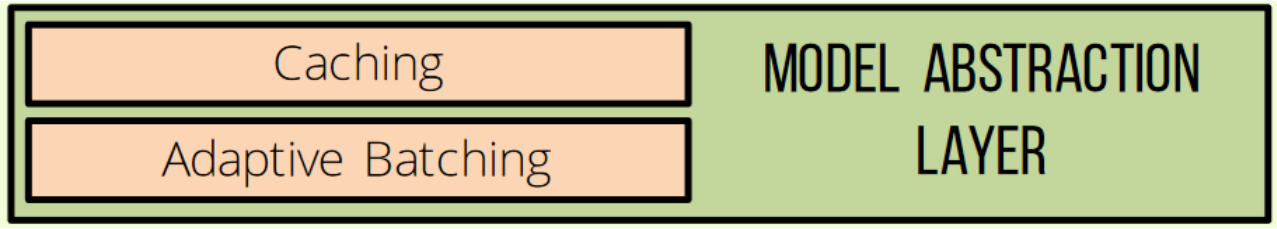
Batching

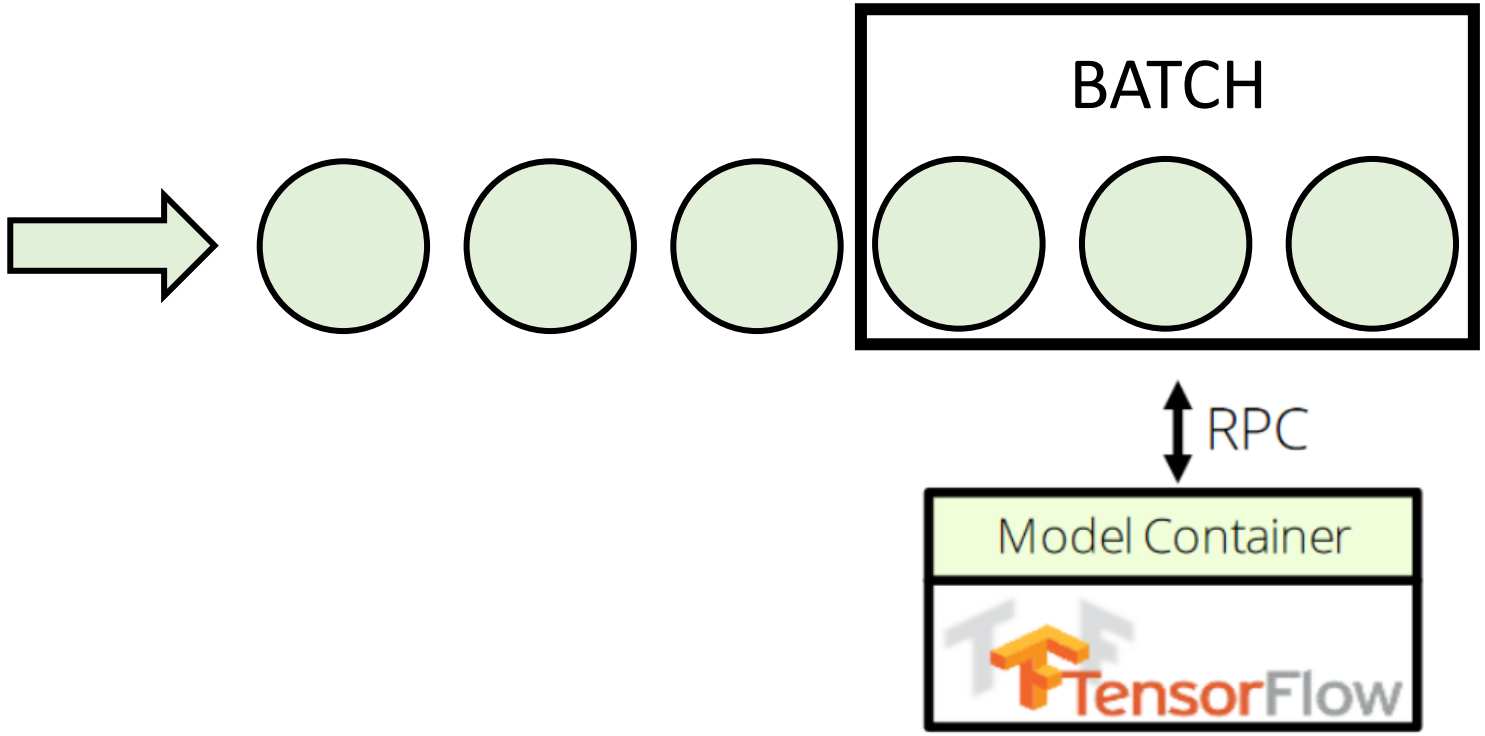
- Frameworks are designed for high throughput batch processing
- Concurrent users generate many simultaneous queries
- Hard to determine the optimal batch size

Clipper's solution:

adaptive batching for best tradeoff between throughput and latency

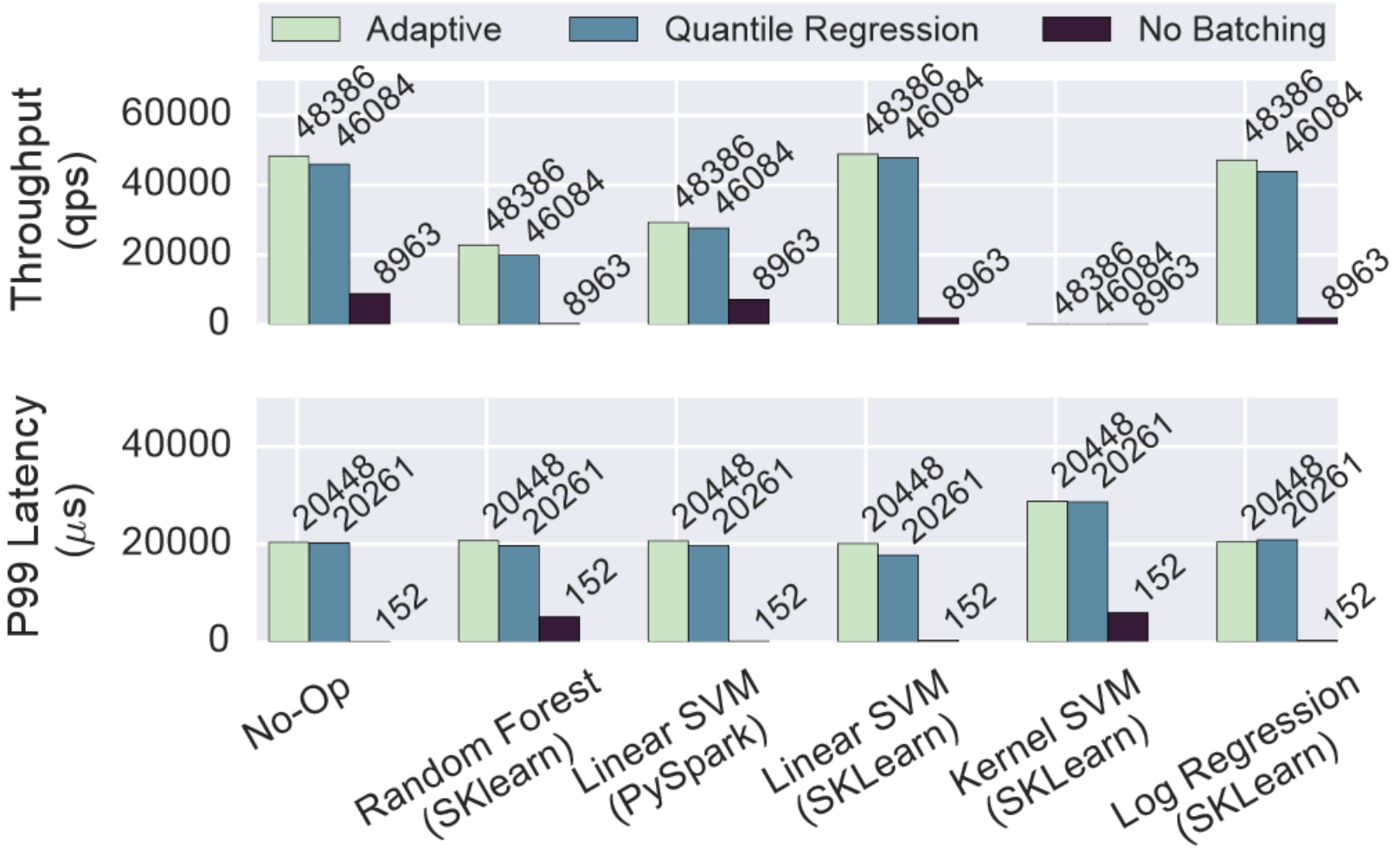
Adaptive Batching



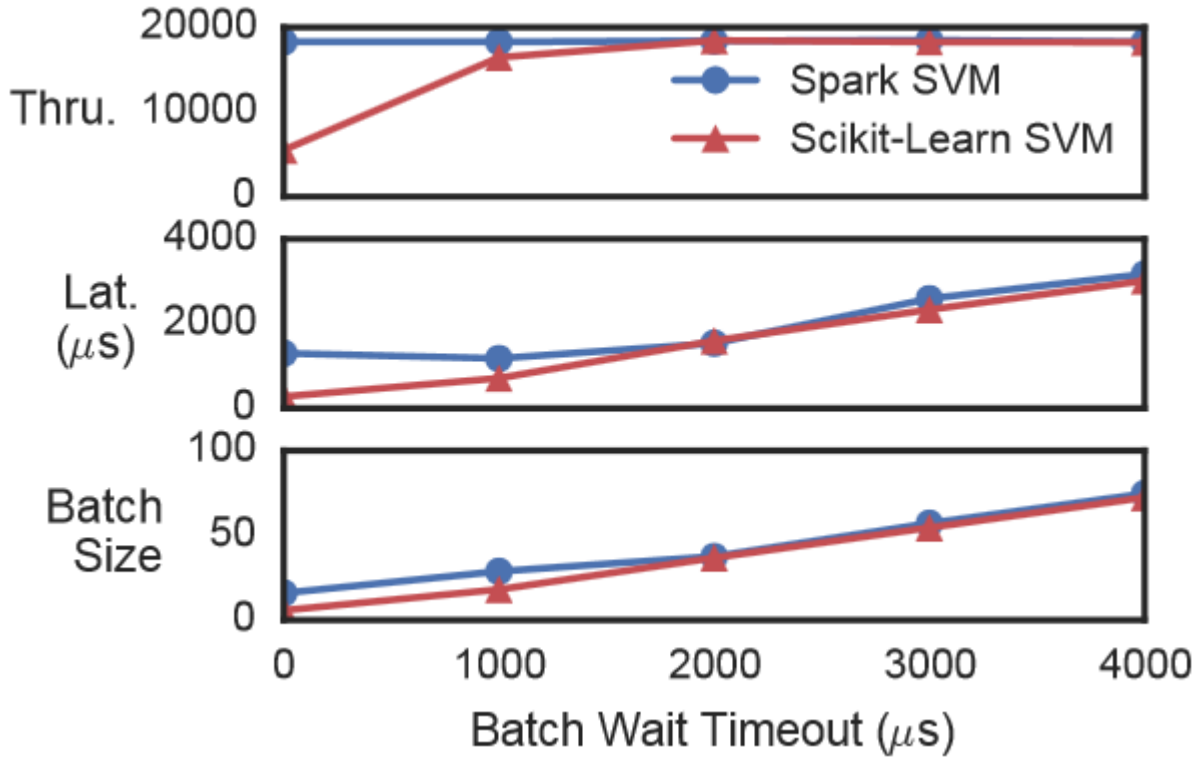


- Developer specifies latency objective
- Increase batch size until latency objective is exceeded
- When latency is exceeded, reduce batch size by a fraction

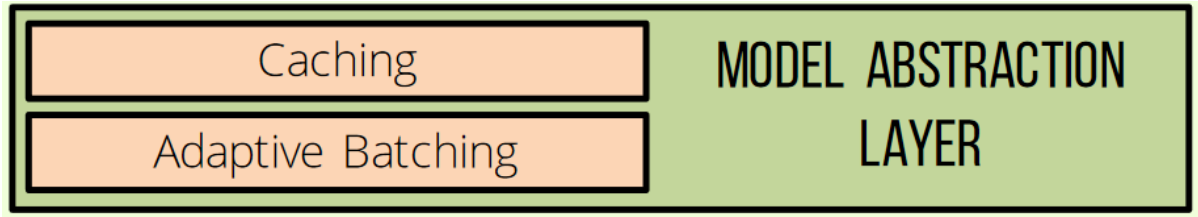
Adaptive Batching

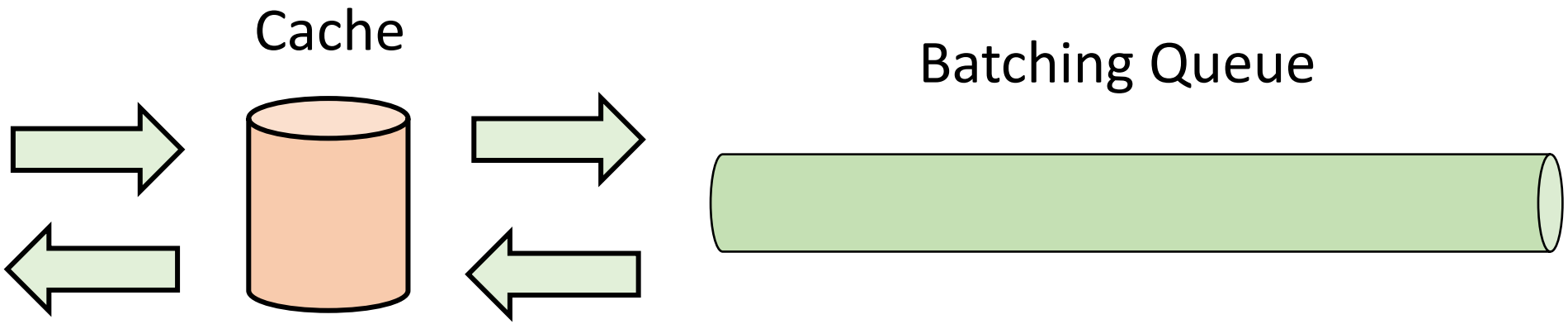


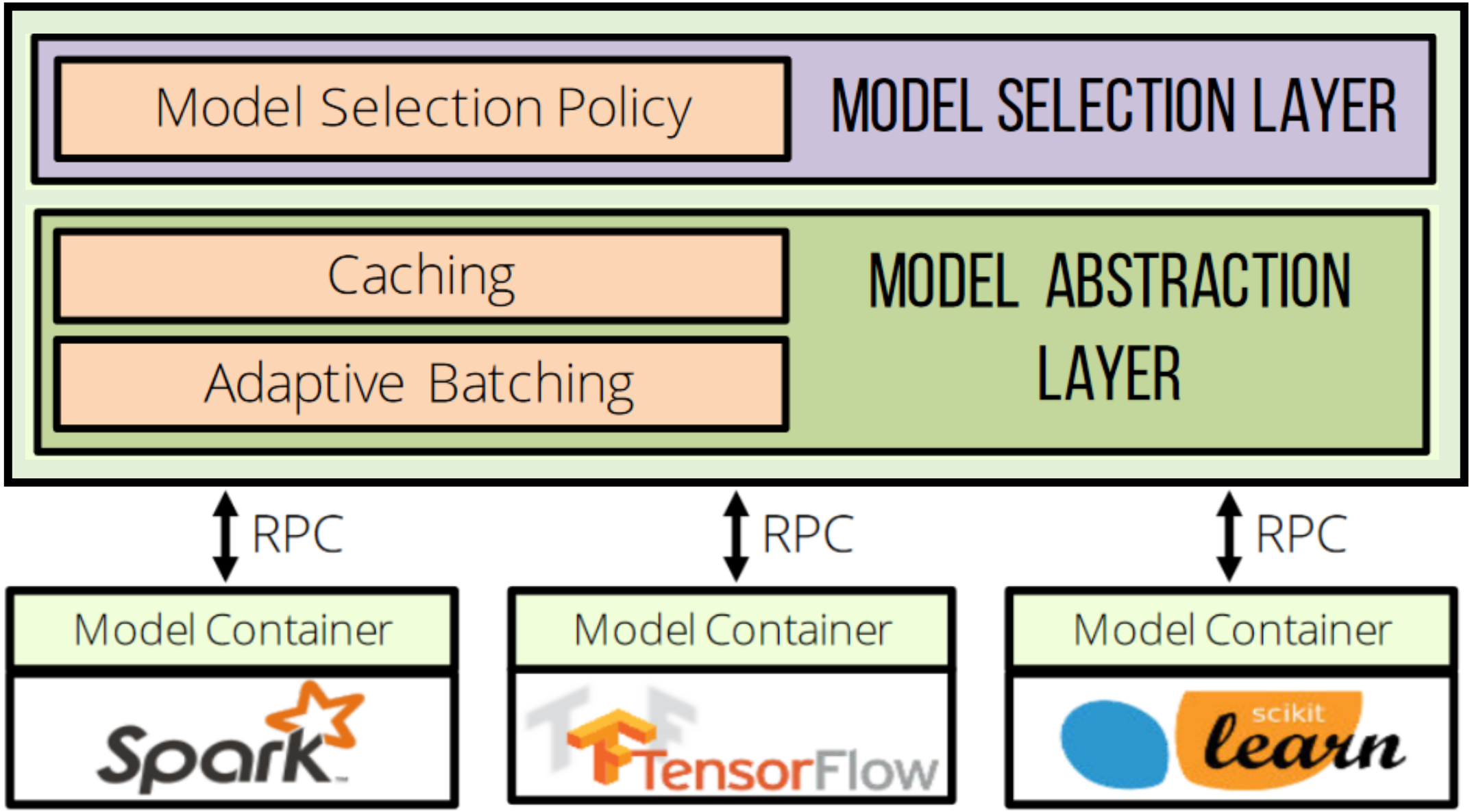
Delayed Batching



Caching


Caching
Adaptive Batching
MODEL ABSTRACTION LAYER


Cache
Batching Queue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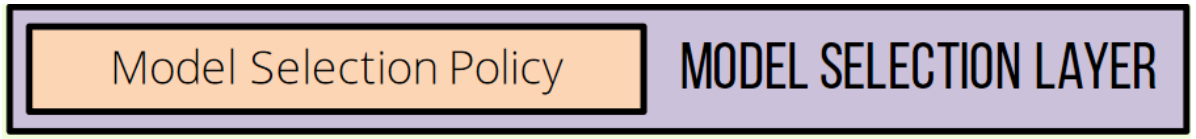
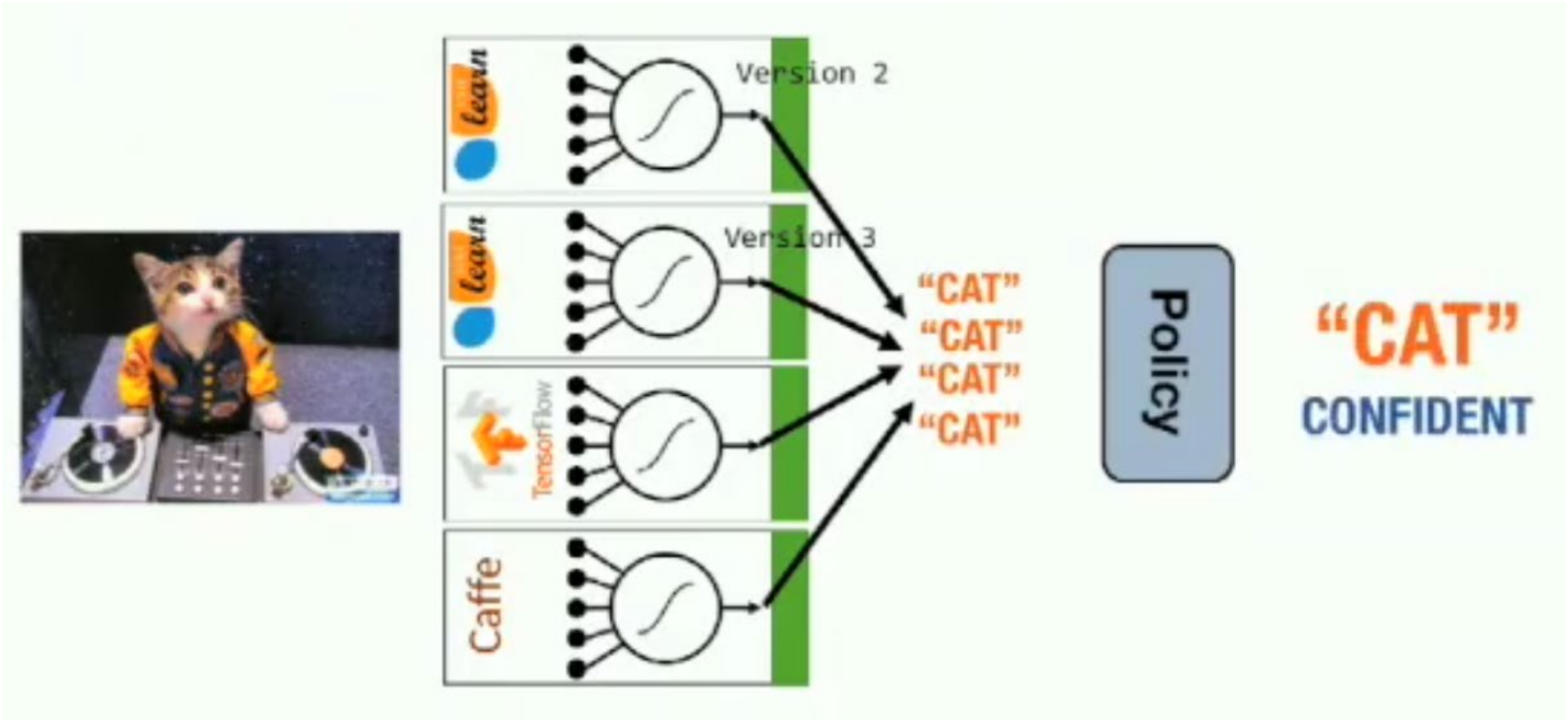
Model Selection Layer

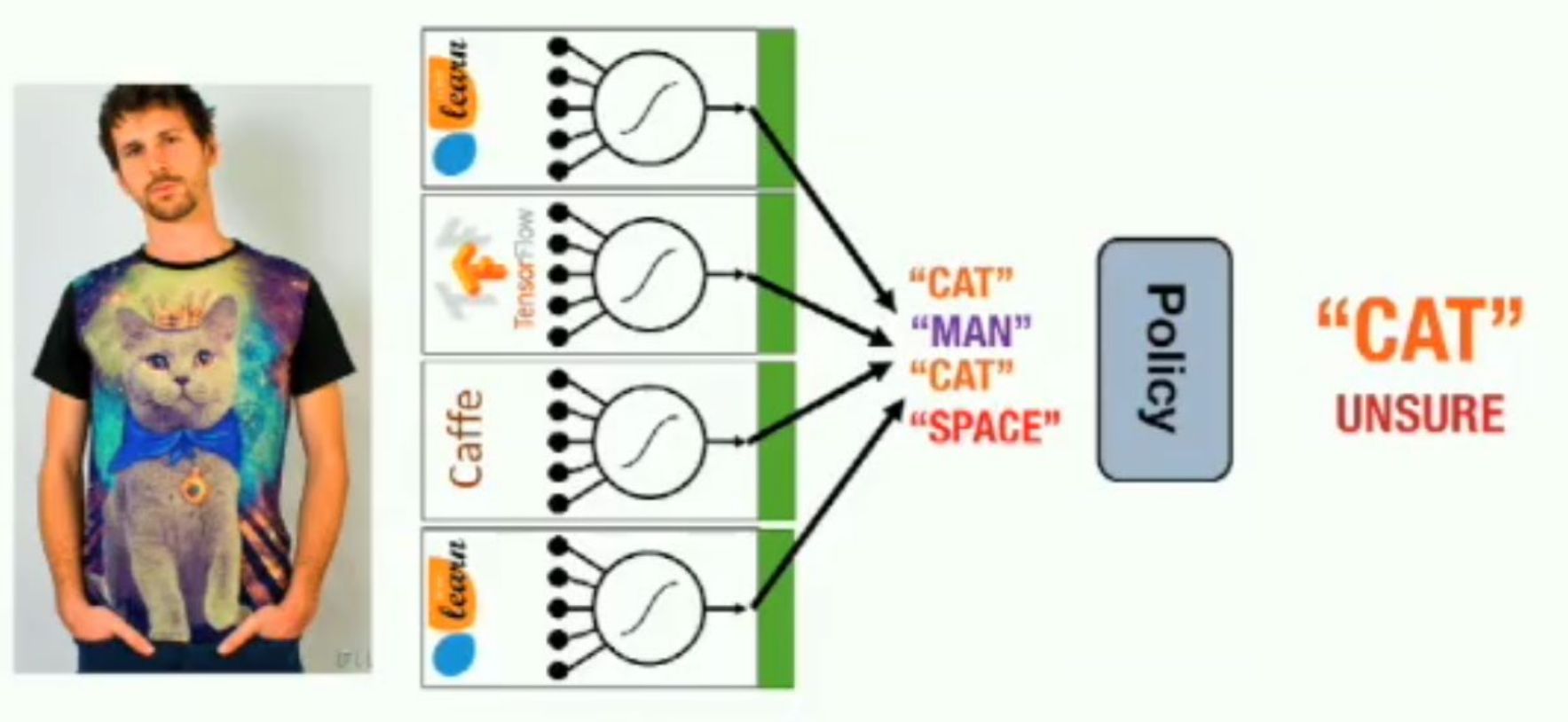


- Support for multiple models
- Ensemble models and return confidence scores
- Support feedback from users
- Abandon slow models, better to return a bad but on time prediction rather than a good but slow prediction

Ensembling


Version 2
Version 3
Tensorflow
Caffe
"CAT"
"CAT"
"CAT"
"CAT"
Policy
"CAT"
CONFIDENT

Ensembling


learn
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Caffe
learn
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"MAN"
"CAT"
"SPACE"
Policy
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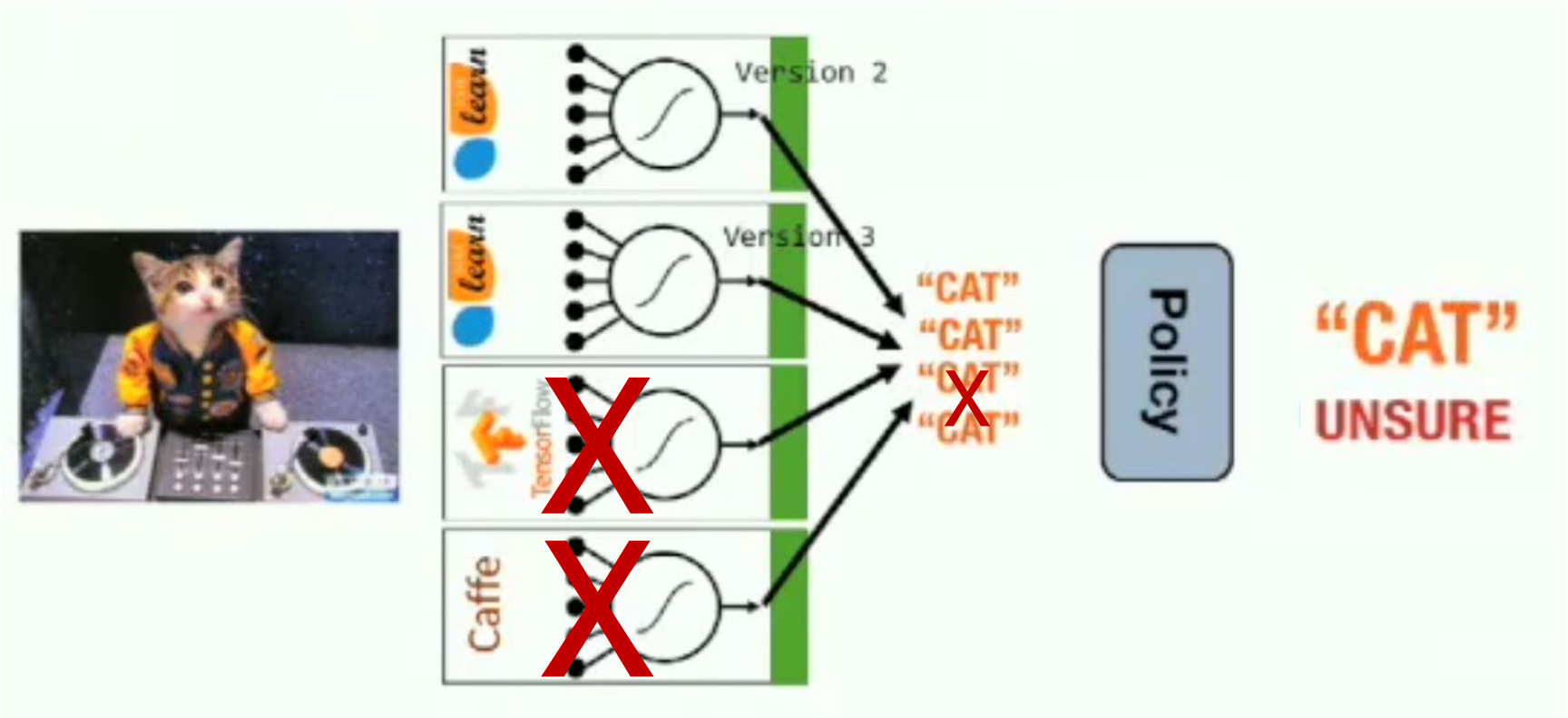
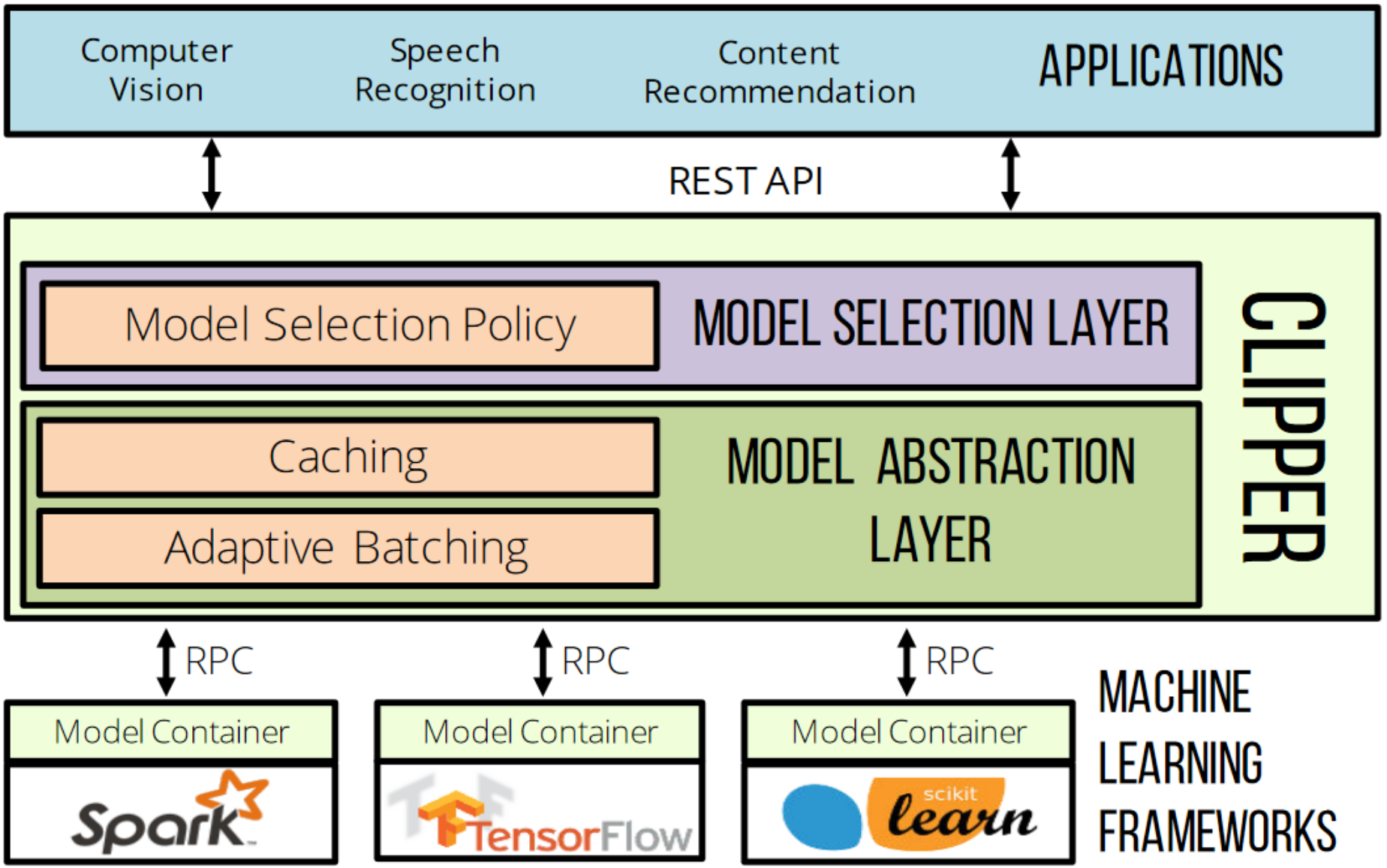
UNSURE

Straggler Mitigation

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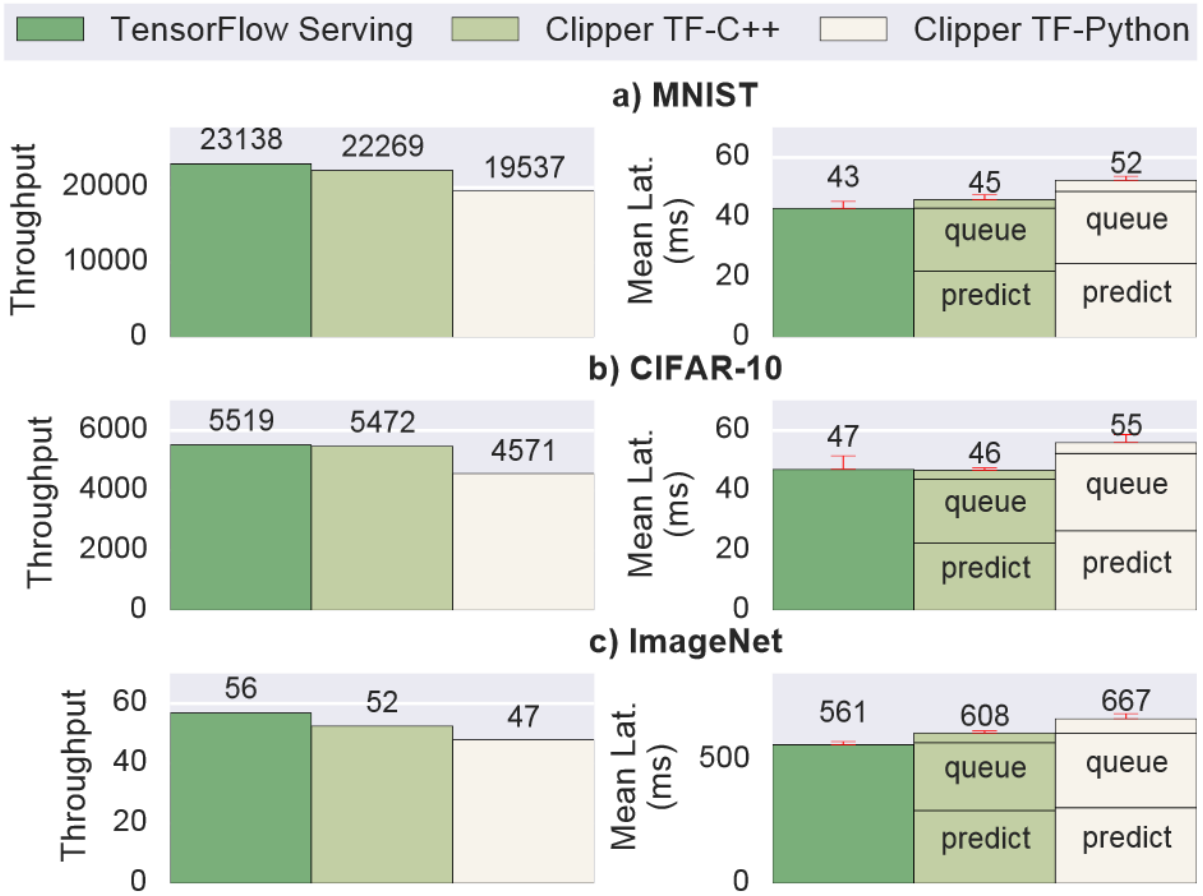
MACHINE LEARNING FRAMEWORKS

Compared to one-off system

- TensorFlow serving
  - Built specifically to serve TensorFlow models
  - Optimized for TensorFlow, tightly coupled
  - Doesn't support multiple frameworks
  - Fewer features than Clipper

Compared to one-off system



Compared to one-off systems

Clipper:

- Supports multiple frameworks and models
- Dynamically selects the optimal batch sizes
- Dynamically selects the best models via ensembling
- And is as performant as one-off systems

Downsides

- Treats each model like a black-box
- No low-level framework optimizations
- Can’t make assumptions about how frameworks execute

Serving DNNs like **Clockwork**: Performance Predictability from the Bottom Up

Arpan Gujarati*, Reza Karimi†, Safya Alzayat*, Wei Hao*, Antoine Kaufmann*, Ymir Vigfusson†, Jonathan Mace*

**Max Planck Institute for Software Systems* *†Emory University*

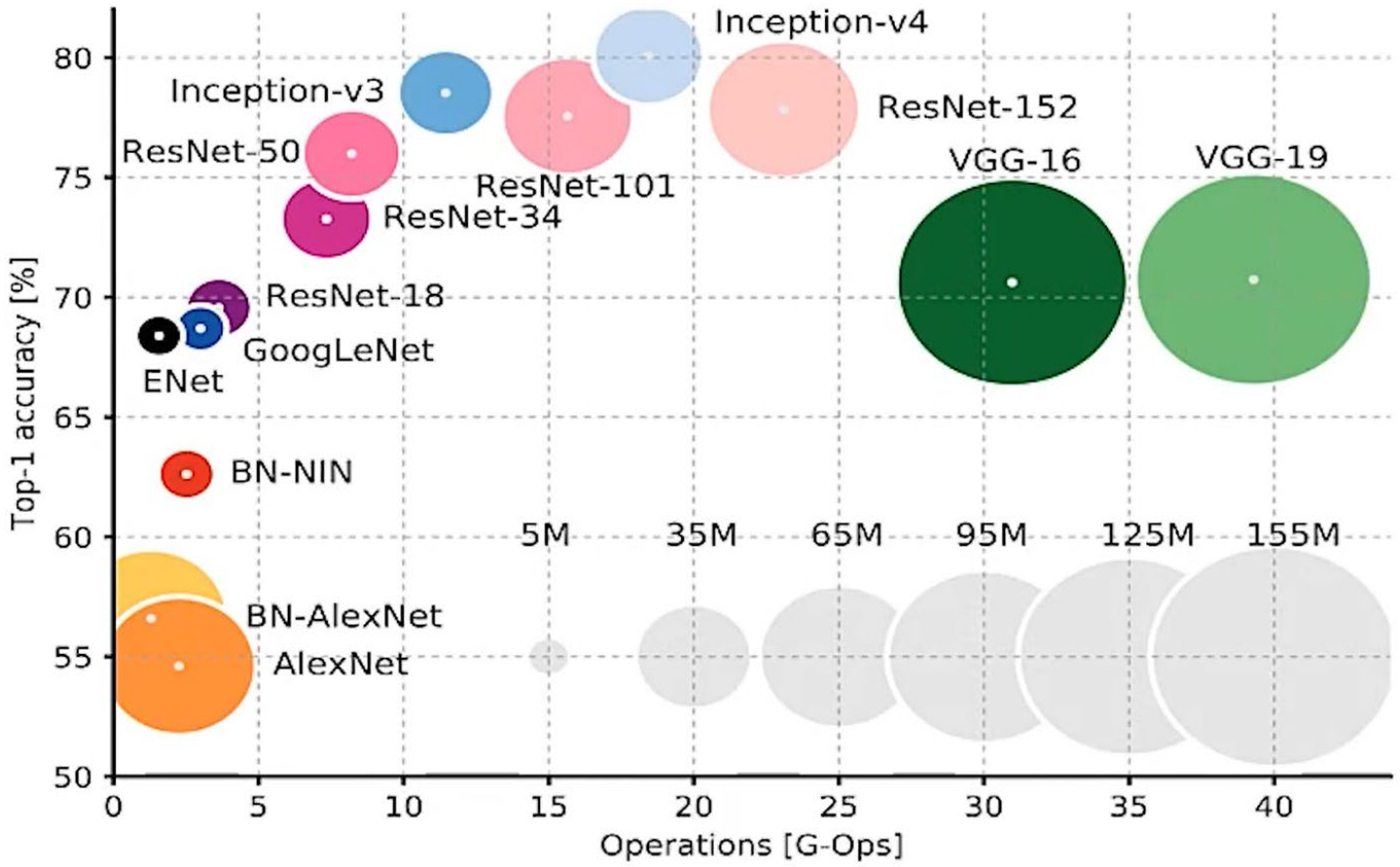
Inferences

- Why is inference important?
  - Model inference now on critical path of web requests
  - Facebook serves over 200,000,000,000,000+ inferences/day
  - 100+ companies developing hardware for accelerated ML inference
- Why is inference complex?
  - Too many models for many different tasks (with vastly different requirements)
- Solution – model serving systems
  - Hosted services that take pre-trained ML models and serve inference requests made to the models

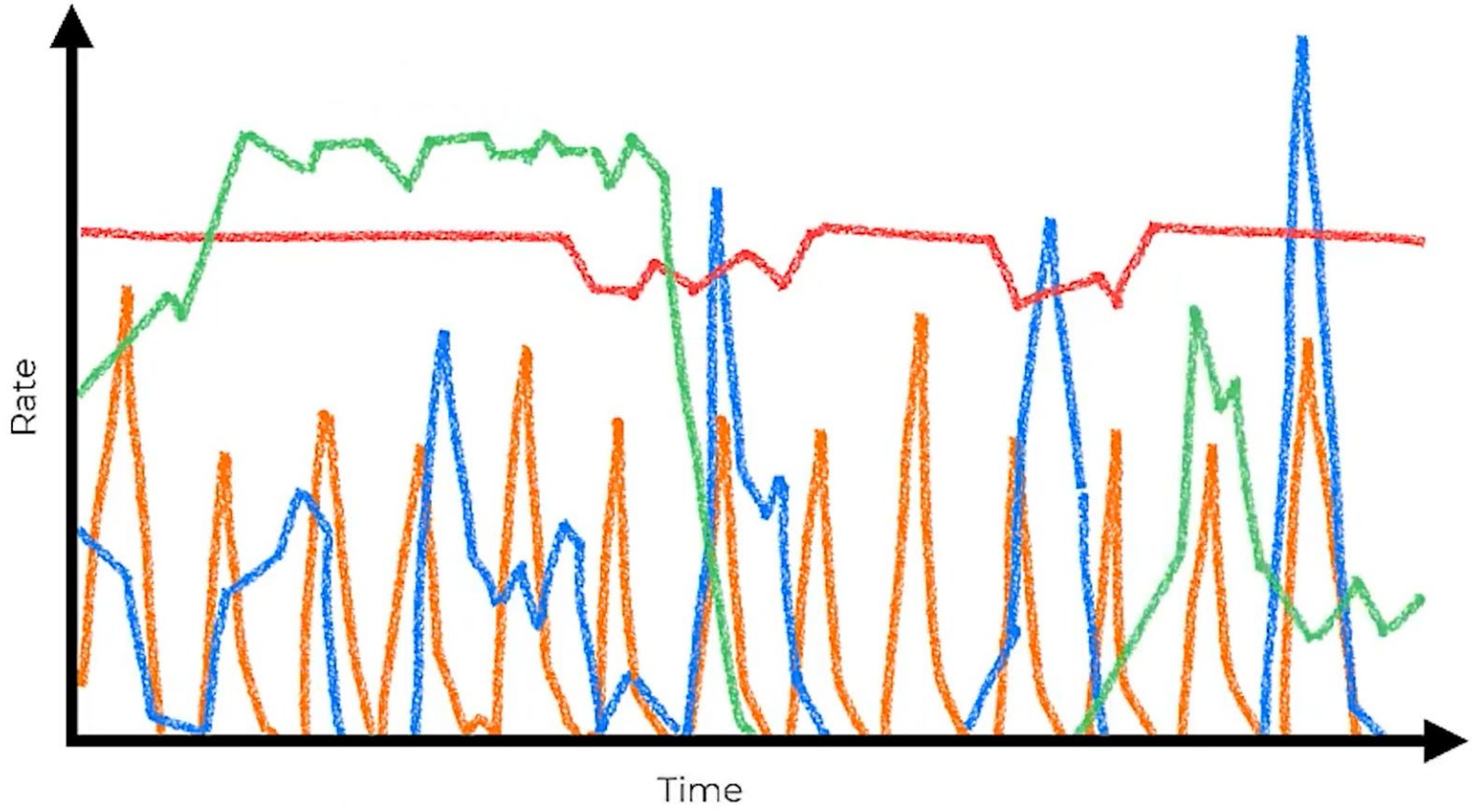
Inferences

- Inference requests have an inherent **deadline**
- Seek to bound latency, ideally provide SLOs
- Need to curtail tail latency

Model Serving Systems – Model Ecosystem



Model Serving Systems – Request Patterns



Model Serving Systems – Current Status

- Existing model serving architectures
  - Fundamentally assume constituent systems have unpredictable latency performance
  - Best effort techniques to curtail variability cascade unpredictability to other components and propagate tail latency to higher layers
  - Variability stems from internal design decisions (caching, concurrency, OS…)
- Current approaches to latency
  - Dedicate GPUs to models, lots of batching
  - Add more hardware, trading efficiency and utilization for throughput

Model Serving Systems – Hardware Costs

ResNet-50	Latency	Throughput	Cost
CPU	175.0 ms	6 req/s	$
GPU	2.8 ms	350 req/s	**$$$**

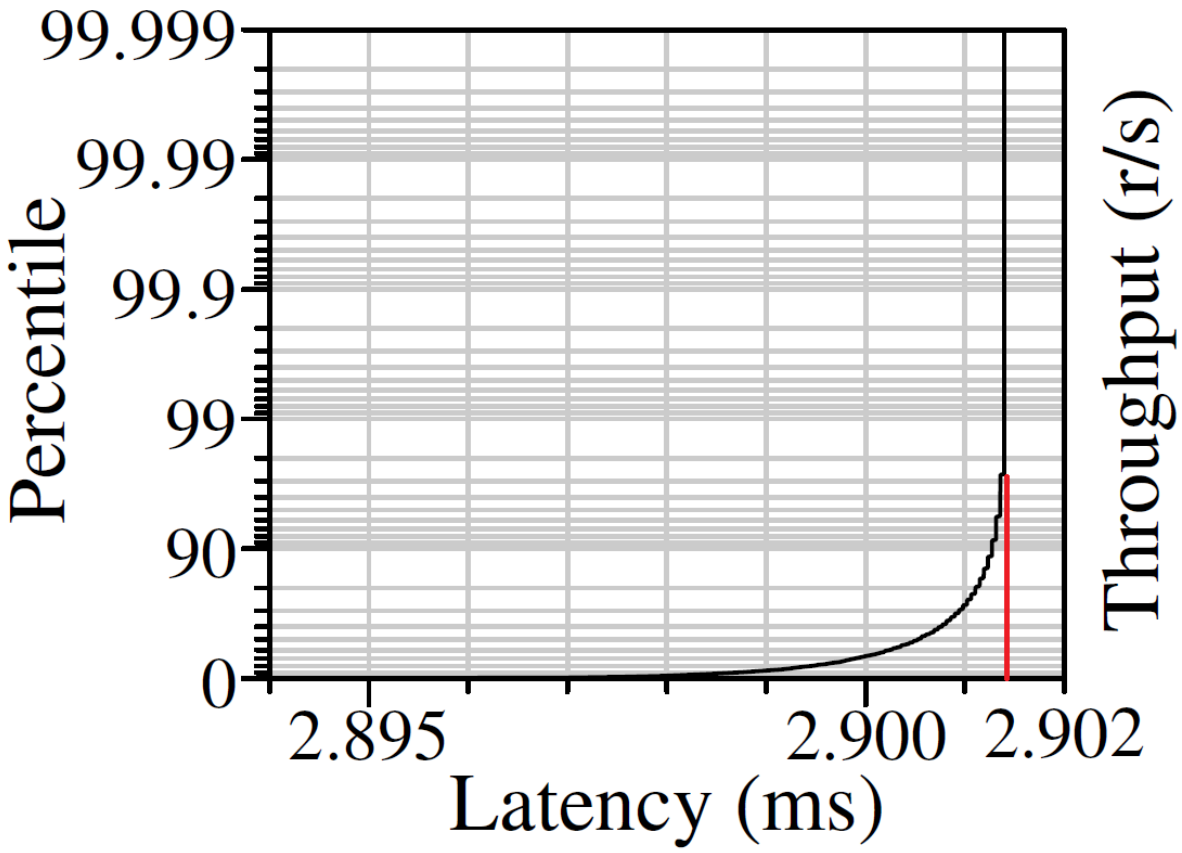
Clockwork – What is it?

- Fully distributed model serving system with predictable end-to-end performance
- Achieves 100ms latency targets for 99.9999% of requests simultaneously on thousands of models
- Mitigates tail latency by reducing unpredictability at the underlying layers and components

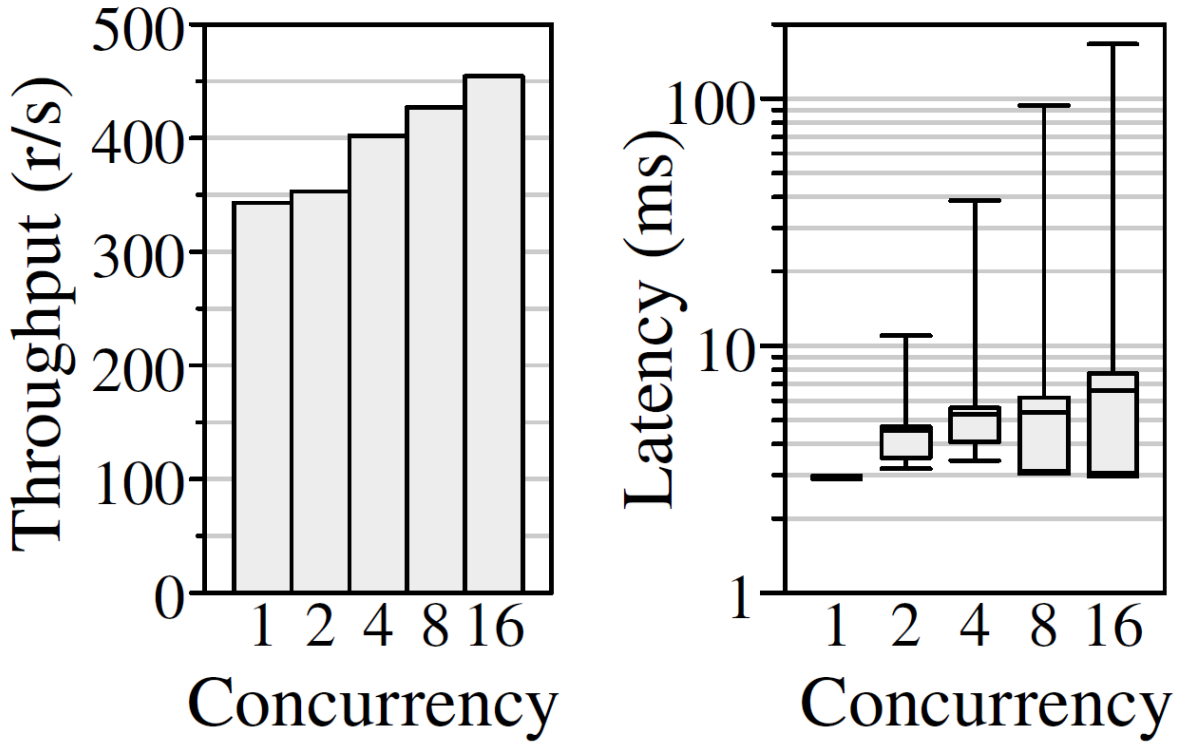
Clockwork – Core Assumption

- Inference using DNN models has deterministic performance
  - Inference request carries a fixed-size input tensor
  - Input copied to GPU over PCIe interconnect
  - DNN itself is a pre-defined sequence of tensor multiplications and activation functions (and lacks any conditional branching)
  - These operations are applied to the input tensor one-at-a-time to convert the input into an output tensor
  - Output is also a fixed-size tensor, which is copied back to the main memory over the PCIe interconnect

Clockwork – 1-thread latency



Clockwork – Throughput vs Latency



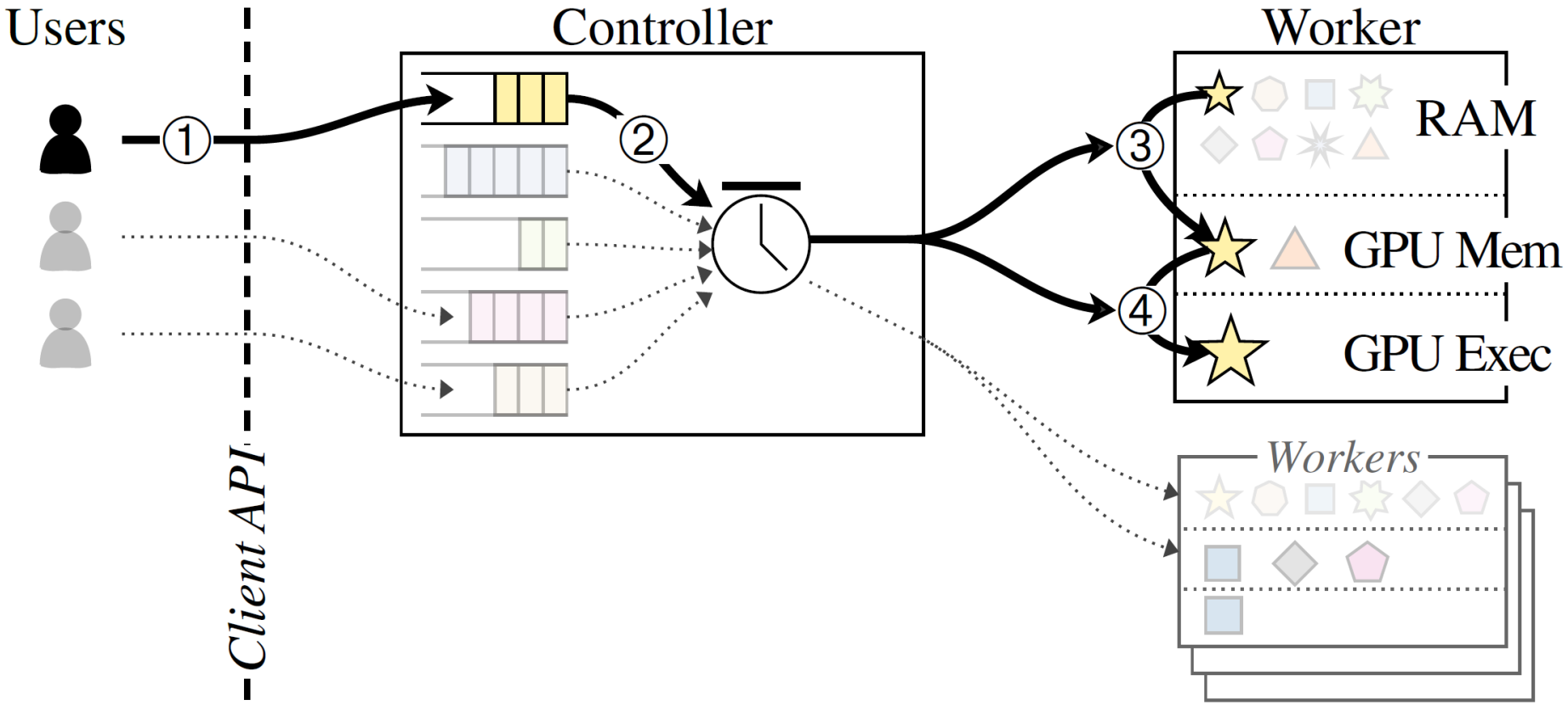
Latency

- Current approaches to latency
  - Ignore the problem; allow volatility to propagate to later requests
  - Match worst case latency for all requests
  - Scale resources
  - Add a feedback mechanism

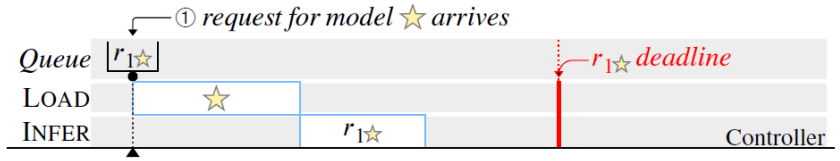
Clockwork – Predictability

- A predictable system from the bottom up
- Restrict choices available to the lower system layers
  - Hardware level
  - OS level
  - Application level
- *Consolidate choices* in the upper layers; force the lower layers to follow a narrow (and nearly deterministic) path of possible choices

Clockwork – Design Overview



Clockwork – Example



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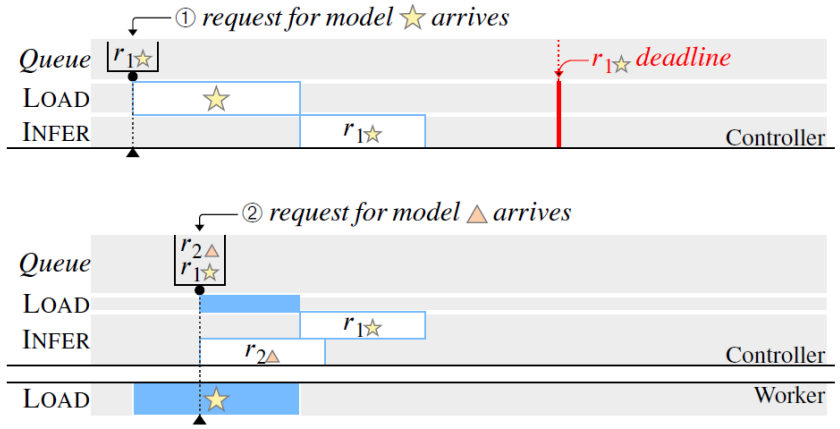

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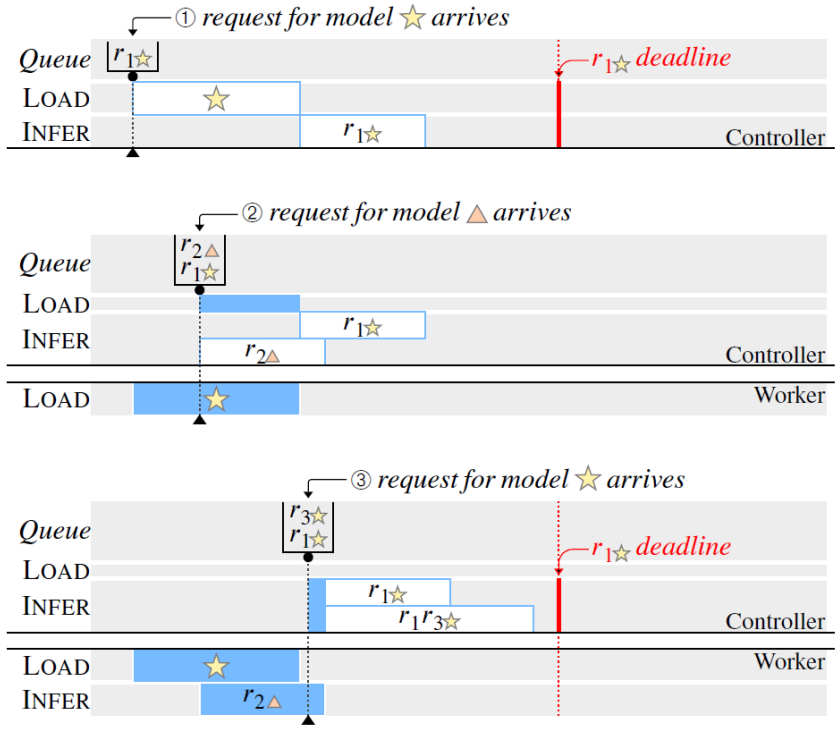

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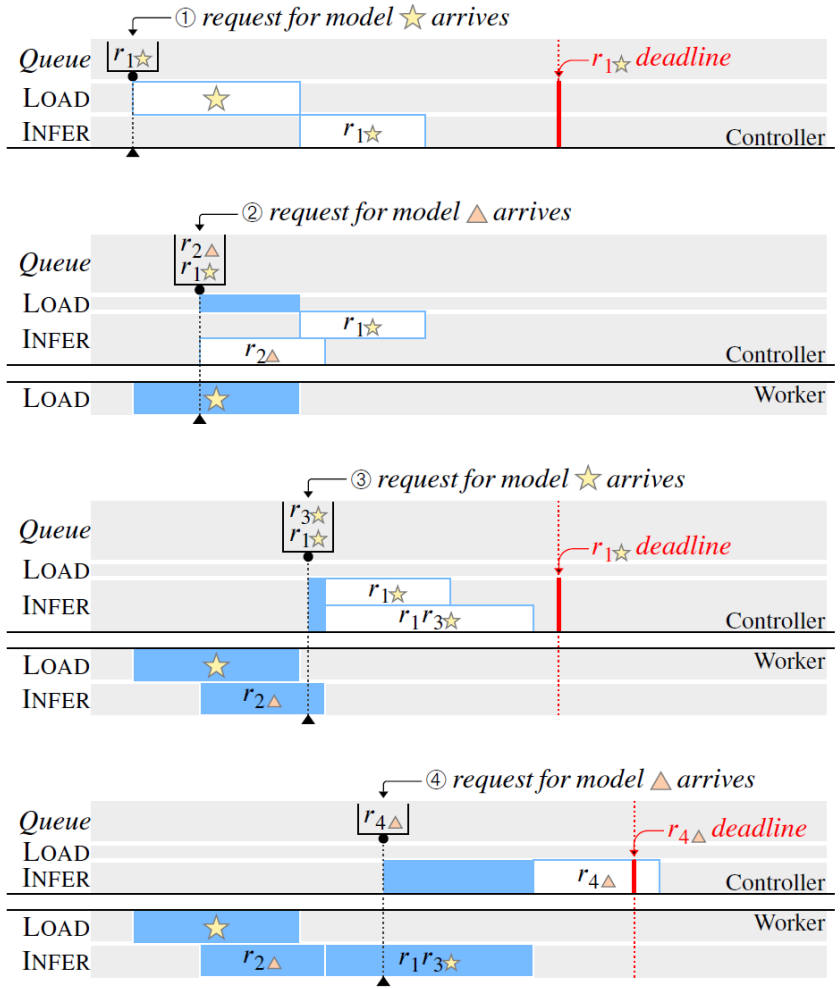

Clockwork – Transfer & Execution Times

Model Family	Model	IO Size (kB)		Weights		GPU Execution Latency (ms)				
		Input	Output	Size (MB)	Transfer (ms)	B1	B2	B4	B8	B16
DenseNet	densenet169	602	4	56.5	4.50	5.18	6.29	8.57	12.82	21.85
Inception v3	inceptionv3	1073	4	95.3	7.77	4.46	6.85	10.99	16.45	26.17
Mobile Pose	mobile_pose_mobilenetv3	590	209	19.0	1.55	1.29	1.92	3.13	5.71	11.62
ResNet	resnet18	602	4	46.7	3.81	1.27	1.86	2.73	4.06	7.02
	resnet50	602	4	102.3	8.33	2.61	3.78	5.61	9.13	15.67
	resnet152	602	4	240.9	19.58	7.71	11.14	16.21	26.48	44.60

Clockwork – Predictable DNN Worker

- Memory management
  - Managed memory and caches can be unpredictable
  - Memory used as cache introduces variability between cache hits and misses
  - GPU memory not large enough to hold all models
  - Host-to-GPU memory transfer slower than DNN inference execution
  - Clockwork treats GPU memory as cache
  - Workers expose LOAD and UNLOAD actions to controller for copying models to and removing models from the GPU memory with deterministic latency

Clockwork – Predictable DNN Worker

- Inference Execution
  - Hardware interactions can be unpredictable
  - Controller only sends INFER request when model is loaded in GPU
  - INFER broken down into 3 steps:
    - INPUT
    - EXEC
    - OUTPUT
  - While INPUT and OUTPUT might coincide, only a single EXEC is run at a time
  - Avoids unpredictable behavior caused by multiple concurrent EXECs

Clockwork – Predictable DNN Worker

- Interface with controller
  - External factors can trigger performance variance
  - Controller sends detailed timing instructions with each command

`type`	INFER, LOAD, or UNLOAD
`earliest`	the time when this action may begin executing
`latest`	when this action will be rejected

  - Actions that can not start within window are cancelled
  - Allows workers to quickly get back on schedule after unexpected delay
  - Worker sends the result of each action back to the controller

Clockwork – Central Controller

- Modelling worker performance
  - Controller maintains per-worker per-model performance profile
  - Profiles updated continuously based to response from worker
  - Also tracks actions and memory state at every worker

Clockwork – Central Controller

- Action scheduler
  - Proactively manage action schedules for workers
  - Estimate tight but realistic ‘earliest’ and ‘latest’ time intervals
  - Balance load by mixing ‘hot’ and ‘cold’ inferences among workers

Clockwork – Implementation

- Models
- DNN workers
- Central controller

Clockwork – Implementation

- Models
  - Weights and kernels
  - Memory metadata
  - Profiling models

Clockwork – Implementation

- DNN workers
  - Managing model weights in memory
    - Workspace, IOCache and PageCache
    - Actions and results

Clockwork – Implementation

- Central controller
  - Managing worker state
  - Scheduling INFER requests
  - Scheduling LOAD requests

Clockwork – Implementation

- Central controller
  - Managing worker state
    - Memory state
    - Action profiles
    - Pending actions

Clockwork – Implementation

- Central controller
  - Scheduling INFER requests
    - Each model has a request queue per batch size
      - New requests queued into every batch queue

Model Family	Model	IO Size (kB)		Weights		GPU Execution Latency (ms)				
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Mobile Pose	mobile_pose_mobilenetv3	590	209	19.0	1.55	1.29	1.92	3.13	5.71	11.62
ResNet	resnet18	602	4	46.7	3.81	1.27	1.86	2.73	4.06	7.02
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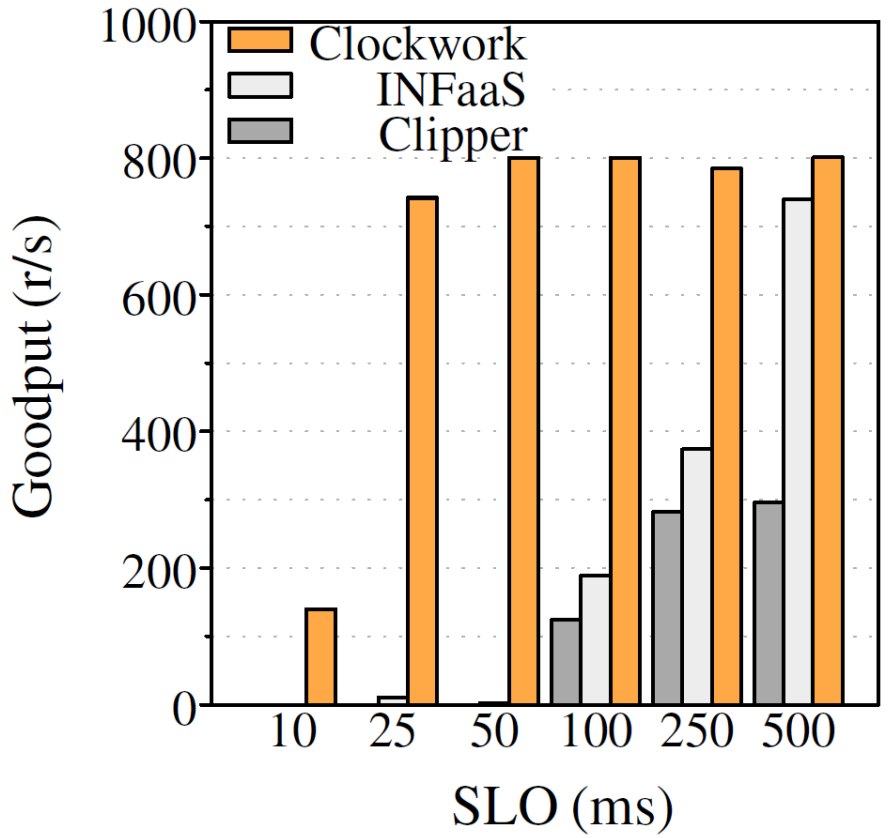
Clockwork – Implementation

- Central controller
  - Scheduling LOAD requests
    - Maintains *load* and *demand* statistics for each model and GPU

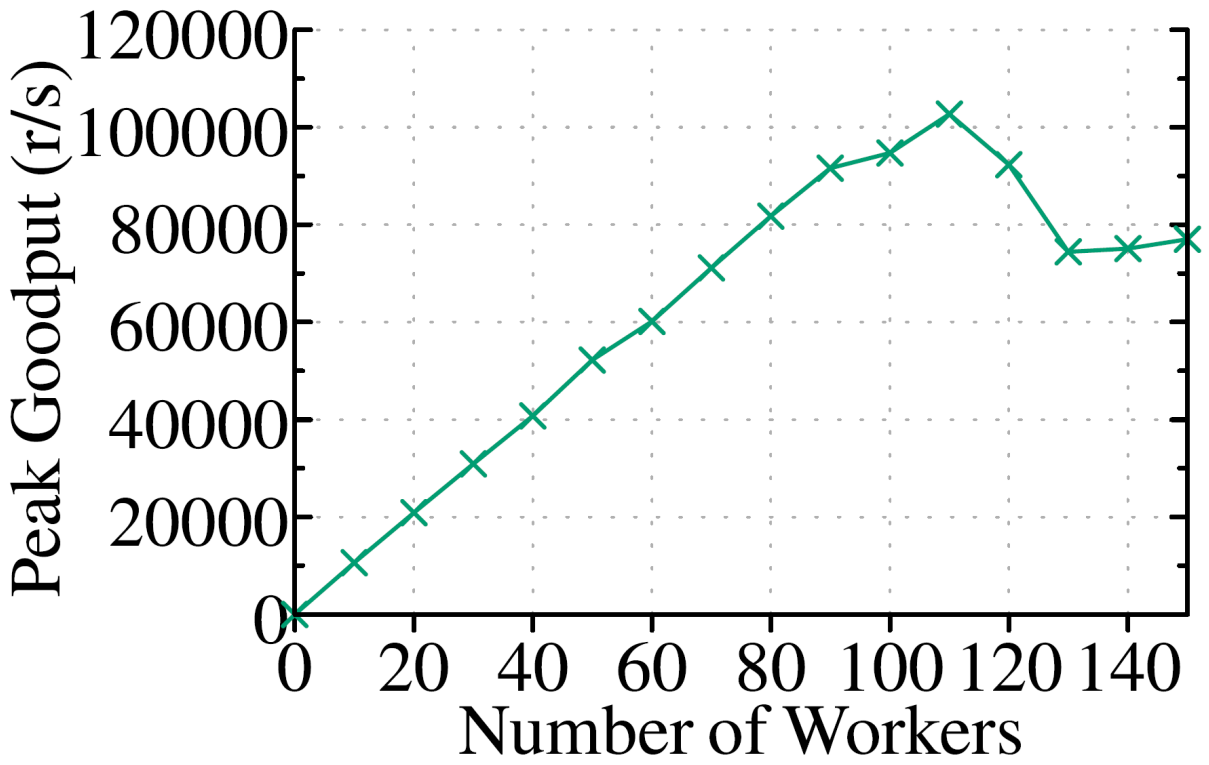
d_m the total demand for each model m
$a_{m,g}$ the demand allocation of model m on GPU g
$\ell_g = \sum_m a_{m,g}$ the total load on each GPU g

$$p_{m,g} = d_m - \sum_g a_{m,g} \cdot \frac{\text{capacity}_g}{\ell_g}$$

Clockwork – Comparison



Clockwork – Scaling



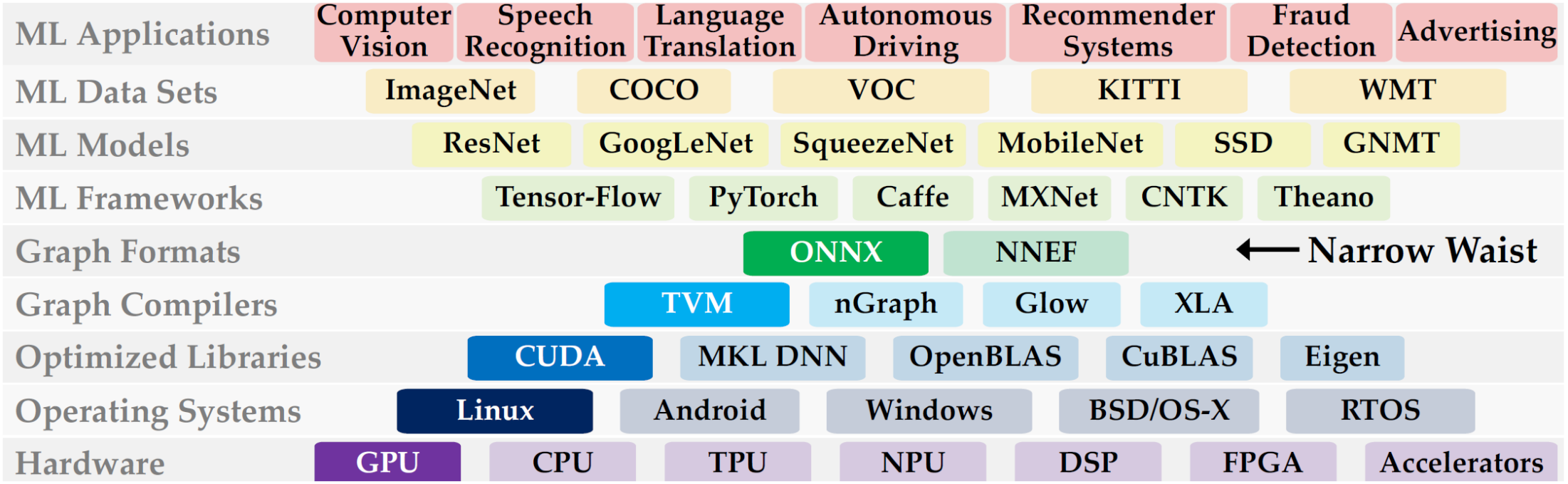
Clockwork – Performance

- Replay workload trace of Microsoft Azure Functions (MAF)
- SLO target: 100 ms
- Goodput average: 9638 r/s
- Total requests: 208,000,000
- Failed requests: 58

Model Family	Count	Model Variants
DenseNet [36]	4	121, 161, 198, 201
DLA [75]	1	34
GoogLeNet [67]	1	
Inception [68]	1	v3
Xception [68]	1	
MobilePose [33]	4	SPRN18, MNv3, RN18, RN50
ResNeSt [78]	4	14, 26, 40, 101
ResNet [30]	22	18, 18b, 34, 34b, 50, 50b, 50c, 50d, 50s, 50-1.8x, 101, 101b, 101c, 101d, 101s, 101-1.9x, 101-2.2x, 152, 152b,152c, 152d, 152s
ResNet-v2 [31]	5	18, 34, 50, 101, 152
ResNeXt [73]	3	50-32, 101-32, 101-64
SENet [35]	2	50-32, 101-32
TSN [70]	7	iv1, iv3, r18, r34, r50, r101, r152
Wide ResNet [76]	3	16-10, 28-10, 40-8
Winograd [45]	3	RN18, RN50, RN101

List of models used in experiments.

Model Serving Systems – Narrow Waist Stack



Clockwork – HummingBird

- Scikit-learn is used about 5 times more than PyTorch and TensorFlow combined
- Clockwork is limited to DNNs
- HummingBird converts traditional ML models into ONNX format
- Scope of Clockwork can be extended to cover traditional ML models

Clockwork – Piazza

- Batching inferences

> Hi, I have some questions for the Clockwork paper. I am a little confused about how batching inference requests works. To my understanding, the batch size of a model is pre-defined but when scheduling INFER actions, the paper mentions that 'each model has a request queue per batch size'. Does that mean we can change the batch size of a model? How does that happen?

  - The batch size is the number of inputs appended for parallel execution
  - Models don’t explicitly have a batch size
  - Clockwork predicts the best batching strategy which allows for maximum parallel execution without violating any SLO constraints