CLIPPER: A Low Latency Online Prediction Serving System

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

Hello!

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Contents

For more details, check the original paper at https://arxiv.org/abs/1612.03079

1.

MOTIVATION

Learning

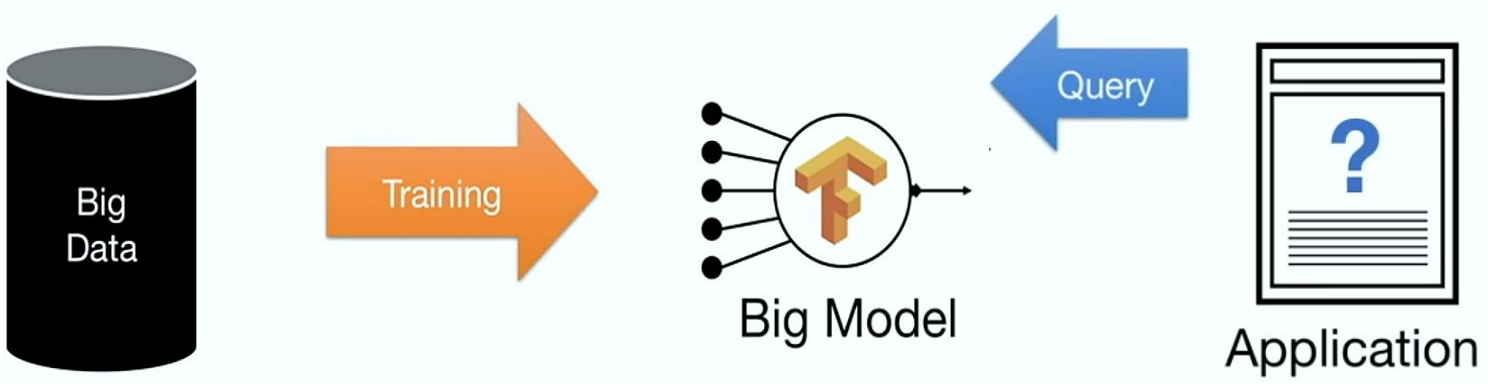
Learning

Timescale: minutes to days

Systems: offline and batch optimized

(*Heavily studied* … major focus of the **AMPLab**)

Learning Inference



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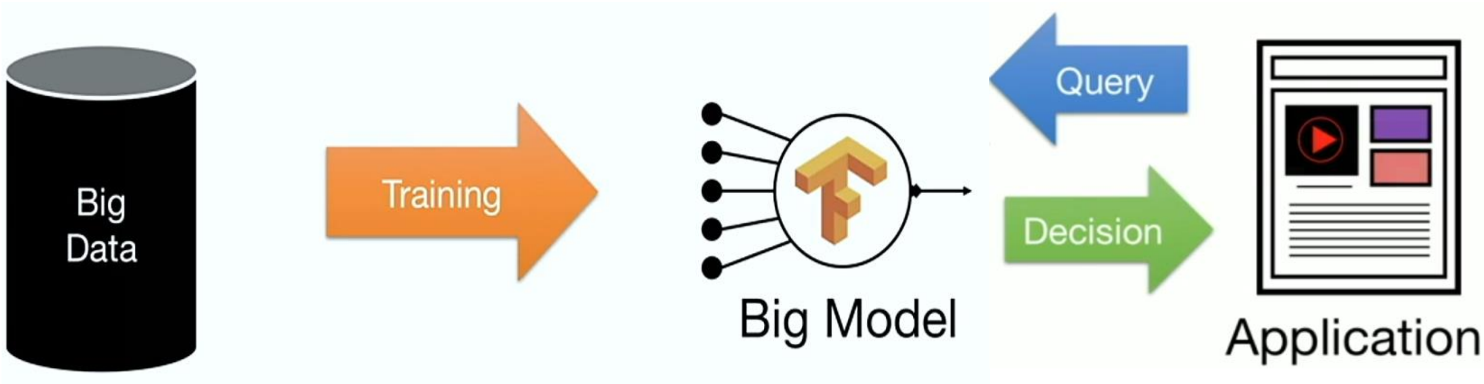
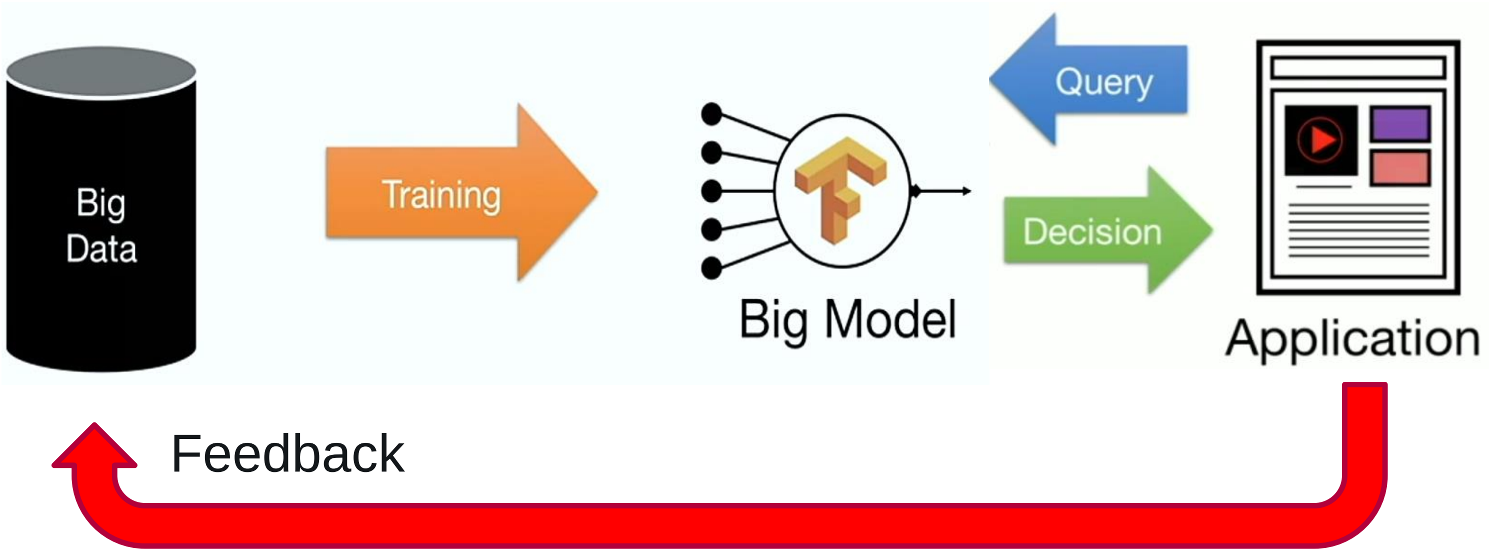


Timescale: ~20 milliseconds

Systems: online and latency optimized

(Less studies ...)

Learning Inference



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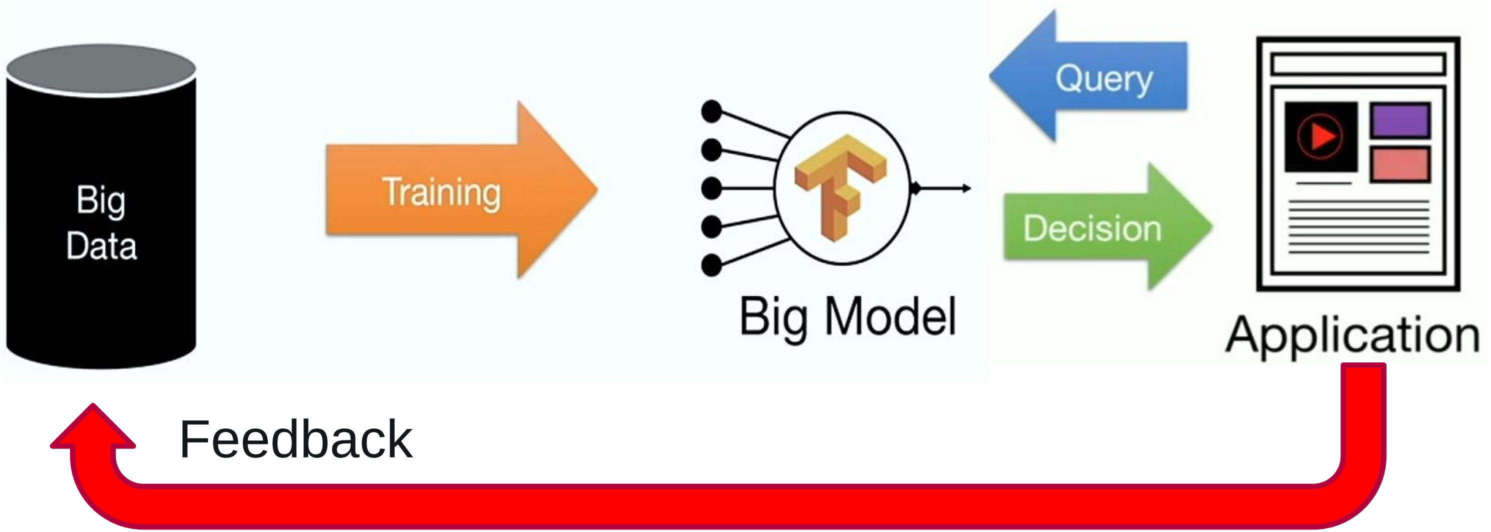


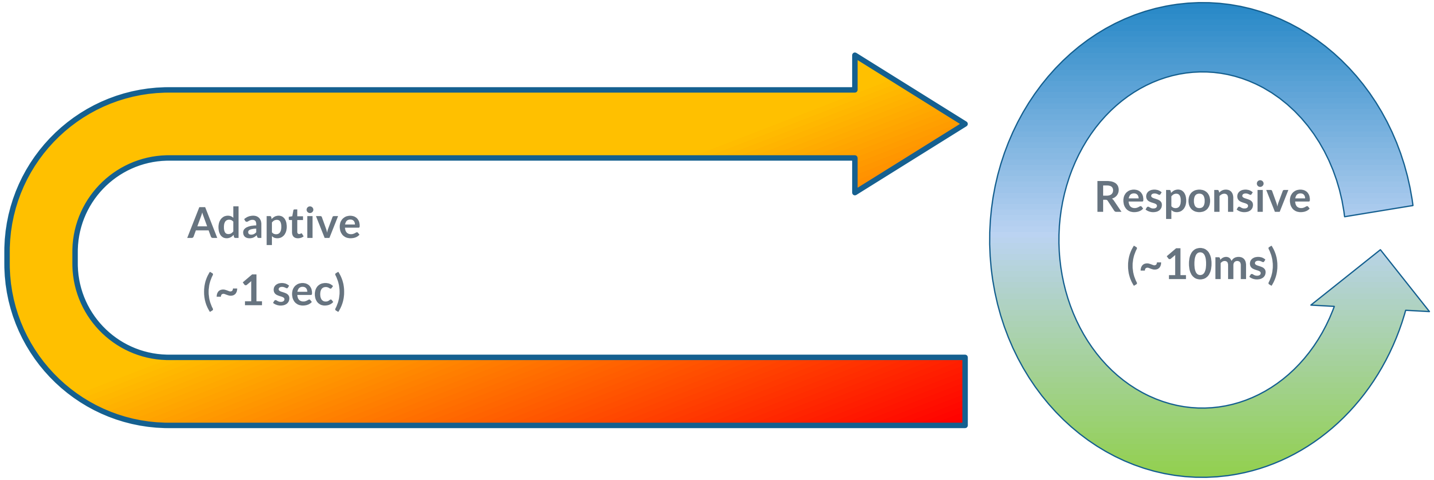
Timescale: hours to weeks

Systems: combination of systems

(Less studies …)

Learning

Inference



Serving Predictions Today: Offline Scoring

Offline Batch System

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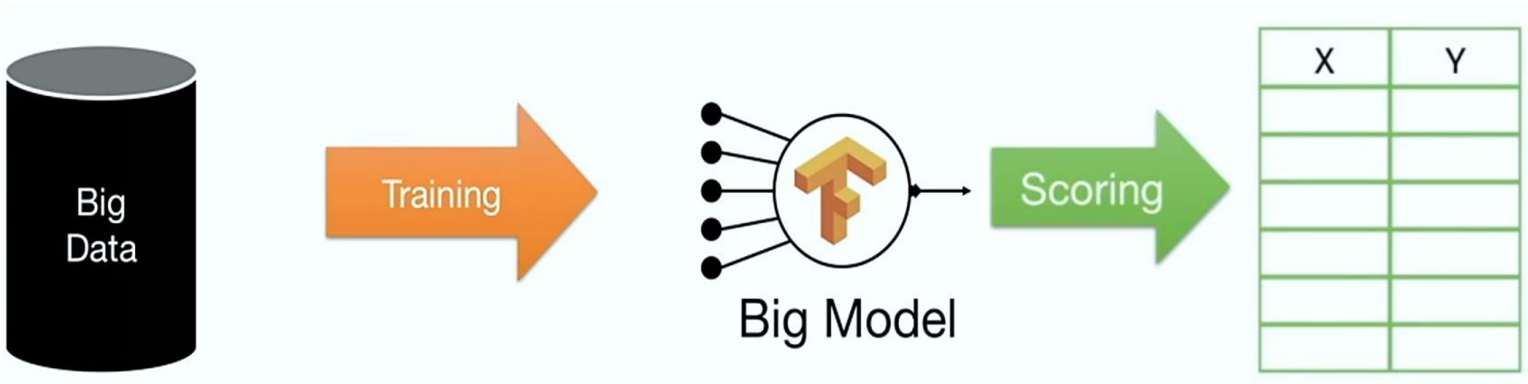
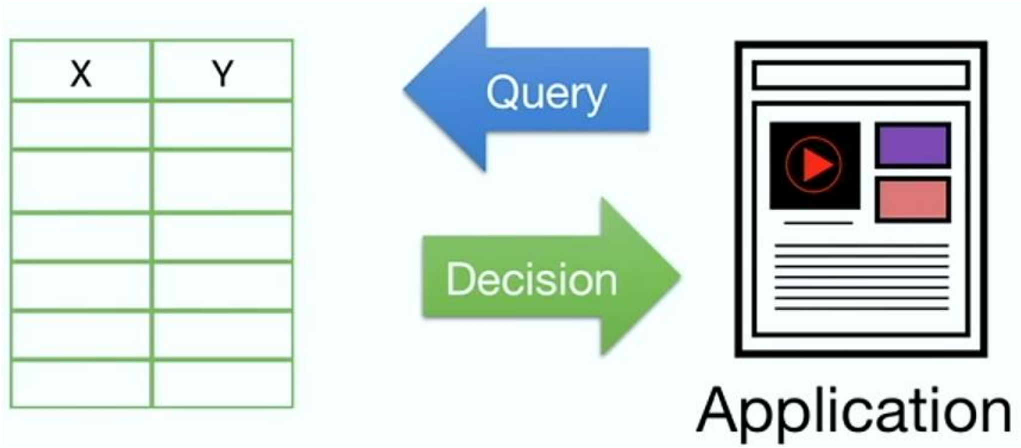


Offline Batch System

Serving Predictions Today: Offline Scoring

Lookup decision in KV-store



Offline Serving System

Serving Predictions Today: Offline Scoring

Problems

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  - Can render and store unneeded predictions

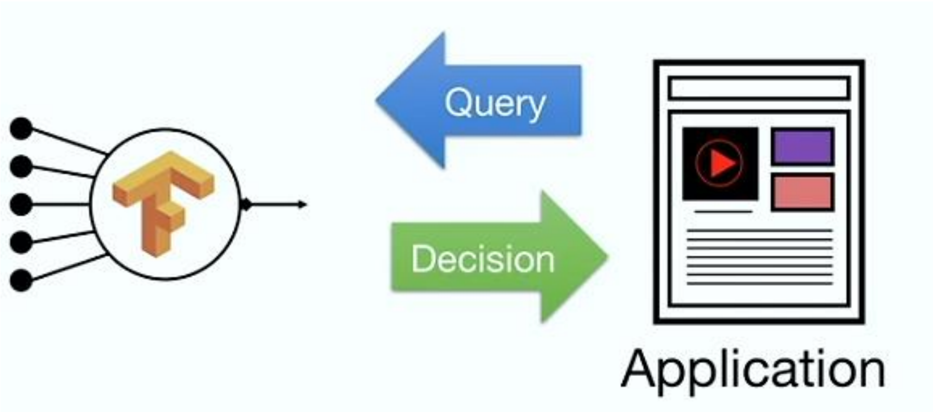
Serving Predictions Today: Offline Scoring

Problems

- Requires full set of queries ahead of time
  - Small and bounded input domain
- Wasted computation and space
  - Can render and store unneeded predictions
- No feedback and costly to update

Serving Predictions Today: Online Scoring

Render prediction with model in real-time

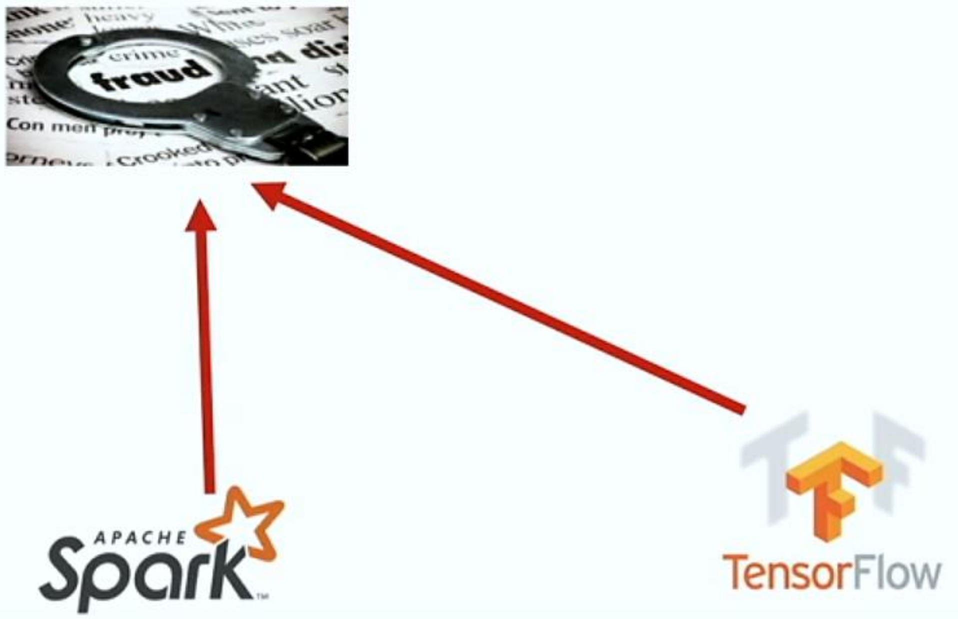


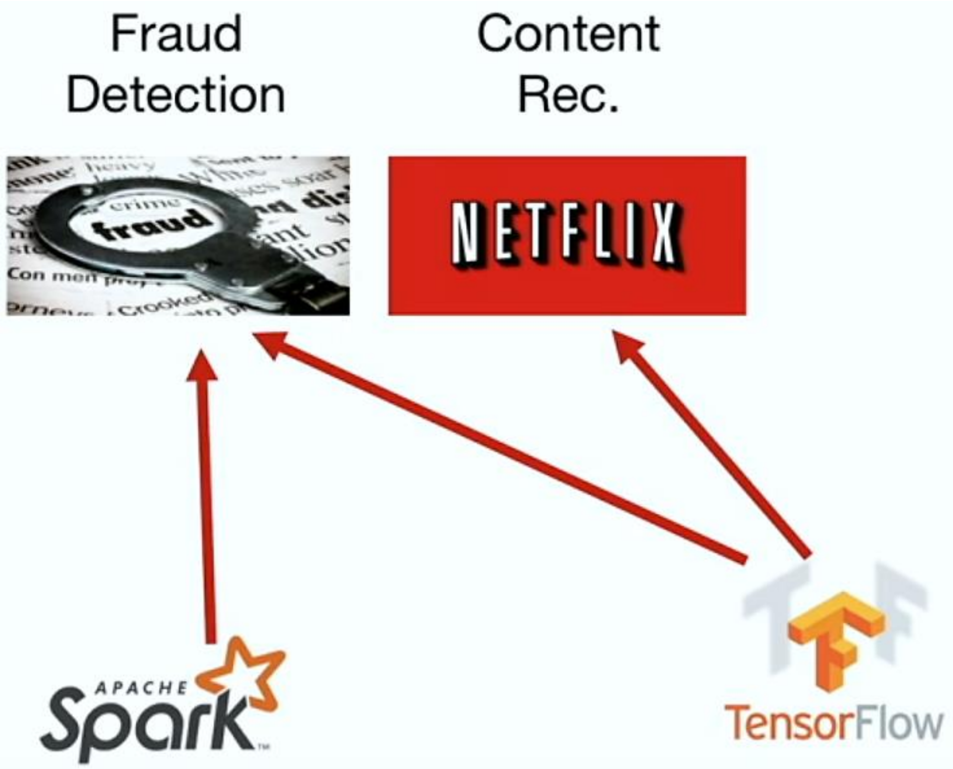
Online Serving System

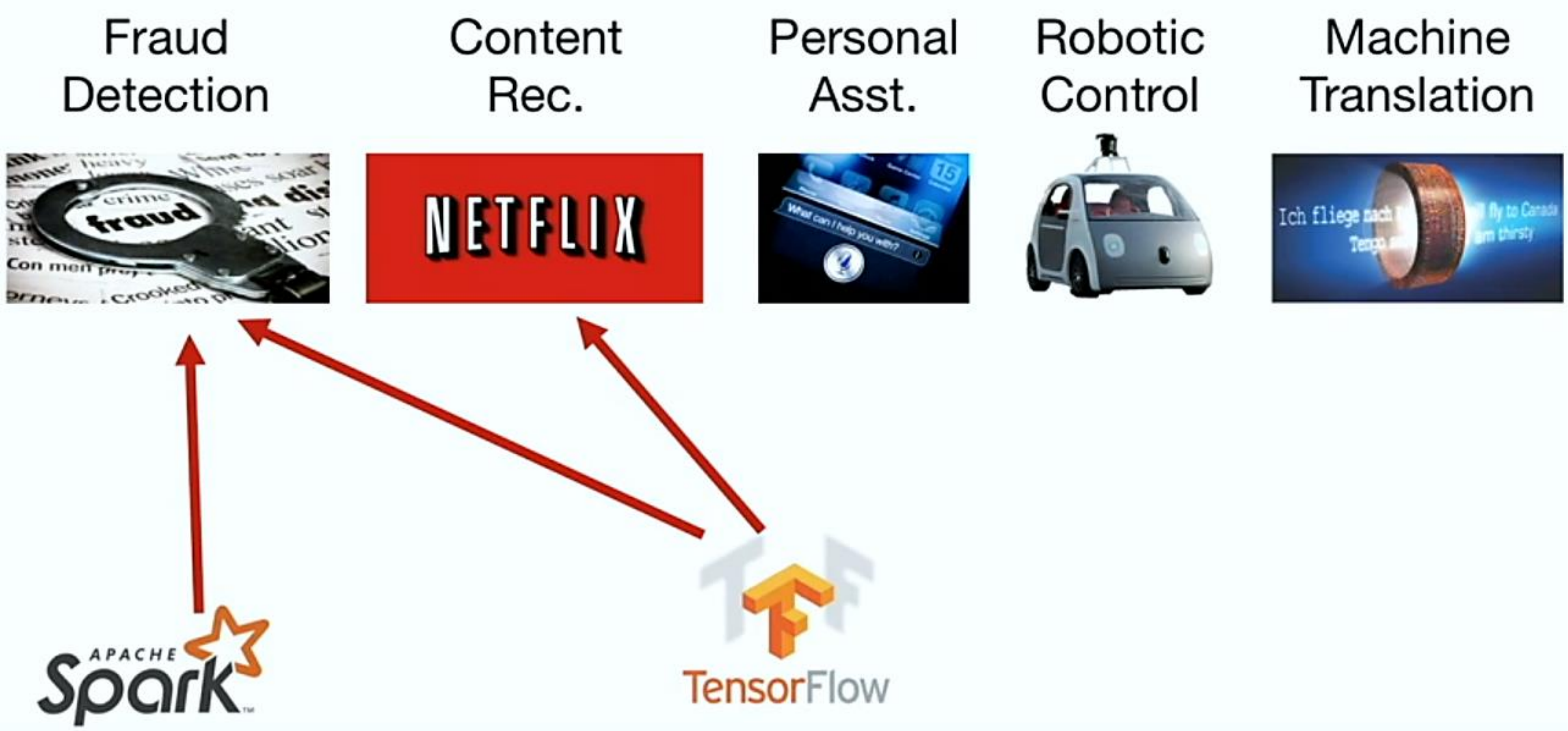
Fraud Detection

APACHE Spark

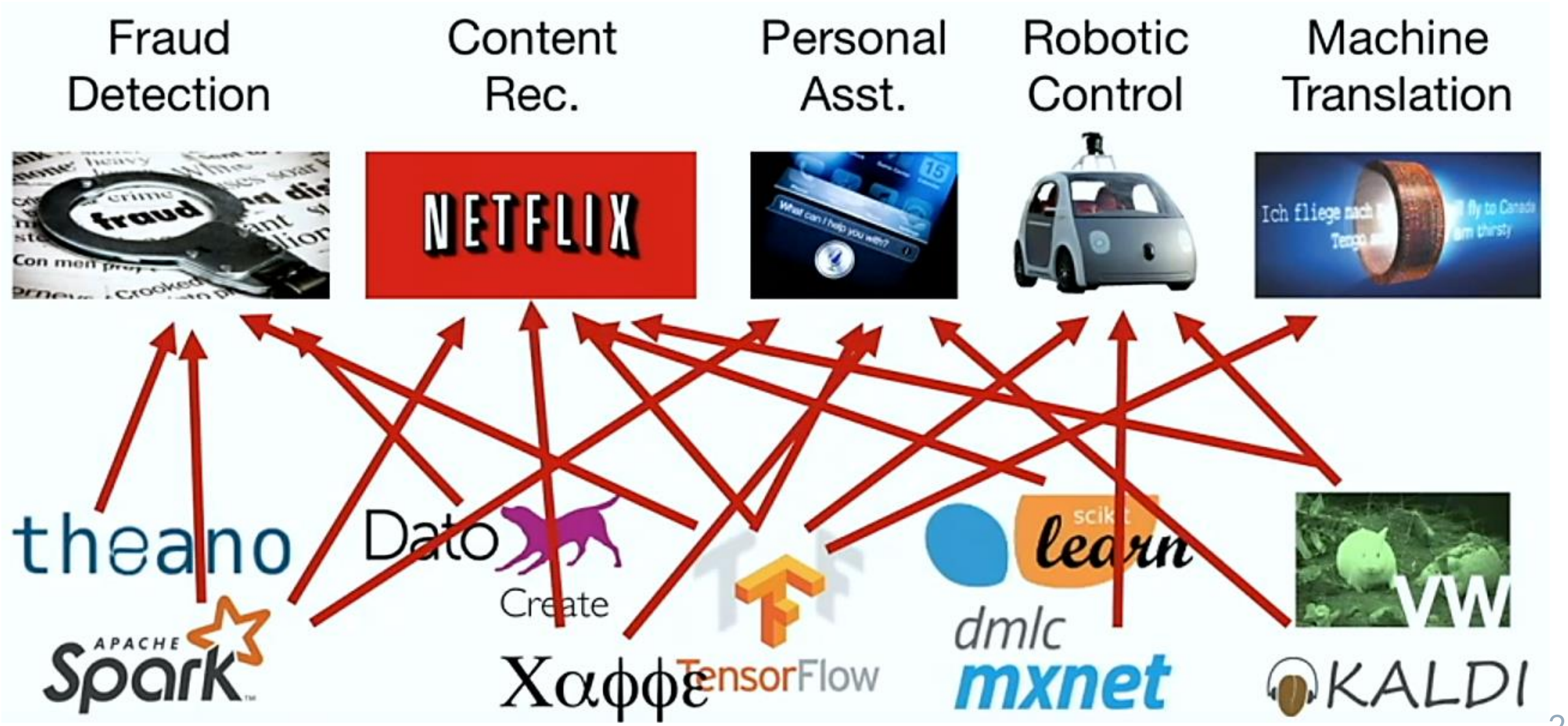
Fraud Detection



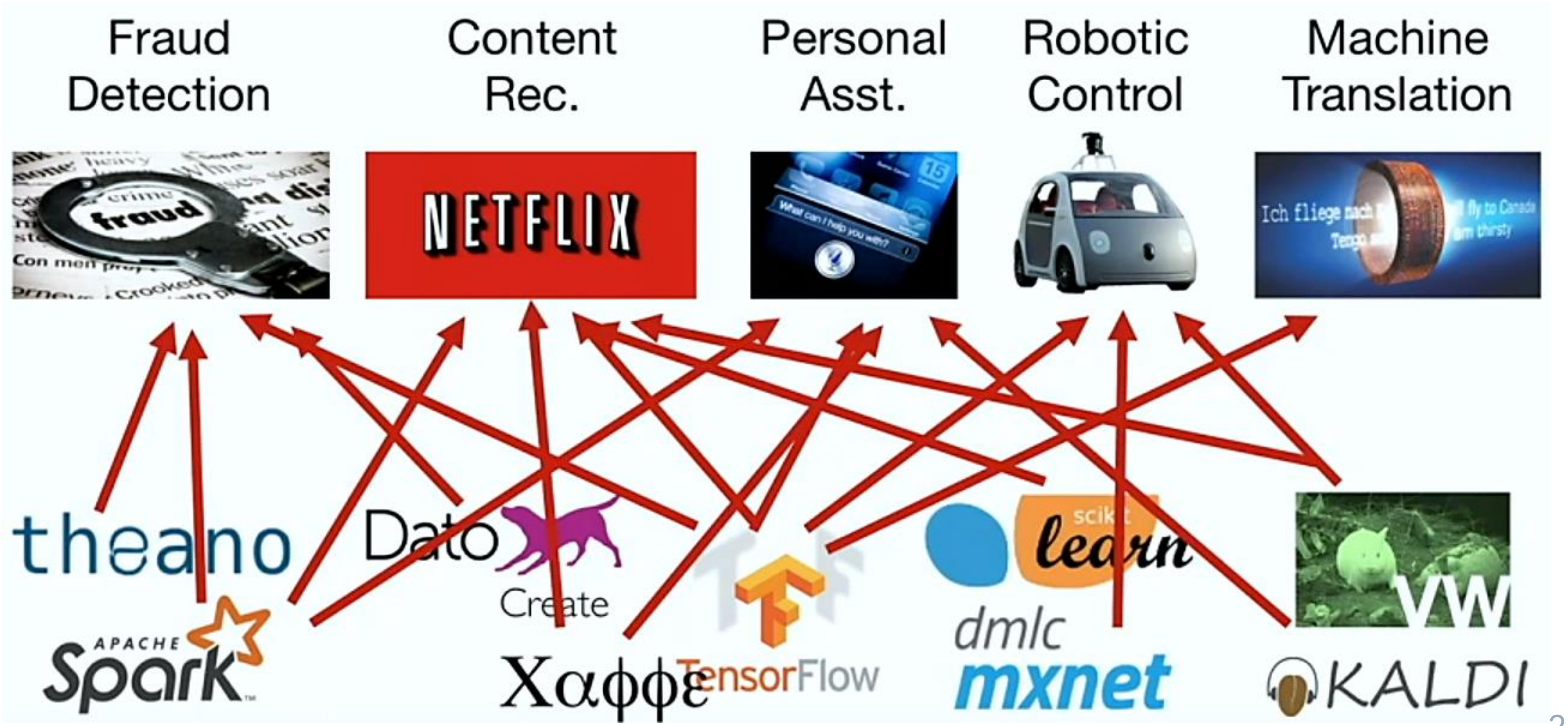

Fraud
Detection
Content
Rec.
fraud
NETFLIX
APACHE
Spark
TensorFlow

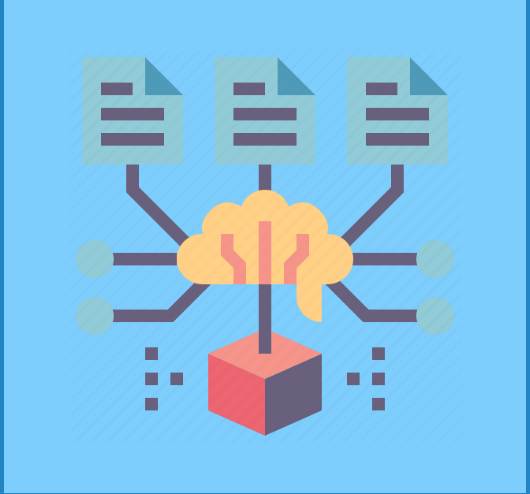

Fraud Detection
Content Rec.
Personal Asst.
Robotic Control
Machine Translation
fraud
NETFLIX
What can I help you with?
APACHE Spark
TensorFlow

Many applications and many models



Can we **decouple** models and applications?





Prediction Serving System

A decoupling system for models and applications

Requirements

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  - Simple deployment and online experimentation
  - Oblivious to system performance and workload demands

2.

CLIPPER

From the Frontend Dev perspective

Clipper

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- Management REST API

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  create_application

  deploy_model()

  replicate_model()

  inspect_instance()

From the Data Scientist perspective

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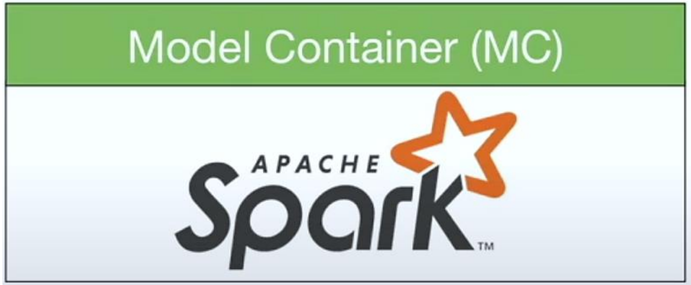
- Implemented in many languages
  - Python
  - Java
  - C/C++
  - R
  - ...

From the Data Scientist perspective

- Model implementation packaged in a container



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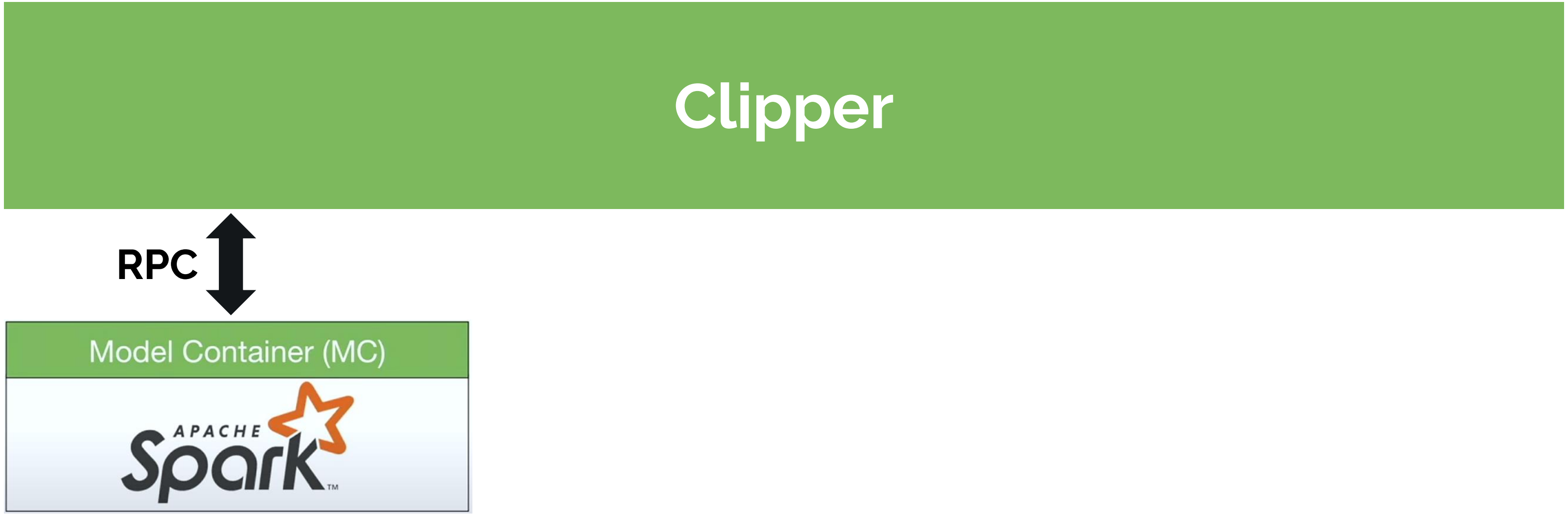

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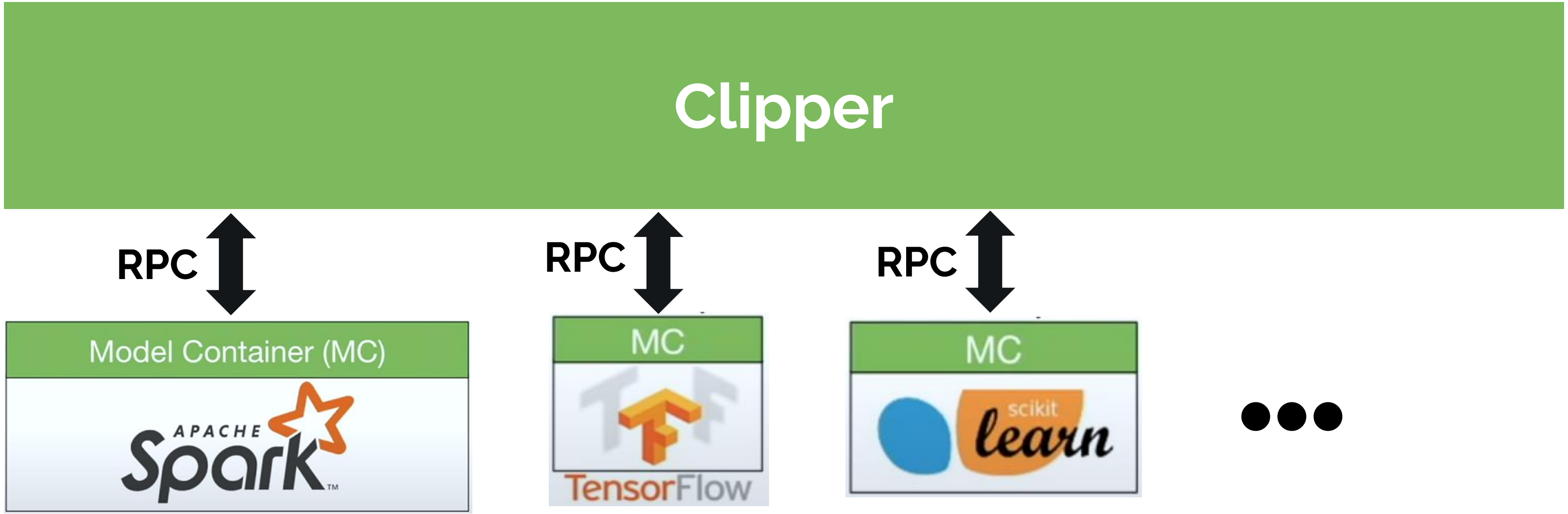

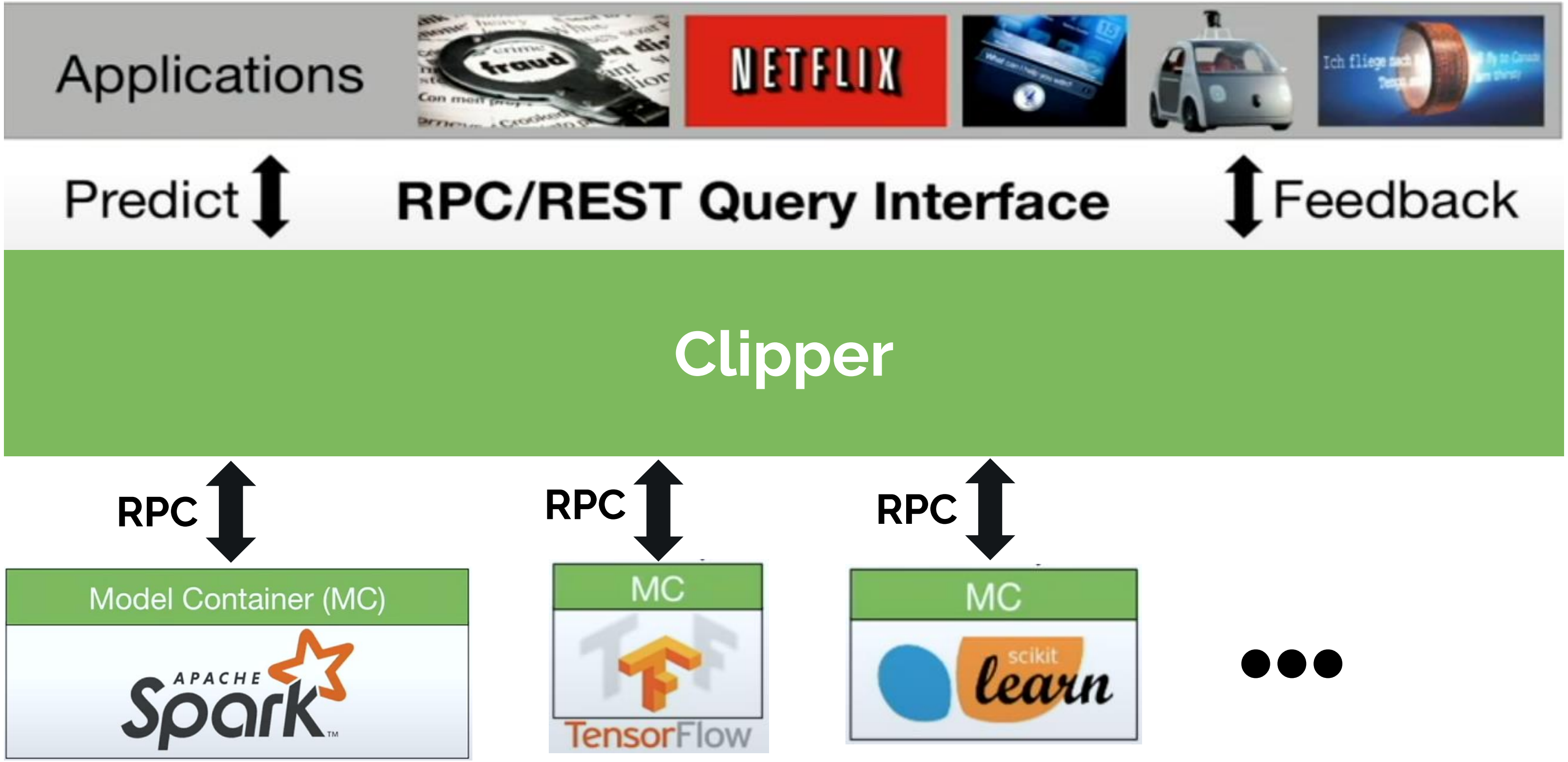
Applications
NETFLIX
Predict
RPC/REST Query Interface
Feedback
Clipper
RPC
RPC
RPC
Model Container (MC)
APACHE Spark
MC
TensorFlow
MC
scikit learn

Challenges

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  - Different type of models (different software, different resource requirements) in a production environment

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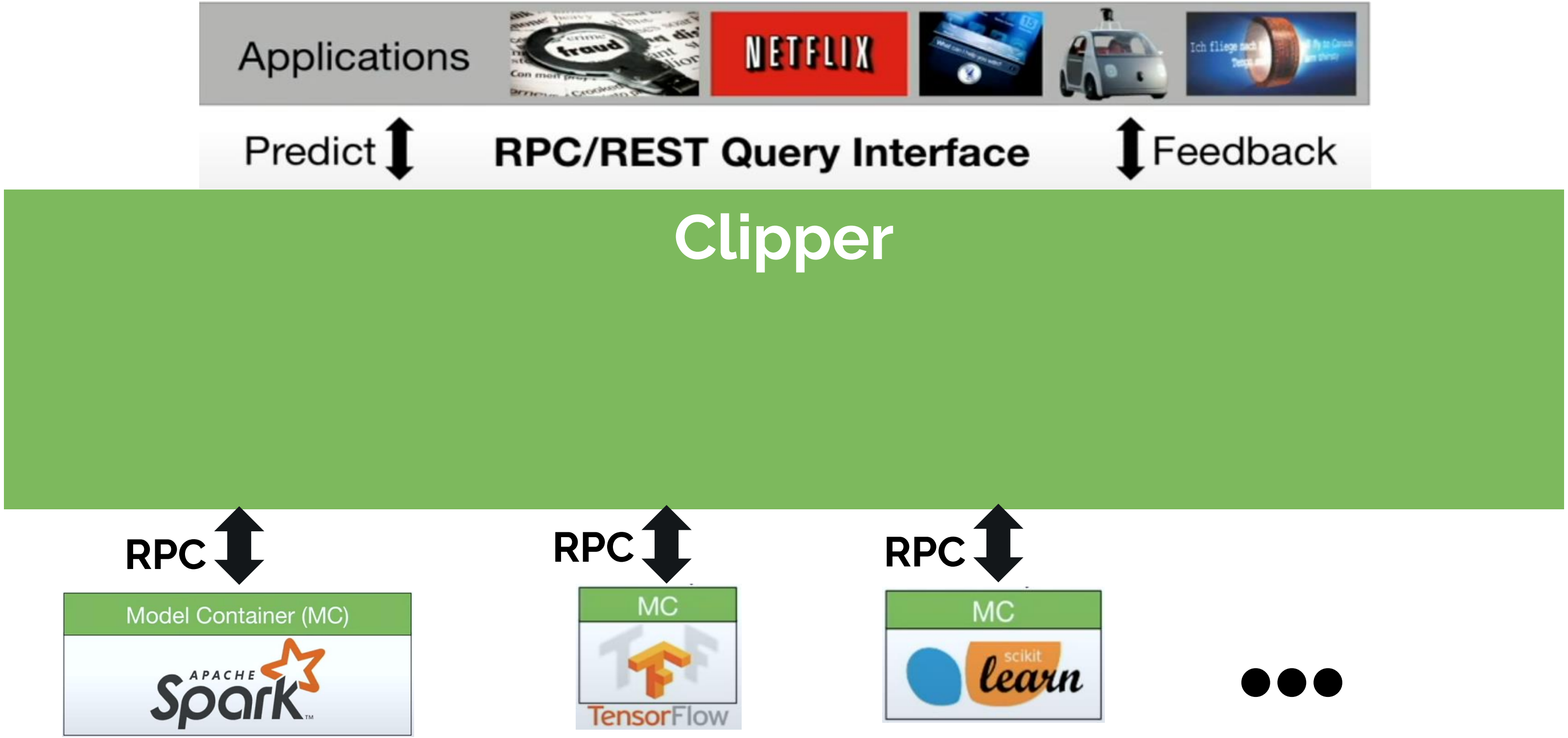
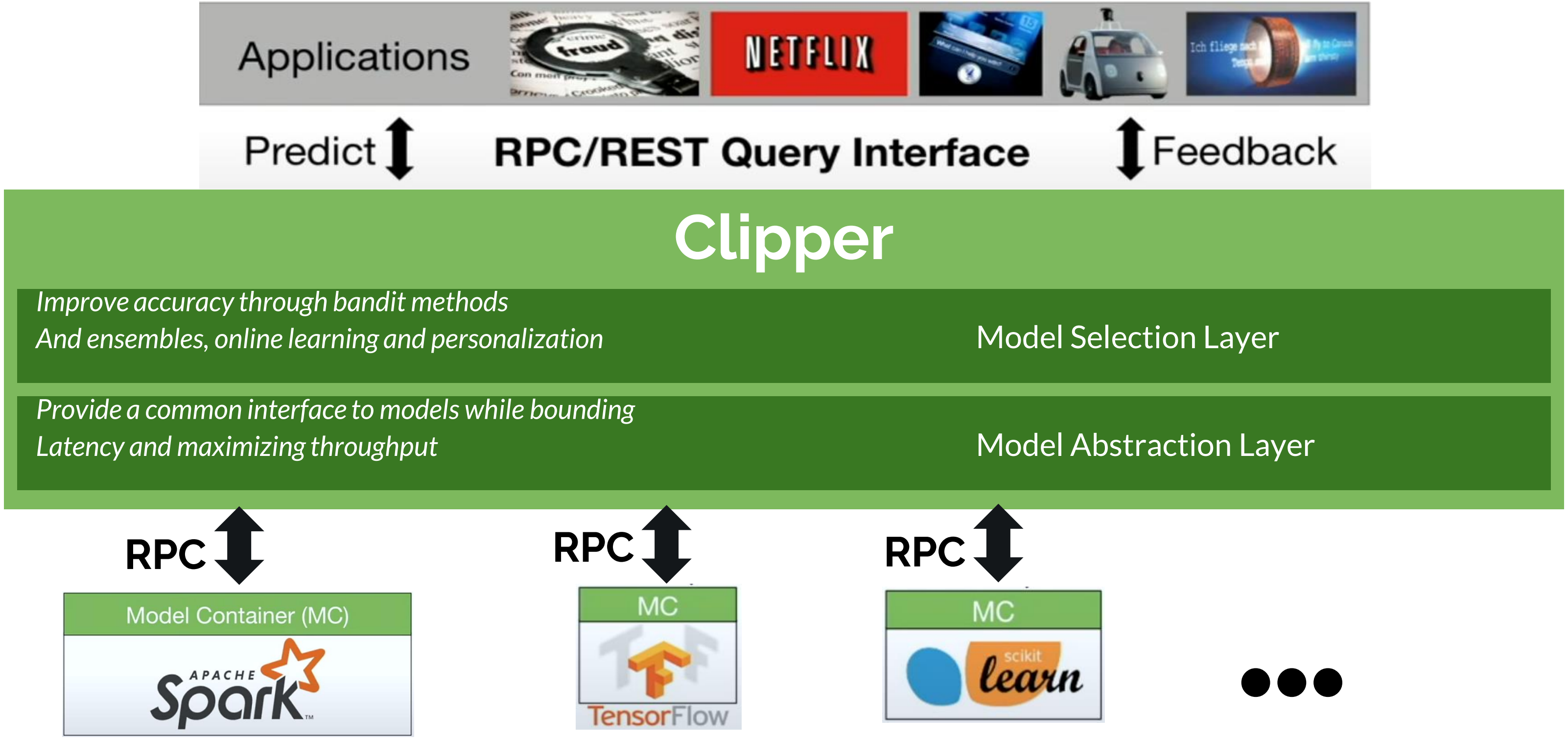
- How to use feedback to improve accuracy in real-time

Clipper Architecture



Clipper Architecture



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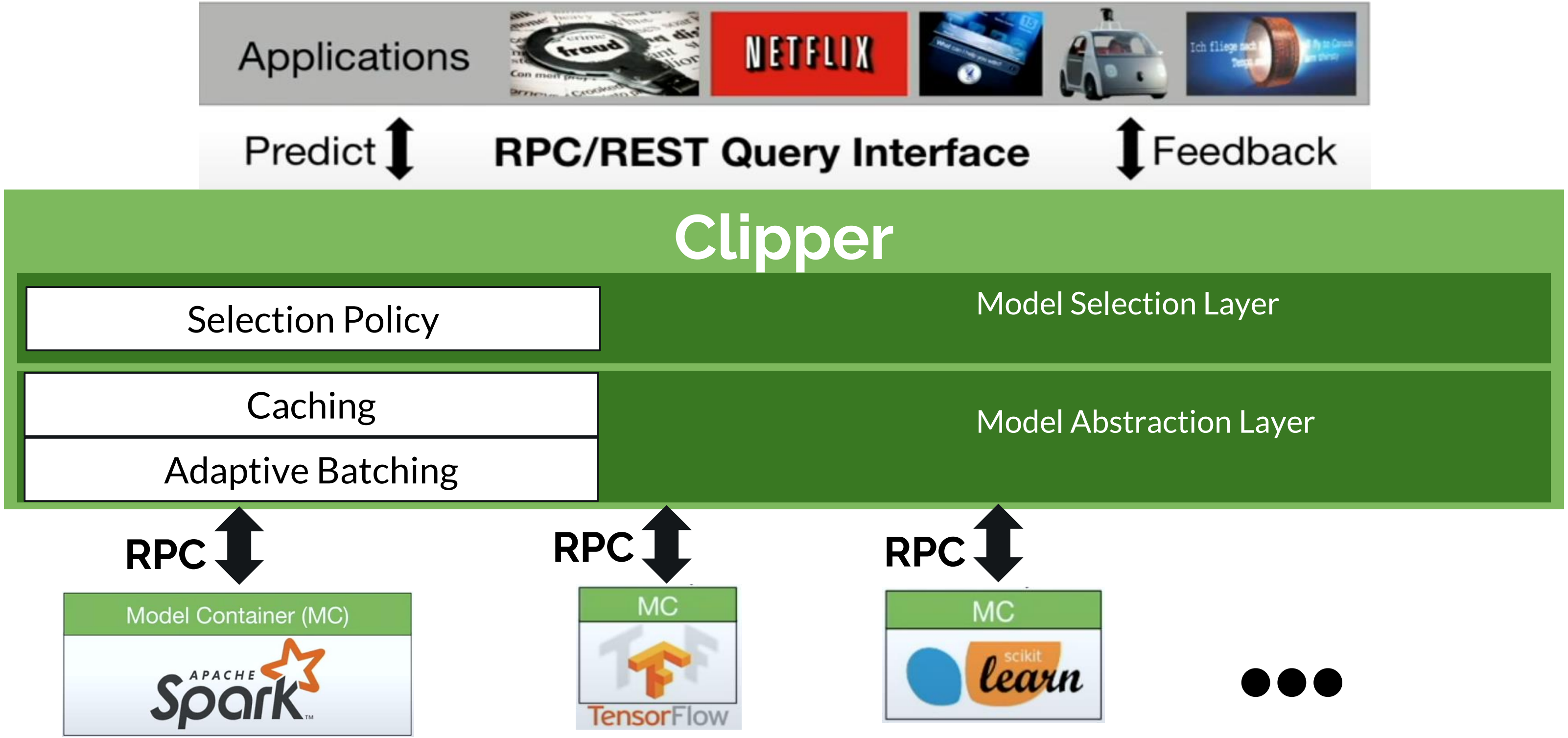
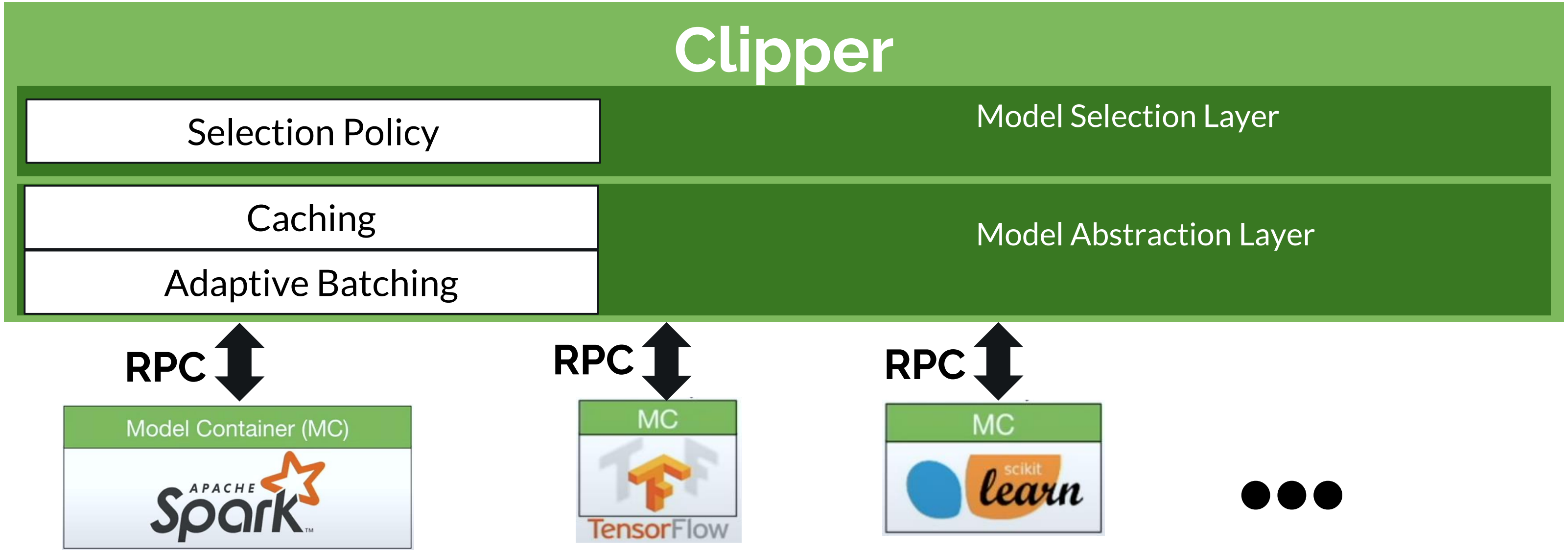
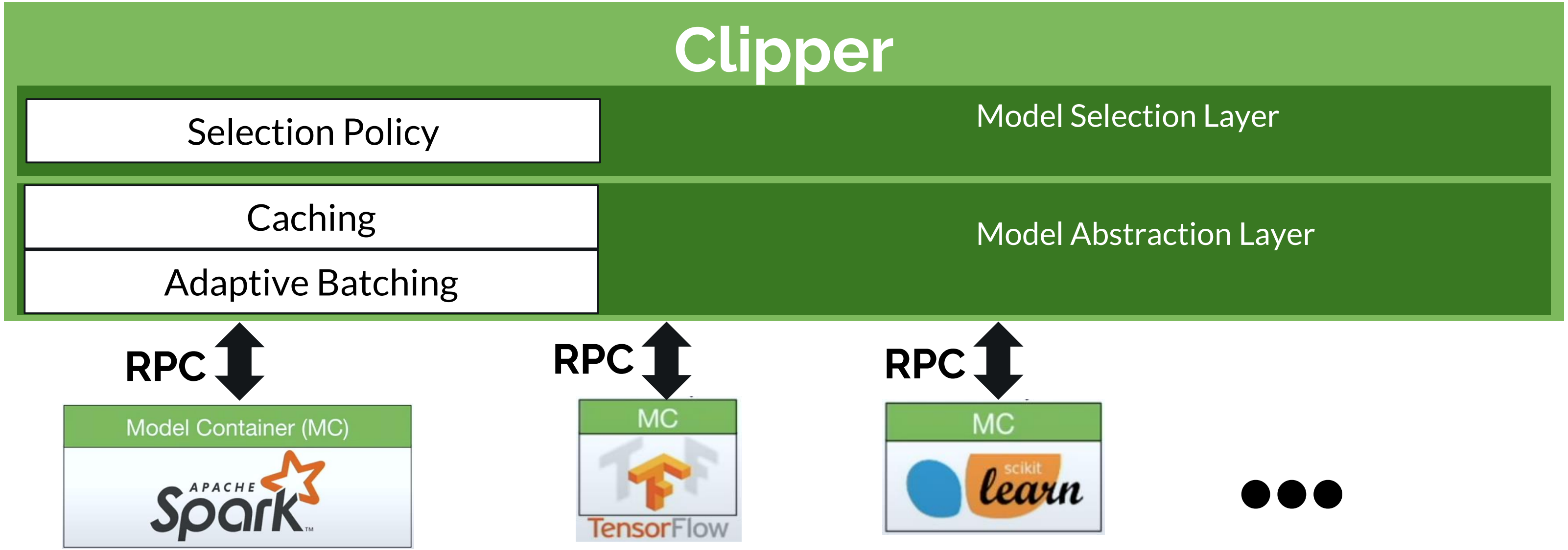




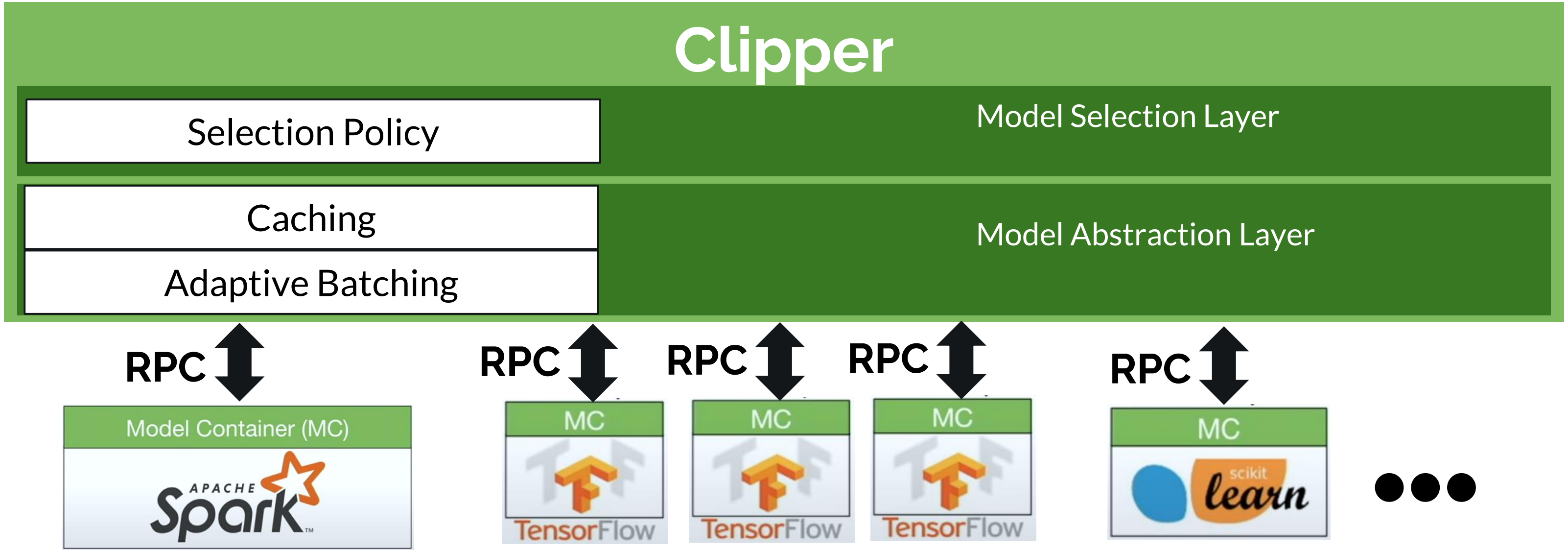
Common interface simplifies deployment:

- Evaluate models using original code and systems



Common interface simplifies deployment:

- ▷ Evaluate models using original code and systems
- ▷ Models run in separate processes as Docker containers
    - ○ Resource isolation



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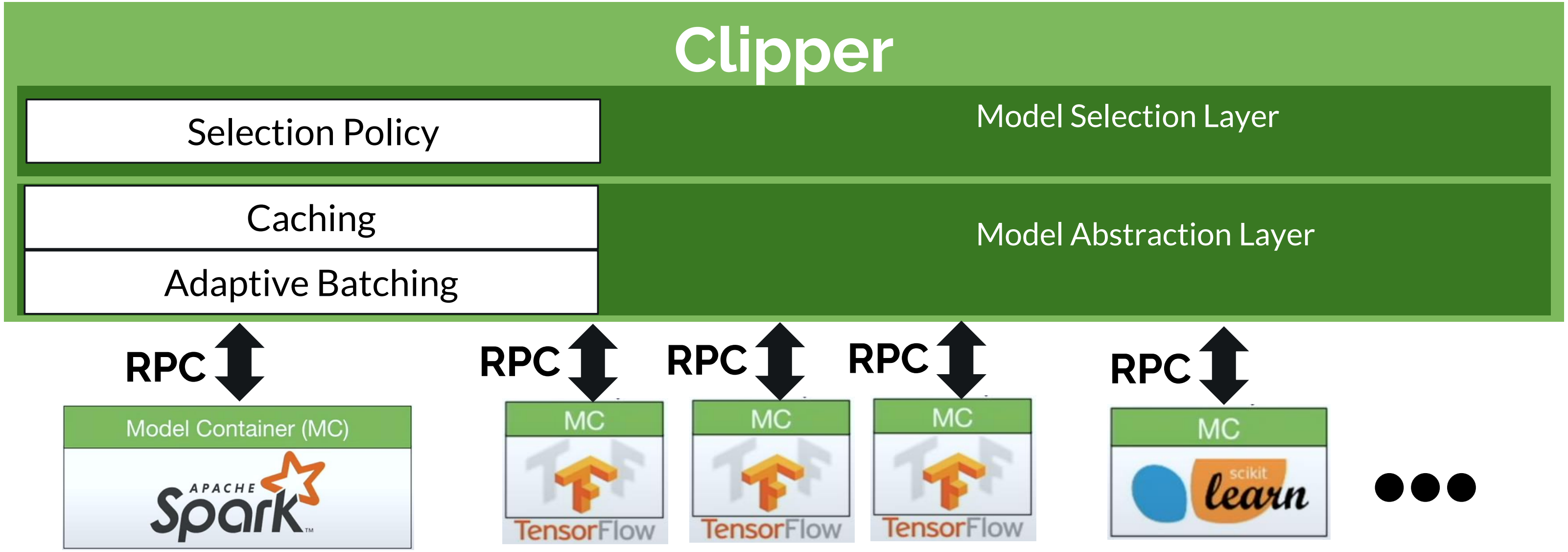

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Problem: frameworks optimized for batch processing not latency

Adaptive Batching to improve throughput

- Why batching helps:

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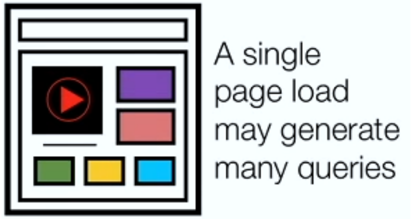

Adaptive Batching to improve throughput

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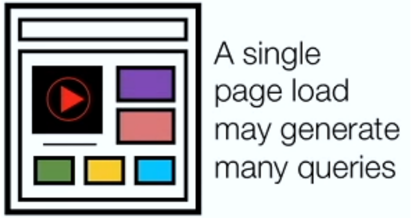

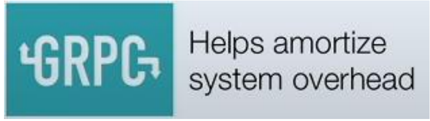

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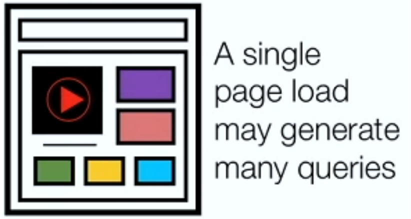

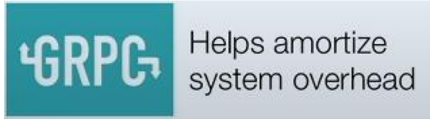

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    - System load

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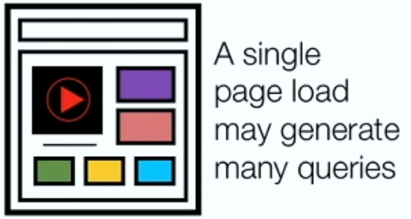

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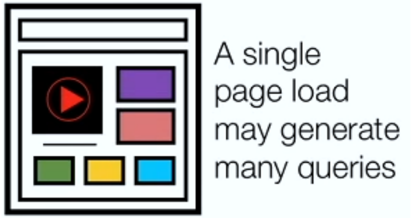

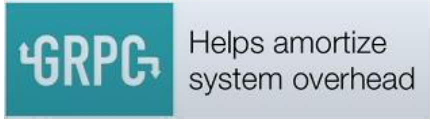

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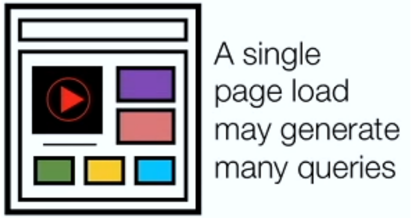

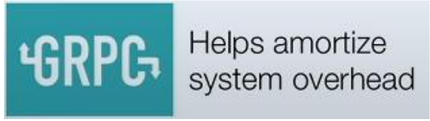

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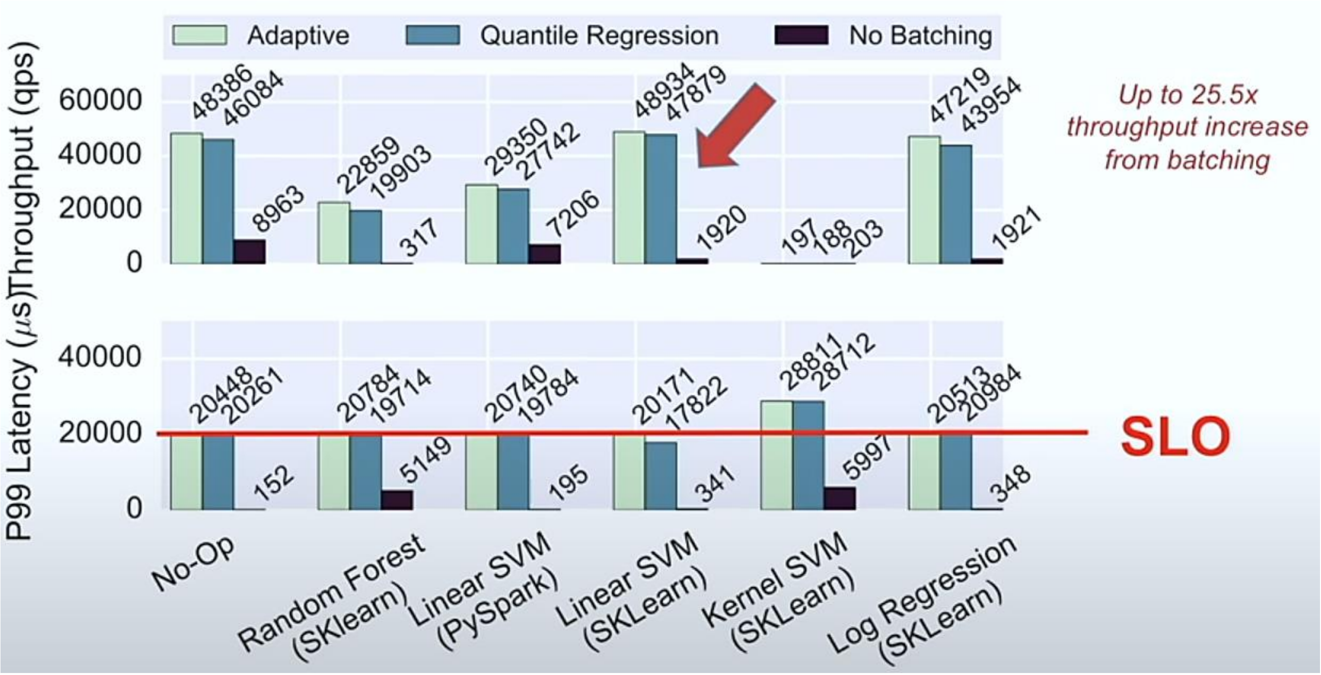
- If latency exceeds SLO cut batch size by a fraction

Batching Results



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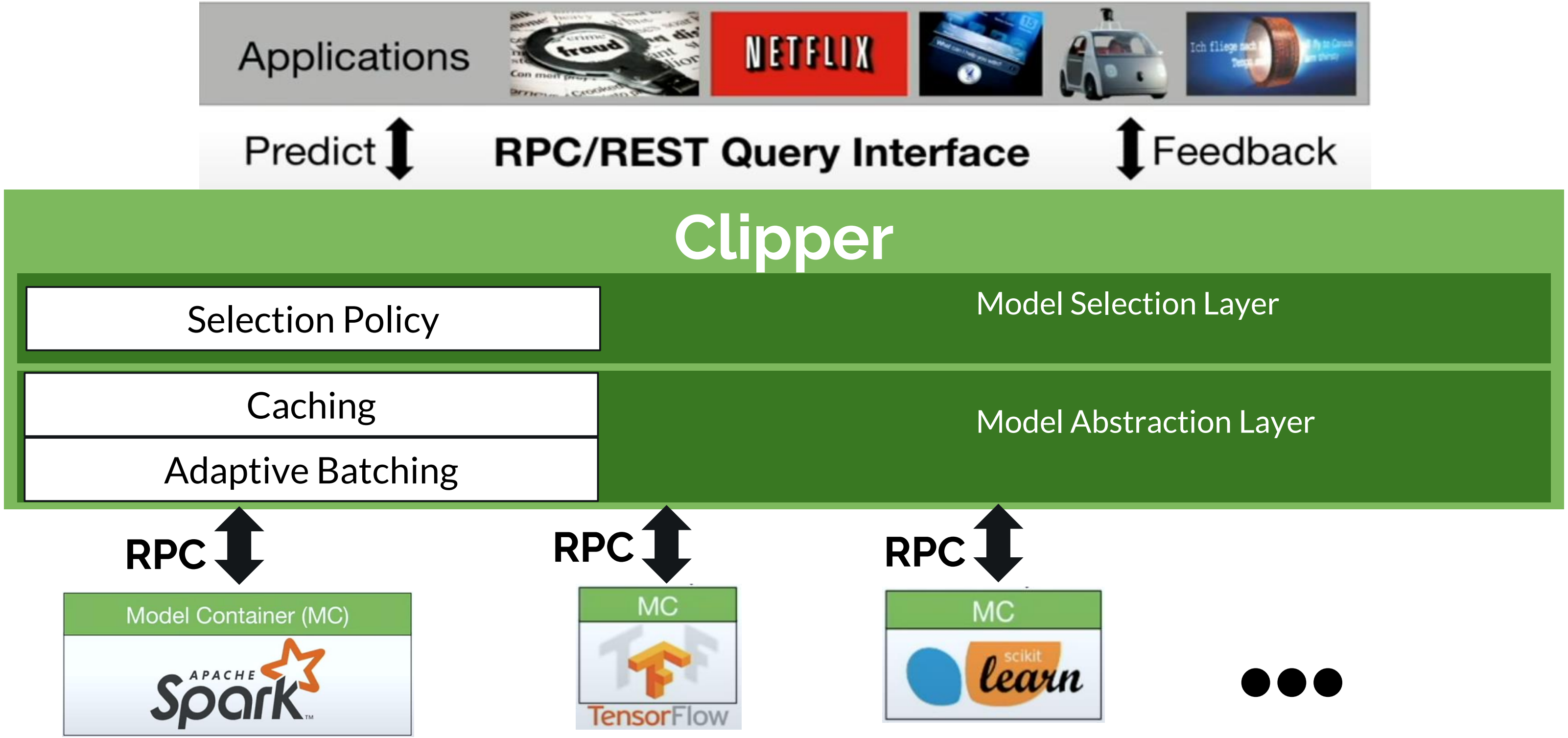

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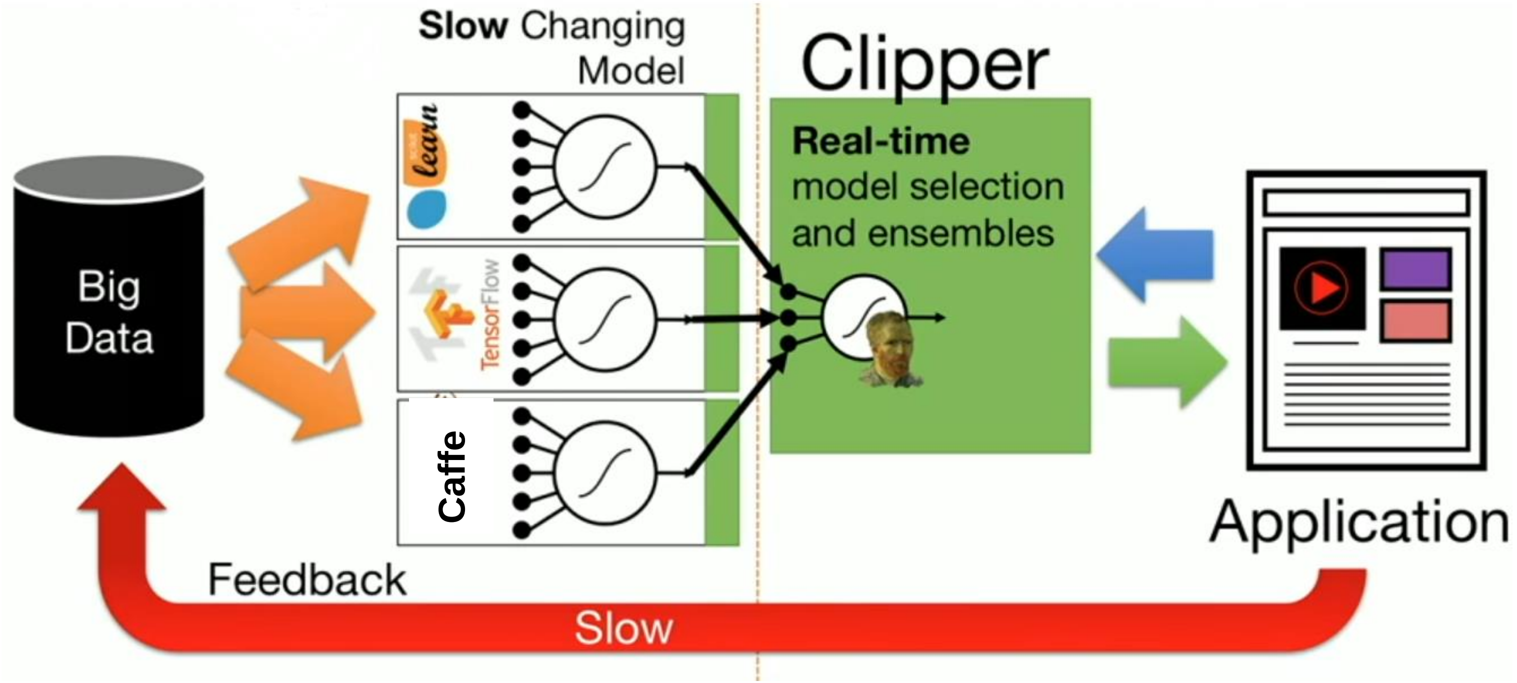

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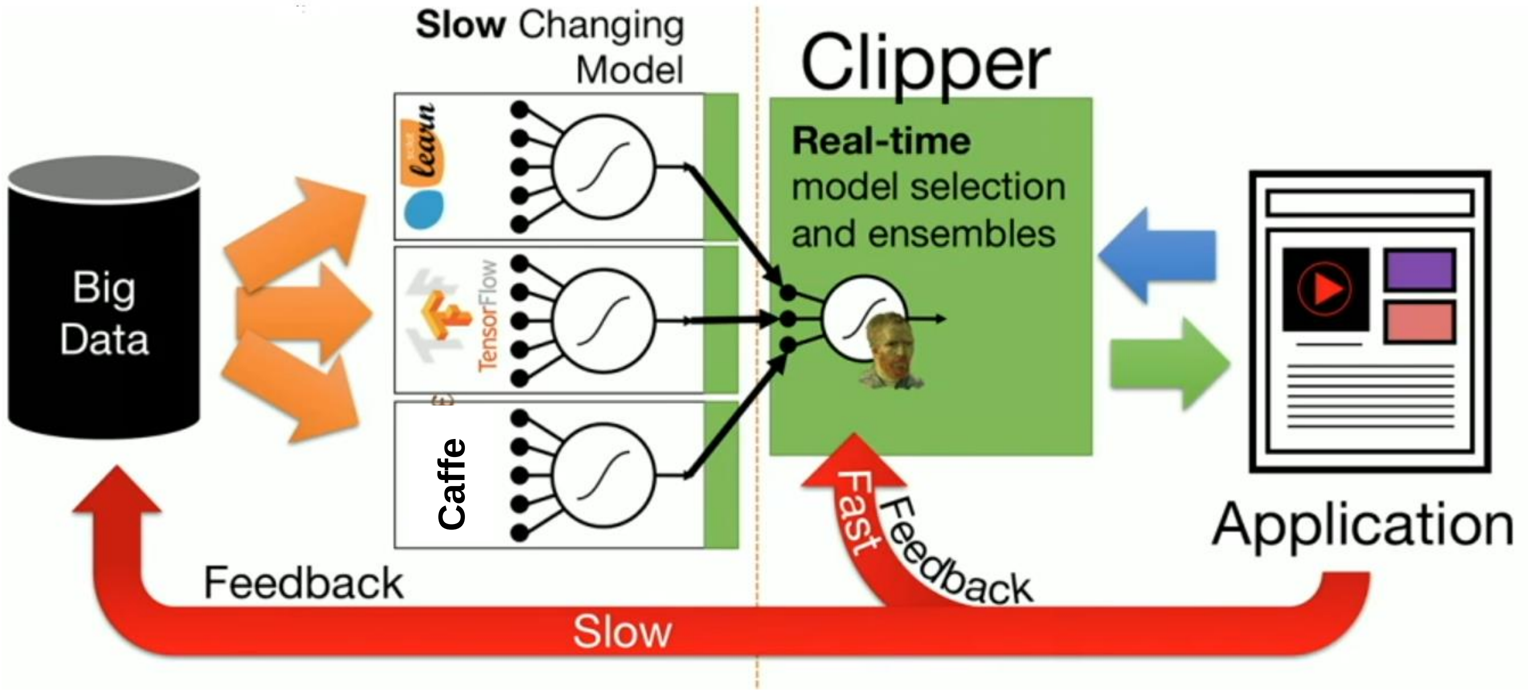
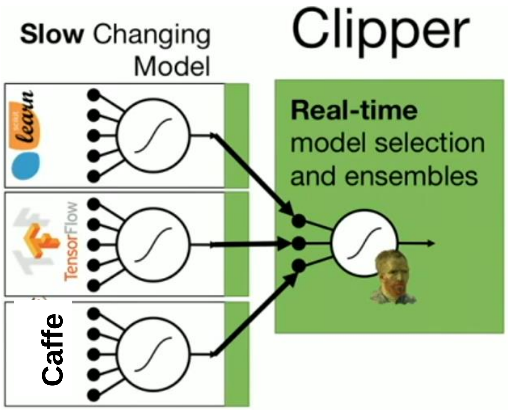


Bring leaning into the Serving Tier

Clipper

Selection Policy

Model Selection Layer



Bring leaning into the Serving Tier

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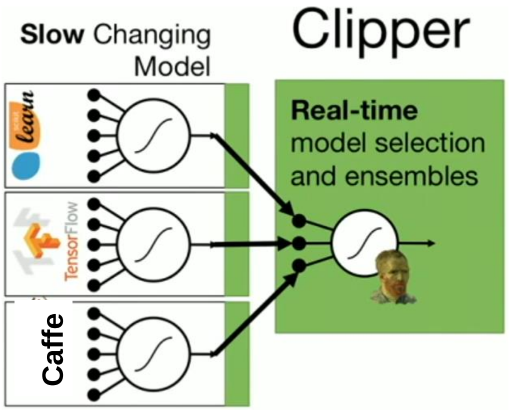
Selection Policy | Model Selection Layer

What can we learn?



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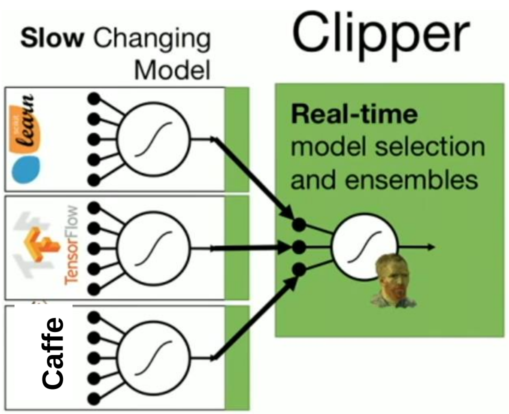
What can we learn?

- Dynamically weight mixture of experts



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What can we learn?

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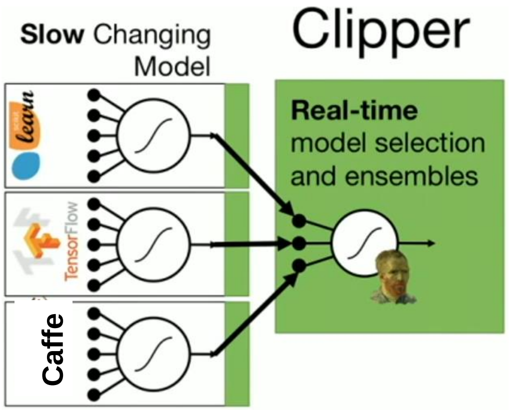

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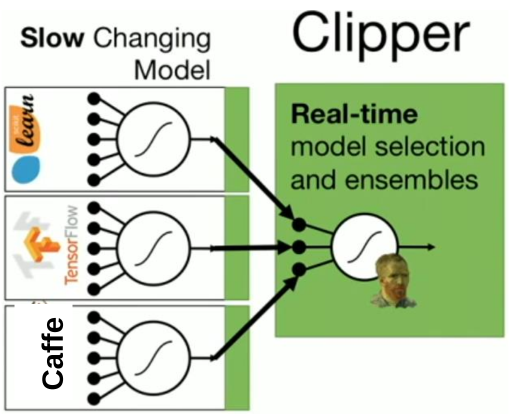
- Use ensemble to estimate prediction confidence



Bring leaning into the Serving Tier

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Model Selection Layer

What can we learn?

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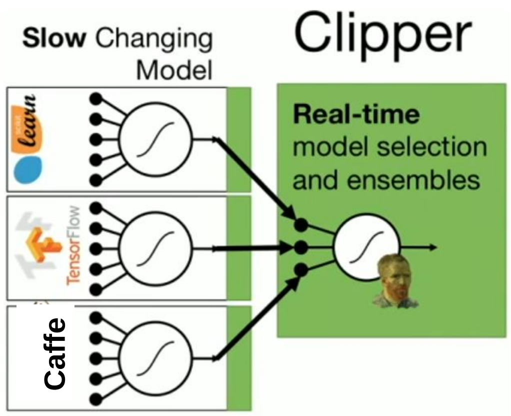
- Select best model for each user
- Use ensemble to estimate prediction confidence
- Don't try to retrain models



3.
RELATED WORK

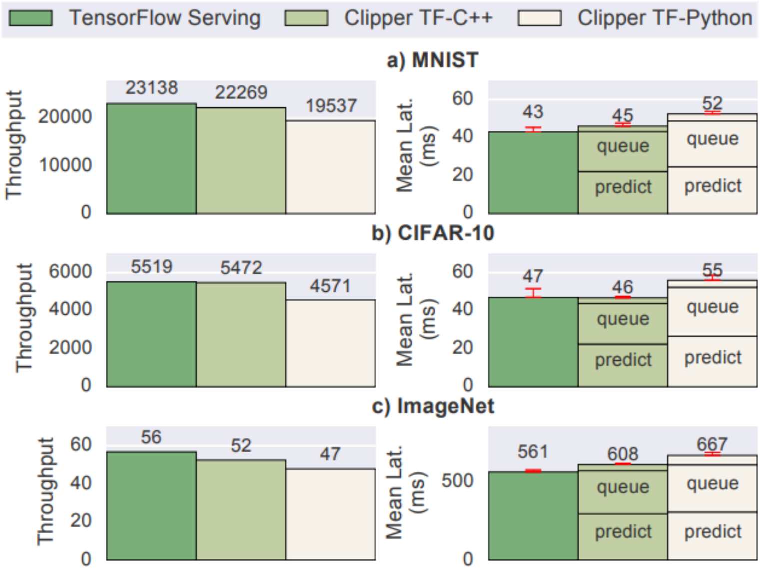
Related Work

- The closest project to clipper are LASER
- Velox is a UC Berkley research project to study personalized prediction serving with Spark
- TensorFlow Serving is the open-source prediction serving system
- Author only compare with TensorFlow, since LASER is not publically available, and the current prototype of Velox has very limited functionality

Comparison with TensorFlow Serving

- TensorFlow Serving also employs batching
- Batch sizes in TensorFlow Serving are static
- TF-serving does not explicitly incorporate prediction latency objectives
- TF-serving does not directly support feedback, dynamic mode selection and composition

Comparison with TensorFlow Serving



By achieving comparable performance across this range of models, we have demonstrated that through careful design and implementation of the system, the modular architecture and substantially broader set of features in Clipper do not come at a cost of reduced performance on core prediction-serving tasks.

▷ Despite Clipper's modular design, we are able to achieve comparable throughput to TensorFlow Serving

4.

CONCLUSION

Final Remarks

- Identified three key challenges of prediction serving: latency, throughput and accuracy
- Proposed a new layered architecture to address these challenges
- New ML frameworks and models can be introduced without modifying end-user applications
- The model abstraction layer lifts caching and adaptive batching strategies above the machine learning frameworks to achieve up to a 26x improvement in throughput

Final Remarks

- The model selection layer enables many models to be deployed concurrently and then dynamically selects and combines predictions from each model to render more robust, accurate, and contextualized predictions
- Compared Clipper to Google's TensorFlow Serving system and achieved parity on throughput and latency performance,

Limitations

- Clipper does not optimize the execution of the models within their respective machine learning frameworks
- Similarly, Clipper does not manage the training or retraining of the base models within their respective frameworks

Most of these limitations follow directly from the design of the Clipper architecture which assumes models are below Clipper in the software stack, and thus are treated as black-box components.

Thanks!

Any questions?

You can find me at:

@username

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