PRETZEL: Opening the Black Box of ML Prediction Serving Systems

Yunseong Lee[s], Alberto Scolari[p], Byung-Gon Chun[s],
Marco Domenico Santambrogio[p], Markus Weimer[m], Matteo Interlandi[m]

SEOUL NATIONAL UNIVERSITY

POLITECNICO MILANO 1863

Microsoft

Machine Learning

Hide details

Session Chair: Rashmi Vinayak, *Carnegie Mellon University*

Ray: A Distributed Framework for Emerging AI Applications

Philipp Moritz, Robert Nishihara, Stephanie Wang, Alexey Tumanov, Richard Liaw, Eric Liang, Melih Elibol, Zongheng Yang, William Paul, Michael I. Jordan, and Ion Stoica, *UC Berkeley*

AVAILABLE MEDIA

Show details

TVM: An Automated End-to-End Optimizing Compiler for Deep Learning

Tianqi Chen and Thierry Moreau, *University of Washington;* Ziheng Jiang, *University of Washington, AWS;* Lianmin Zheng, *Shanghai Jiao Tong University;* Eddie Yan, Haichen Shen, and Meghan Cowan, *University of Washington;* Leyuan Wang, *UC Davis, AWS;* Yuwei Hu, *Cornell;* Luis Ceze, Carlos Guestrin, and Arvind Krishnamurthy, *University of Washington*

AVAILABLE MEDIA

Show details

Gandiva: Introspective Cluster Scheduling for Deep Learning

Wencong Xiao, *Beihang University & Microsoft Research;* Romil Bhardwaj, Ramachandran Ramjee, Muthian Sivathanu, and Nipun Kwatra, *Microsoft Research;* Zhenhua Han, *The University of Hong Kong & Microsoft Research;* Pratyush Patel, *Microsoft Research;* Xuan Peng, *Huazhong University of Science and Technology & Microsoft Research;* Hanyu Zhao, *Peking University & Microsoft Research;* Quanlu Zhang, Fan Yang, and Lidong Zhou, *Microsoft Research*

AVAILABLE MEDIA

Show details

PRETZEL: Opening the Black Box of Machine Learning Prediction Serving Systems

Yunseong Lee, *Seoul National University;* Alberto Scolari, *Politecnico di Milano;* Byung-Gon Chun, *Seoul National University;* Marco Domenico Santambrogio, *Politecnico di Milano;* Markus Weimer and Matteo Interlandi, *Microsoft*

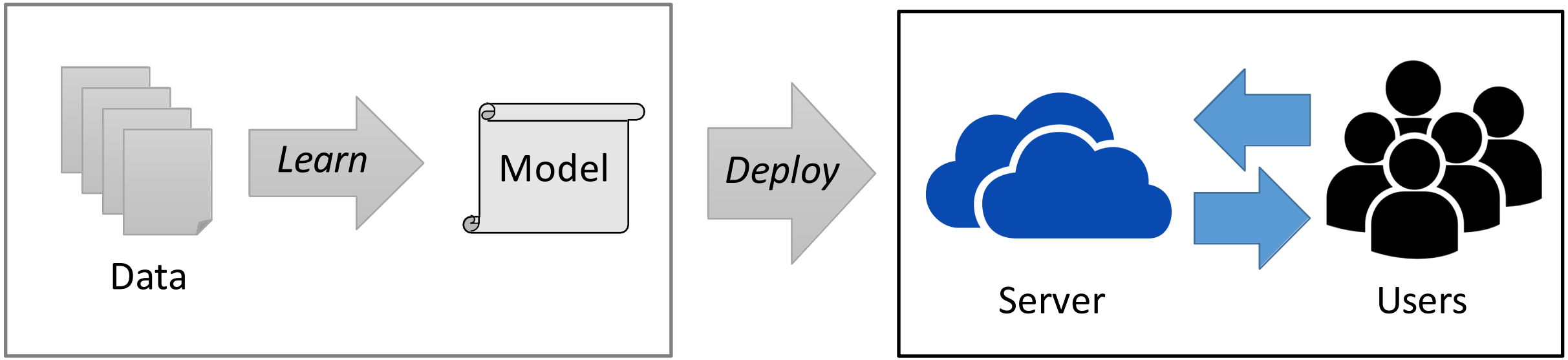
AVAILABLE MEDIA

Show details

Machine Learning Prediction Serving

1. Models are learned from data
2. Models are deployed and served together

Performance goal:
1) Low latency
2) High throughput
3) Minimal resource usage



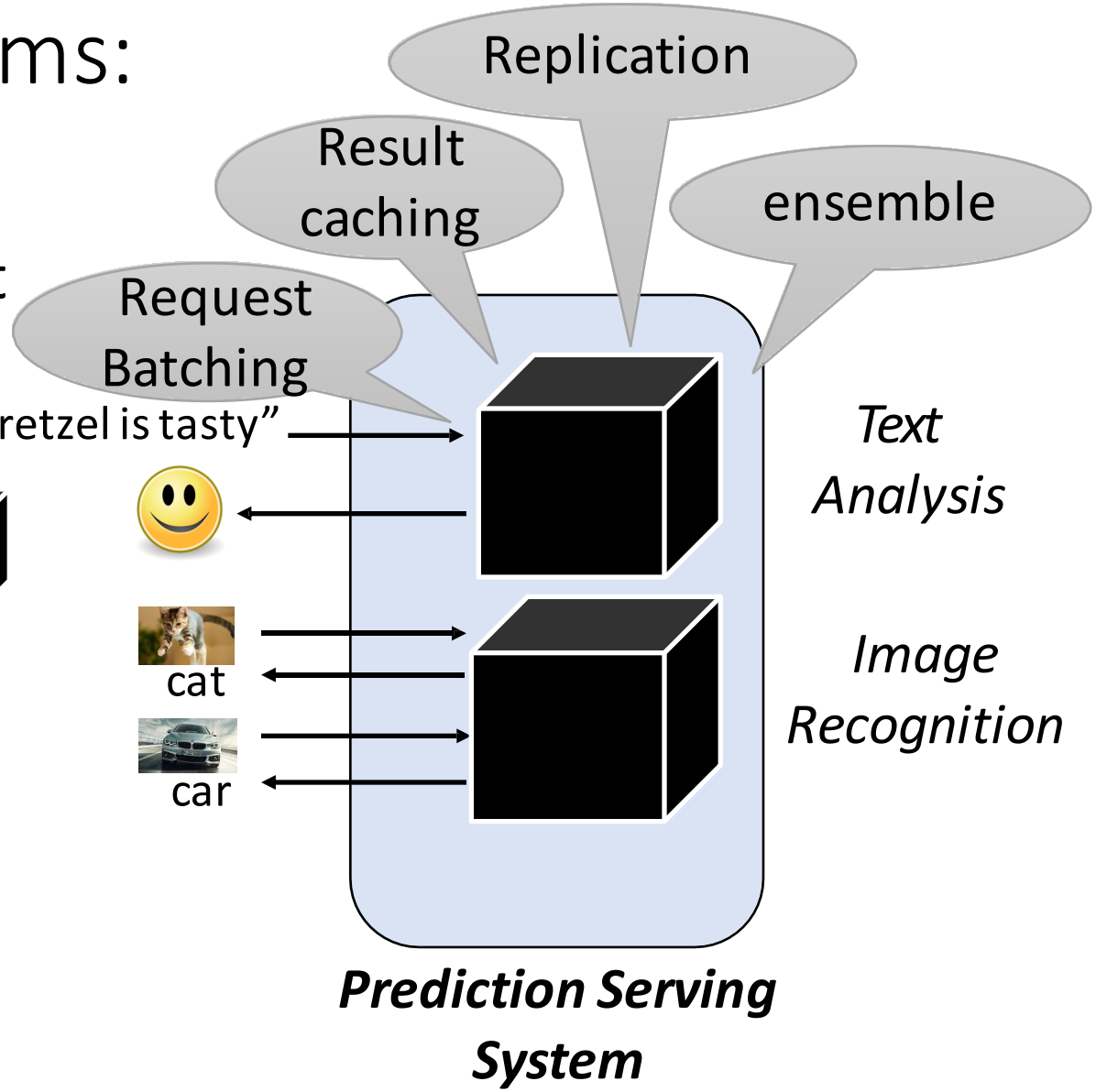
Training

Prediction serving

ML Prediction Serving Systems: State-of-the-art

Clipper riselab UC Berkeley TF Serving Google ML.NET ML.Net Microsoft

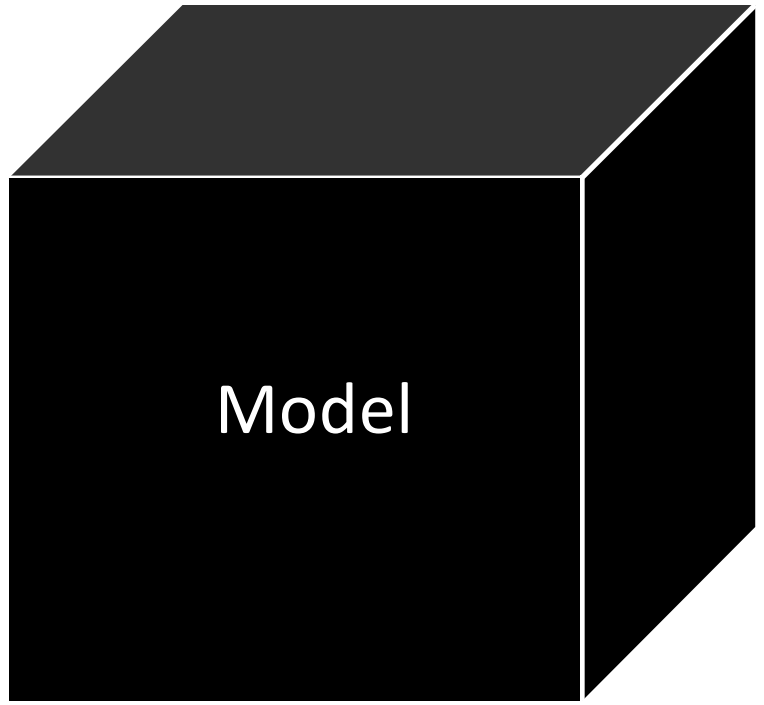
- Assumption: models are black box
  - Re-use the same code in training phase
  - Encapsulate all operations into a function call (e.g., `predict()`)
  - Apply *external* optimizations



How do Models Look inside Boxes?

Pretzel is tasty

(text)



☺ vs. ☹

(positive vs. negative)

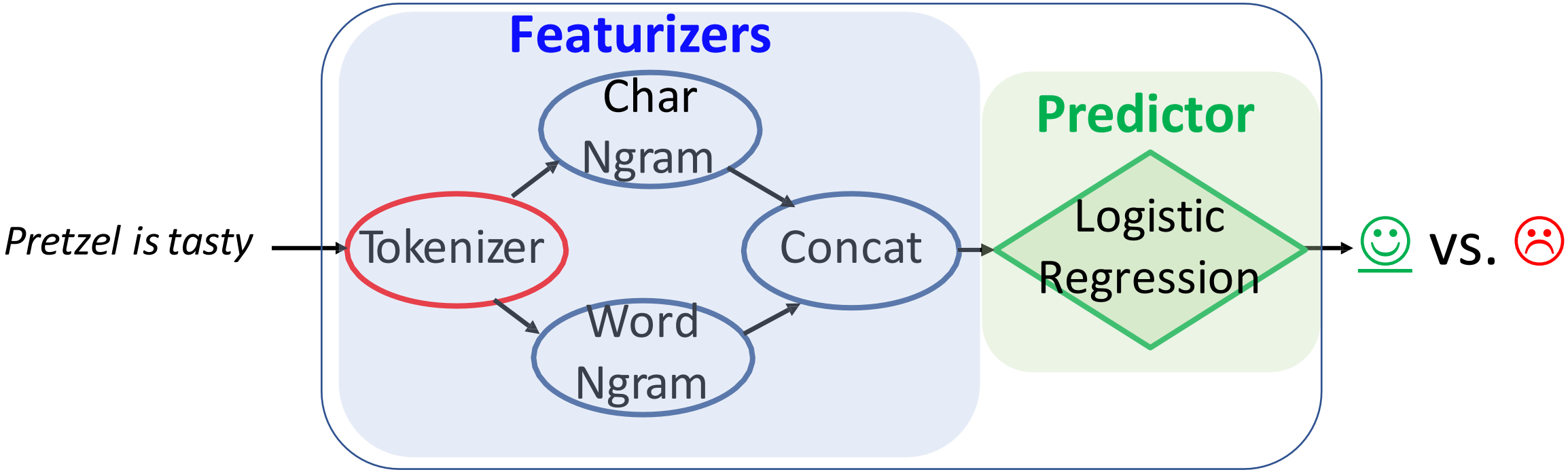
<Example: Sentiment Analysis>

ML.NET

Microsoft

How do Models Look inside Boxes?

DAG of Operators

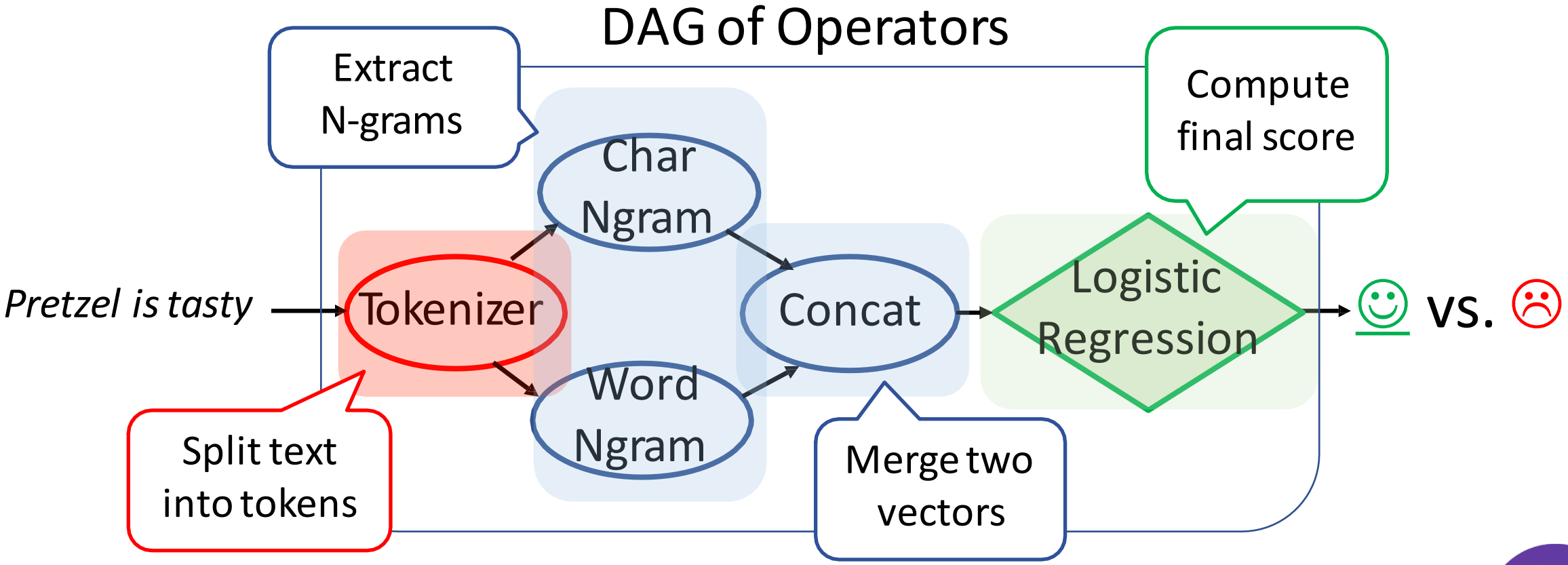


<Example: Sentiment Analysis>

ML.NET

Microsoft

How do Models Look inside Boxes?



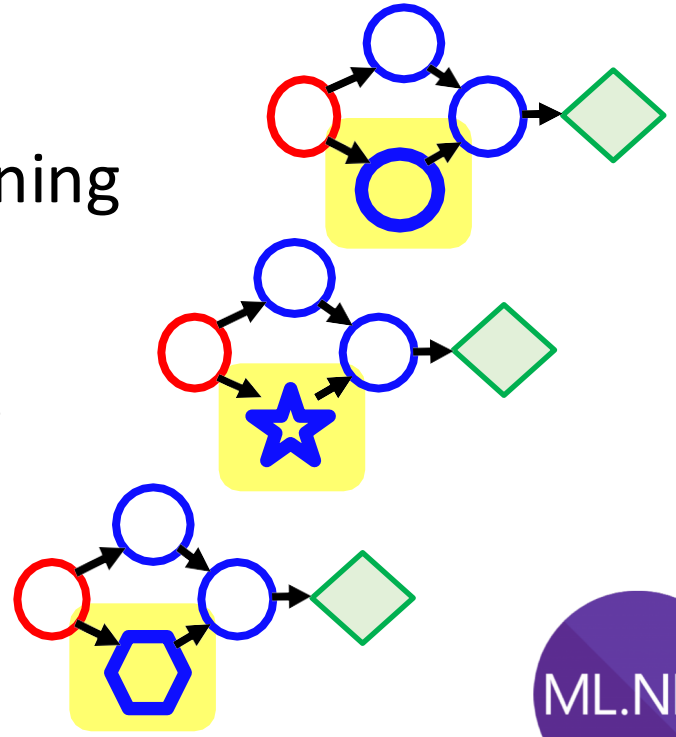
<Example: Sentiment Analysis>

ML.NET

Microsoft

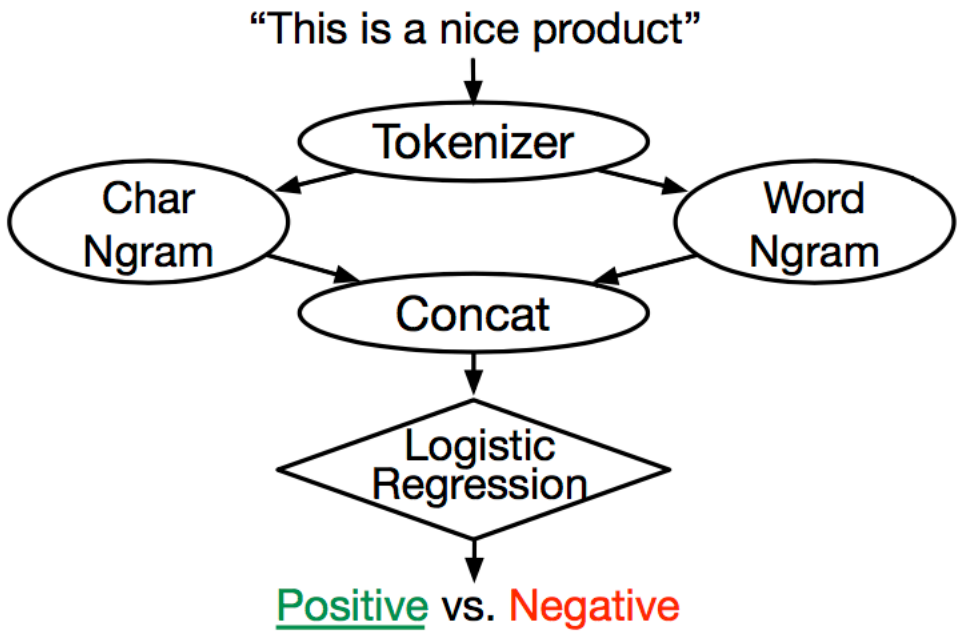
Many Models Have Similar Structures

- Many part of a model can be re-used in other models
- Customer personalization, Templates, Transfer Learning
- Identical set of operators with different parameters



ML.NET

Microsoft



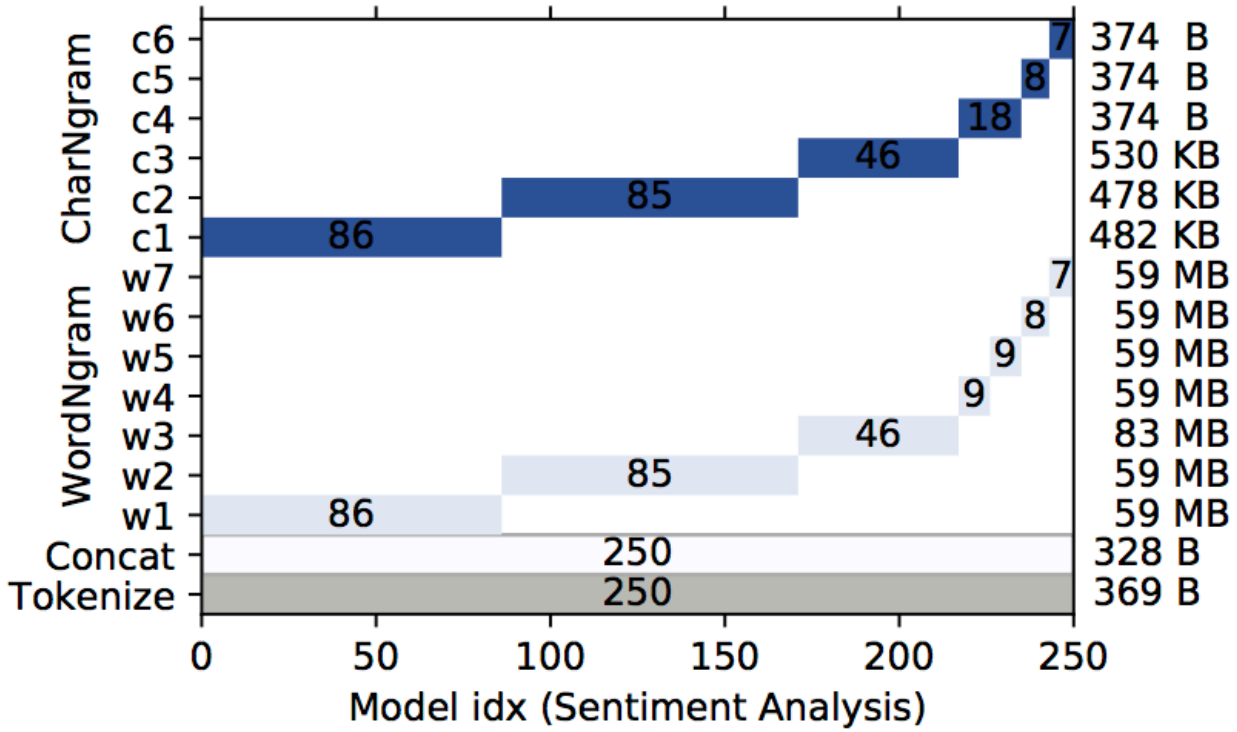


Figure 3: How many identical operators can be shared in multiple SA pipelines. CharNgram and WordNgram operators have variations that are trained on different hyper-parameters. On the right we report operators sizes.

Outline

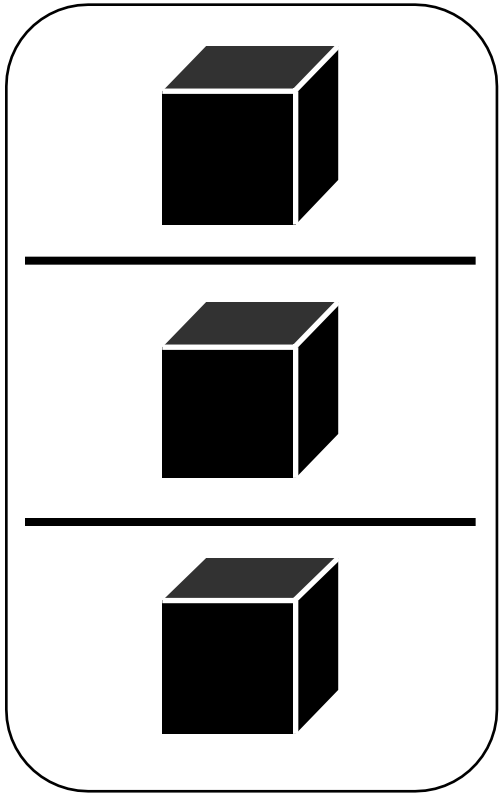
- Prediction Serving Systems
- **Limitations of Black Box Approaches**
- PRETZEL: White-box Prediction Serving System
- Evaluation
- Conclusion

Limitation 1: Resource Waste

- Resources are isolated across Black boxes

1. Unable to share memory space
   ➔ Waste memory to maintain duplicate objects (despite similarities between models)

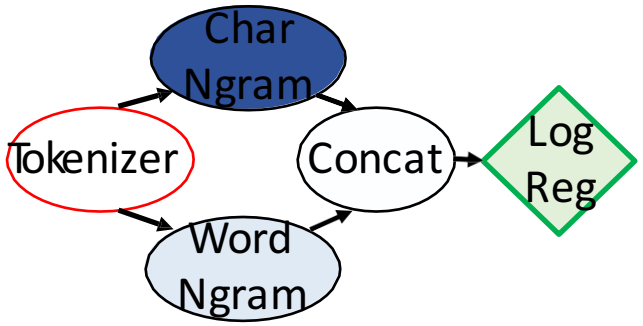
2. No coordination for CPU resources between boxes
   ➔ Serving many models can use too many threads

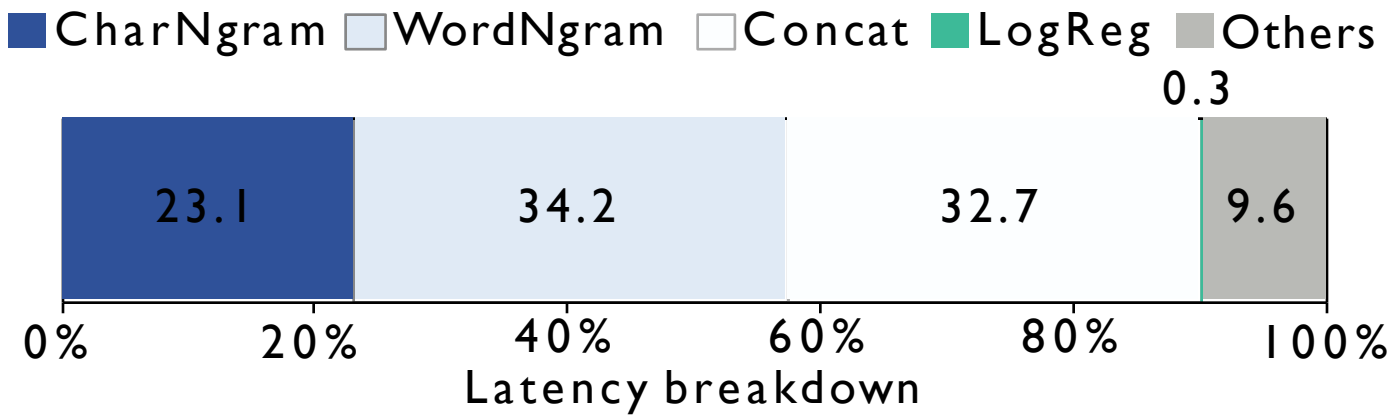


machine

Limitation 2: Inconsideration for Ops' Characteristics

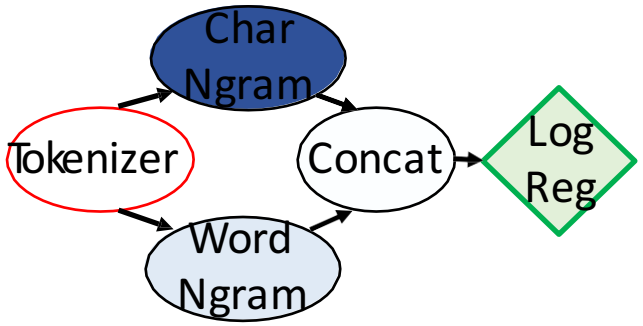
1. Operators have different performance characteristics
   - Concat materializes a vector
   - LogReg takes only 0.3% (contrary to the training phase)
2. There can be a better plan if such characteristics are considered
   - Re-use the existing vectors
   - Apply in-place update in LogReg

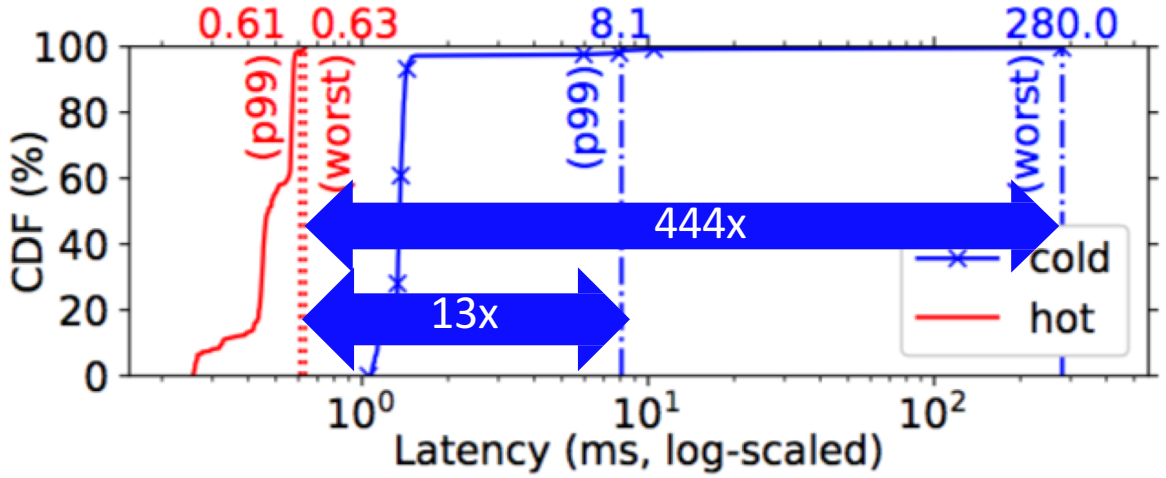




Limitation 3: Lazy Initialization

- ML.Net initializes code and memory lazily (efficient in training phase)
- Run 250 Sentiment Analysis models 100 times
  ➔ cold: first execution / hot: average of the rest 99
- Long-tail latency in the cold case
  - Code analysis, Just–in-time (JIT) compilation, memory allocation, etc
  - Difficult to provide strong Service-Level-Agreement (SLA)





Outline

- (Black-box) Prediction Serving Systems
- Limitations of Black Box Approaches
- **PRETZEL: White-box Prediction Serving System**
- Evaluation
- Conclusion

PRETZEL: White-box Prediction Serving

- We analyze models to optimize the internal execution
- We let models co-exist on the same runtime, sharing computation and memory resources
- We optimize models in two directions:
  1. End-to-end optimizations
  2. Multi-model optimizations

End-to-End Optimizations

Optimize the execution of **individual** models from start to end

1. [Ahead-of-time Compilation]

   Compile operators' code in advance

   → No JIT overhead

2. [Vector pooling]

   Pre-allocate data structures

   → No memory allocation on the data path

Multi-model Optimizations

Share computation and memory **across models**

1. [Object Store]

   Share Operators parameters/weights

   → Maintain only one copy

2. [Sub-plan Materialization]

   Reuse intermediate results computed by other models

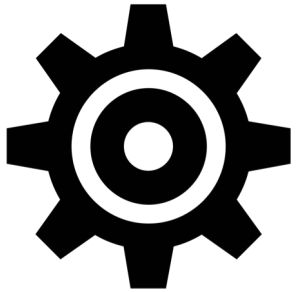
   → Save computation

System Components

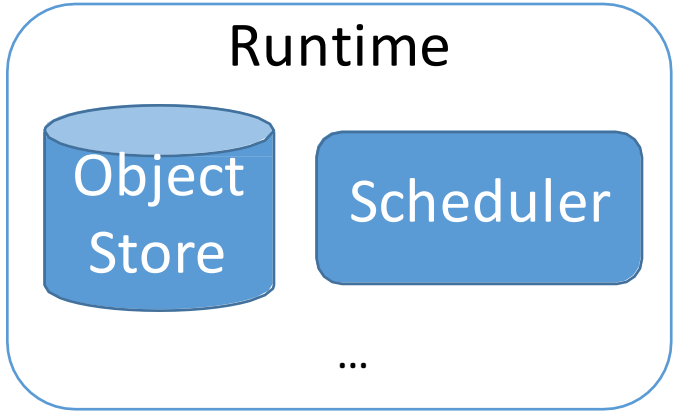
1. Flour: Intermediate Representation

```
var fContext = ...;
var Tokenizer = ...;
return fPrgm.Plan();
```

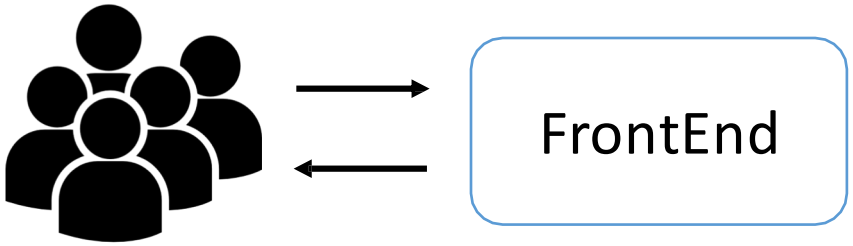
2. Oven: Compiler/Optimizer



3. Runtime: Execute inference queries

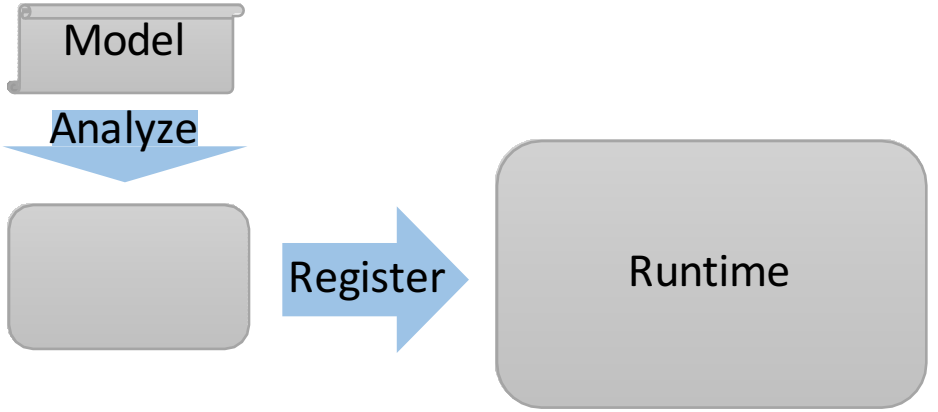


4. FrontEnd: Handle user requests

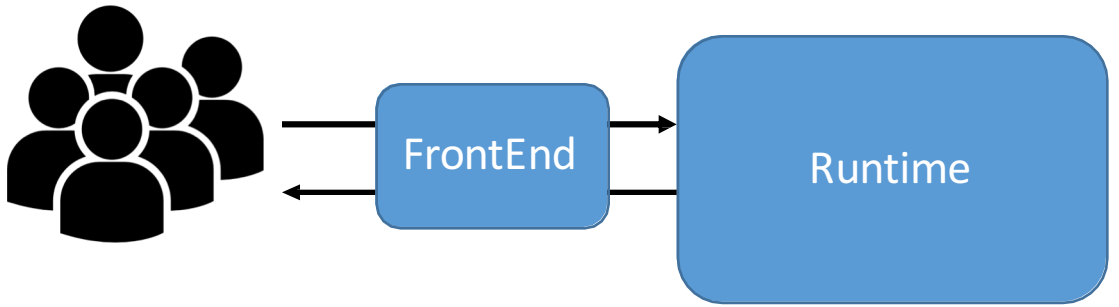


Prediction Serving with PRETZEL

1. Offline
   - Analyze structural information of models
   - Build *ModelPlan* for optimal execution
   - Register *ModelPlan* to Runtime



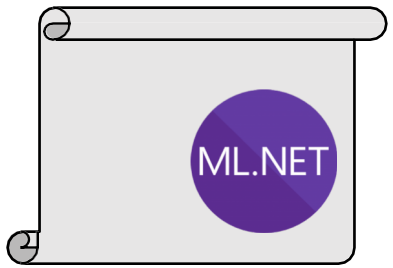
2. Online
   - Handle prediction requests
   - Coordinate CPU & memory resources

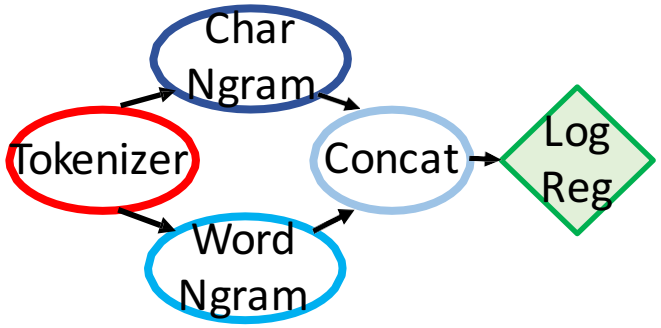


System Design: Offline Phase

1. Translate Model into Flour Program

<Model>





<Flour Program>

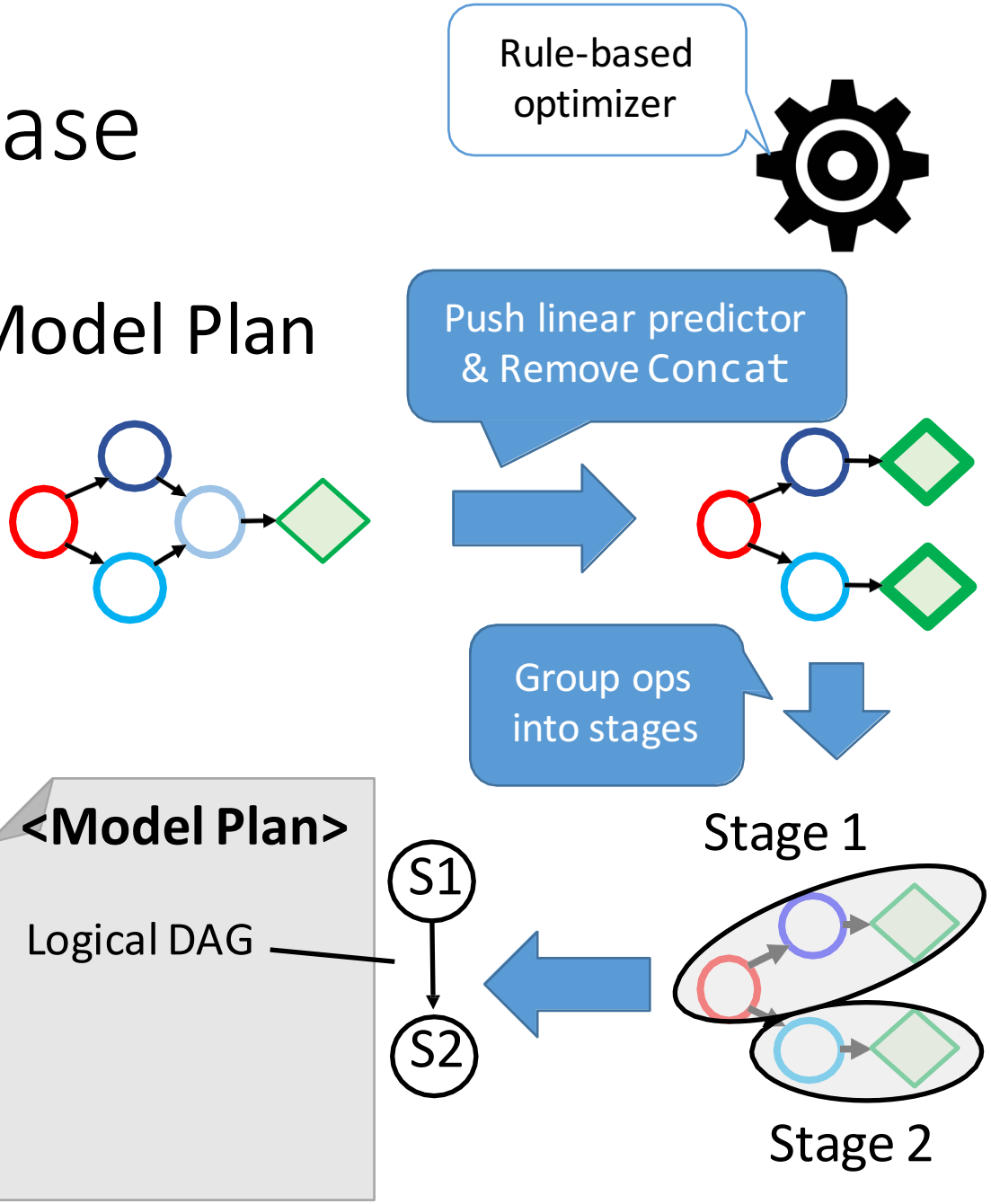
```
var fContext = new FlourContext(...)
var tTokenizer = fContext.CSV
        .FromText(fields, fieldsType, sep)
        .Tokenize();

var tCNgram = tTokenizer.CharNgram(numCNgrms, ...);
var tWNgram = tTokenizer.WordNgram(numWNgrms, ...);
var fPrgrm = tCNgram
                .Concat(tWNgram)
                .ClassifierBinaryLinear(cParams);

return fPrgrm.Plan();
```

System Design: Offline Phase

2. Oven optimizer/compiler build Model Plan

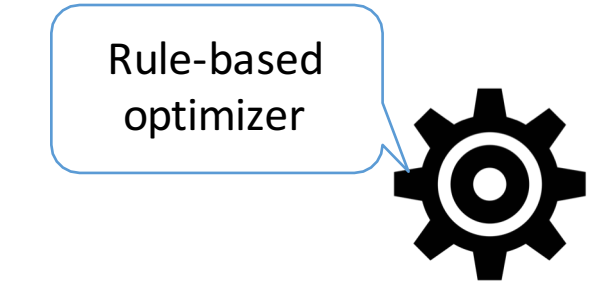
<Flour Program>

```
var fContext = new FlourContext(...)
var tTokenizer = fContext.CSV
        .FromText(fields, fieldsType, sep)
        .Tokenize();

var tCNgram = tTokenizer.CharNgram(numCNgrms, ...);
var tWNgram = tTokenizer.WordNgram(numWNgrms, ...);
var fPrgrm = tCNgram
                .Concat(tWNgram)
                .ClassifierBinaryLinear(cParams);

return fPrgrm.Plan();
```



System Design: Offline Phase

2. Oven optimizer/compiler build Model Plan

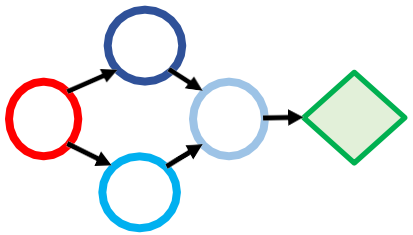


<Flour Program>

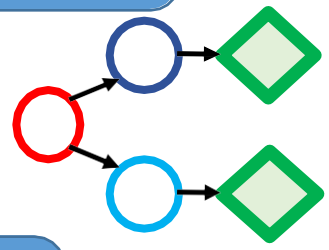
```
var fContext = new FlourContext(...)
var tTokenizer = fContext.CSV
        .FromText(fields, fieldsType, sep)
        .Tokenize();

var tCNgram = tTokenizer.CharNgram(numCNgrms, ...);
var tWNgram = tTokenizer.WordNgram(numWNgrms, ...);
var fPrgrm = tCNgram
                .Concat(tWNgram)
                .ClassifierBinaryLinear(cParams);

return fPrgrm.Plan();
```

e.g., Dictionary, N-gram Length

e.g., dense vs. sparse, maximum vector size



Push linear predictor & Remove Concat



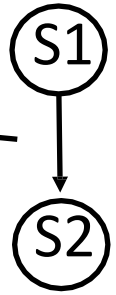
Group ops into stages

<Model Plan>

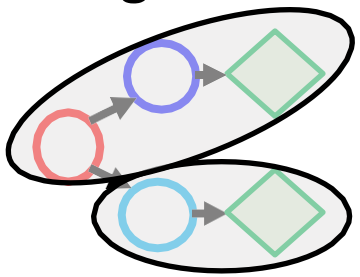
Logical DAG

Parameters

Statistics



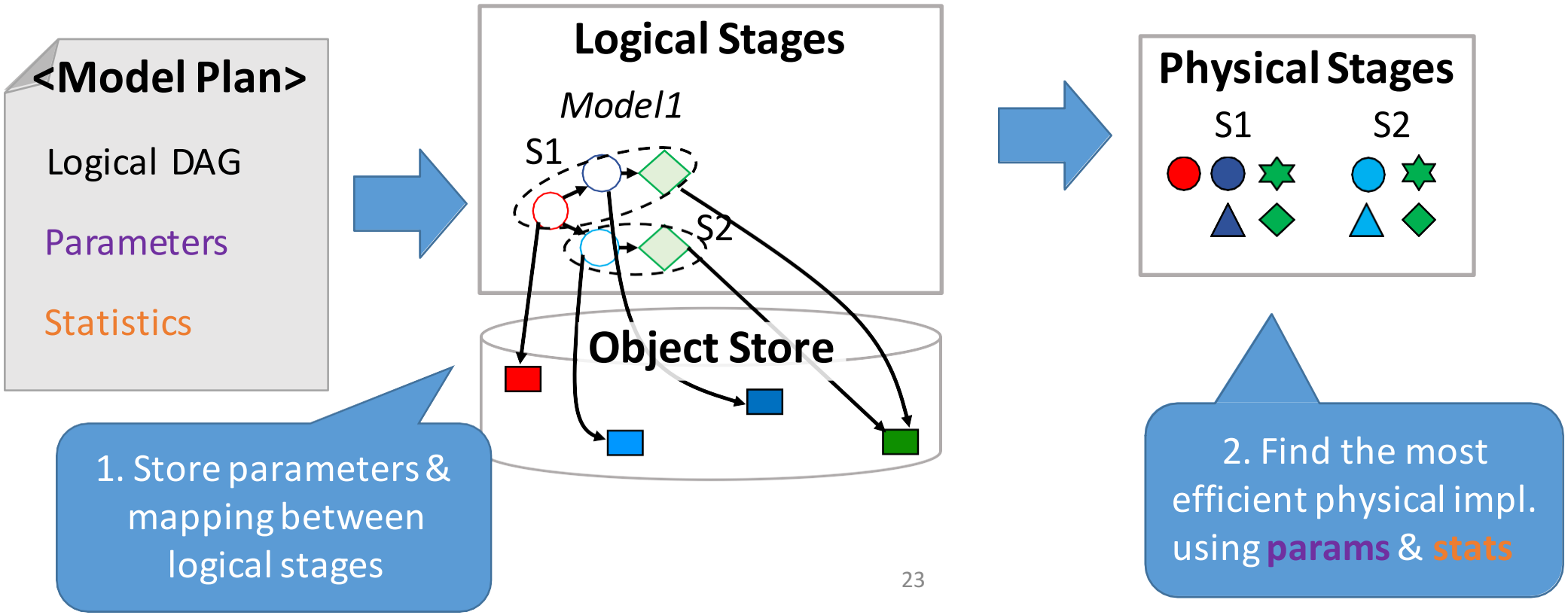
Stage 1



Stage 2

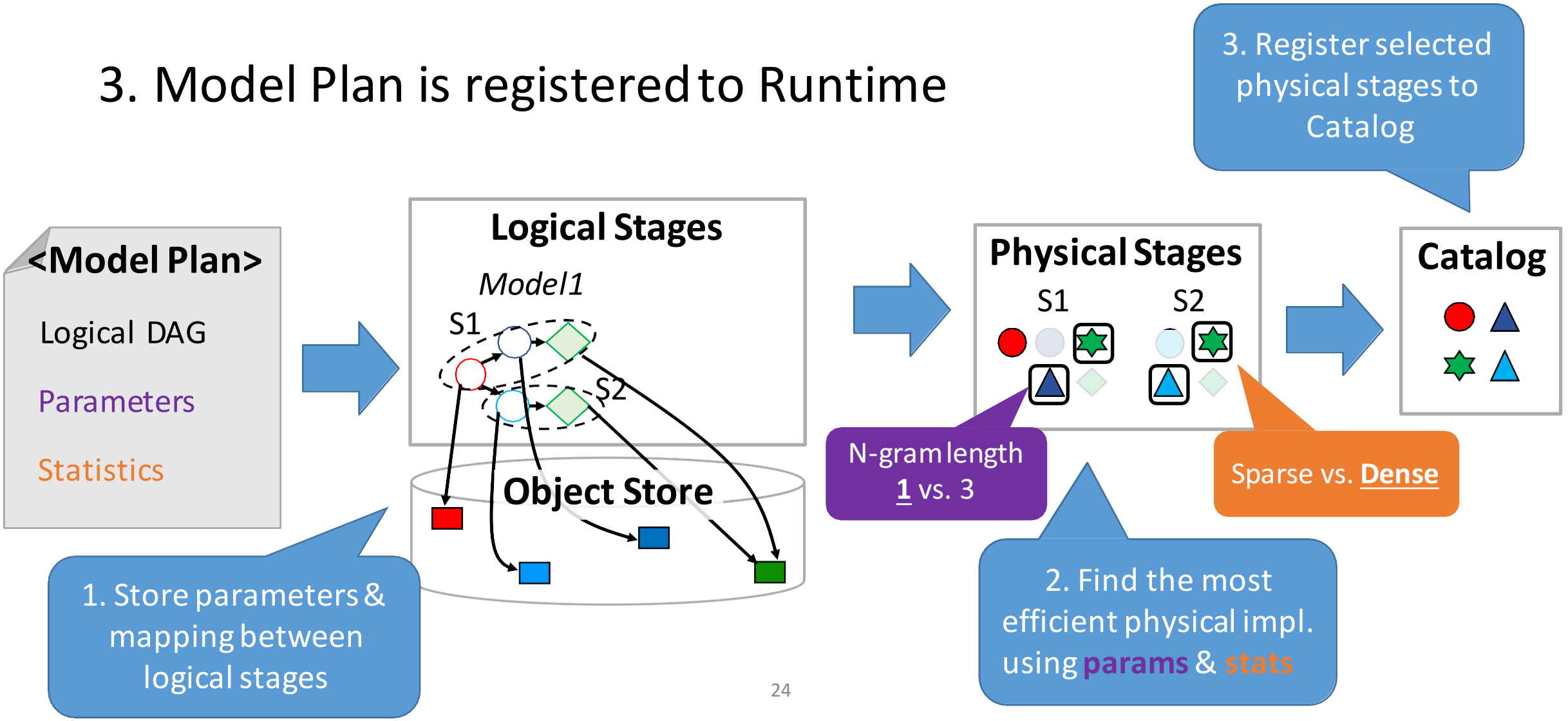
System Design: Offline Phase

3. Model Plan is registered to Runtime

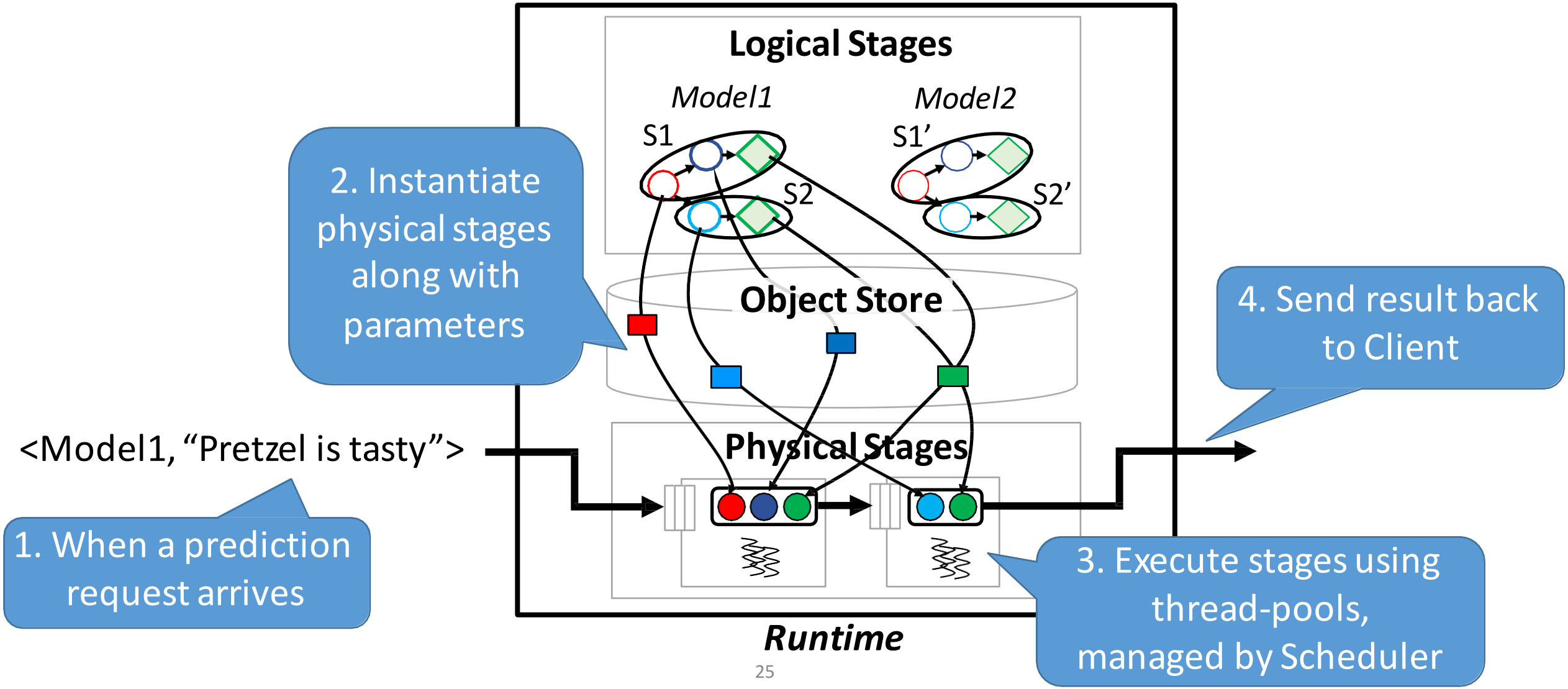


System Design: Offline Phase

3. Model Plan is registered to Runtime



System Design: Online Phase



System Design: Online Phase

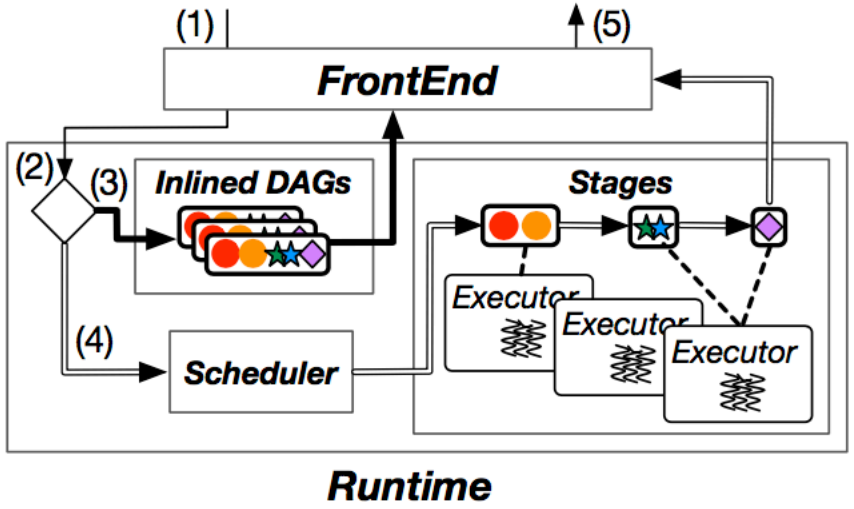


Figure 7: (1) When a prediction request is issued, (2) the Runtime determines whether to serve the prediction using (3) the request/response engine or (4) the batch engine. In the latter case, the Scheduler takes care of properly allocating stages over the Executors running concurrently on CPU cores. (5) The FrontEnd returns the result to the Client once all stages are complete.

Outline

- (Black-box) Prediction Serving Systems
- Limitations of Black box approaches
- PRETZEL: White-box Prediction Serving System
- **Evaluation**
- Conclusion

Evaluation

- Q. How PRETZEL improves performance over black-box approaches?
  - in terms of *latency, memory* and *throughput*

- 500 Models from Microsoft Machine Learning Team
  - 250 Sentiment Analysis (Memory-bound)
  - 250 Attendee Count (Compute-bound)

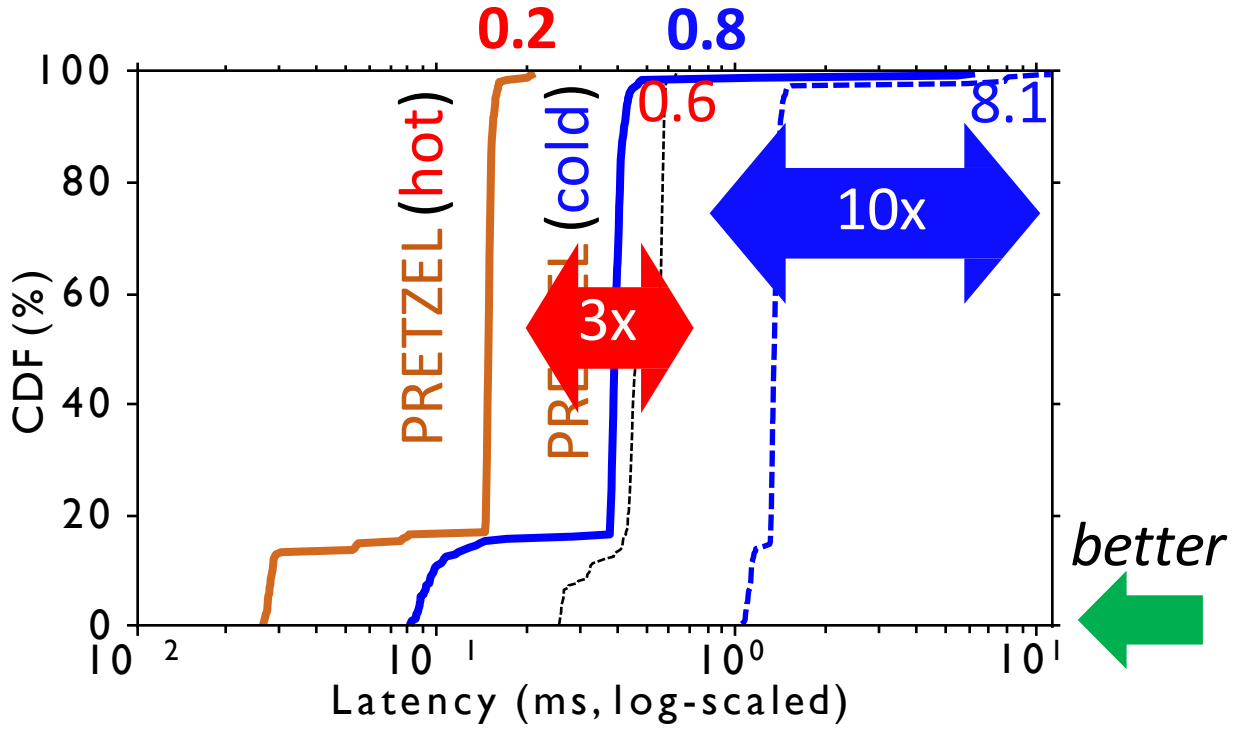
- System configuration
  - 16 Cores CPU, 32GB RAM
  - Windows 10, .Net core 2.0

Evaluation: Latency

- Micro-benchmark (No server-client communication)
  - Score 250 Sentiment Analysis models 100 times for each
  - Compare ML.Net vs. PRETZEL

	ML.Net	PRETZEL
P99 (hot)	0.6	0.2
P99 (cold)	8.1	0.8
Worst (cold)	**280.2**	**6.2**

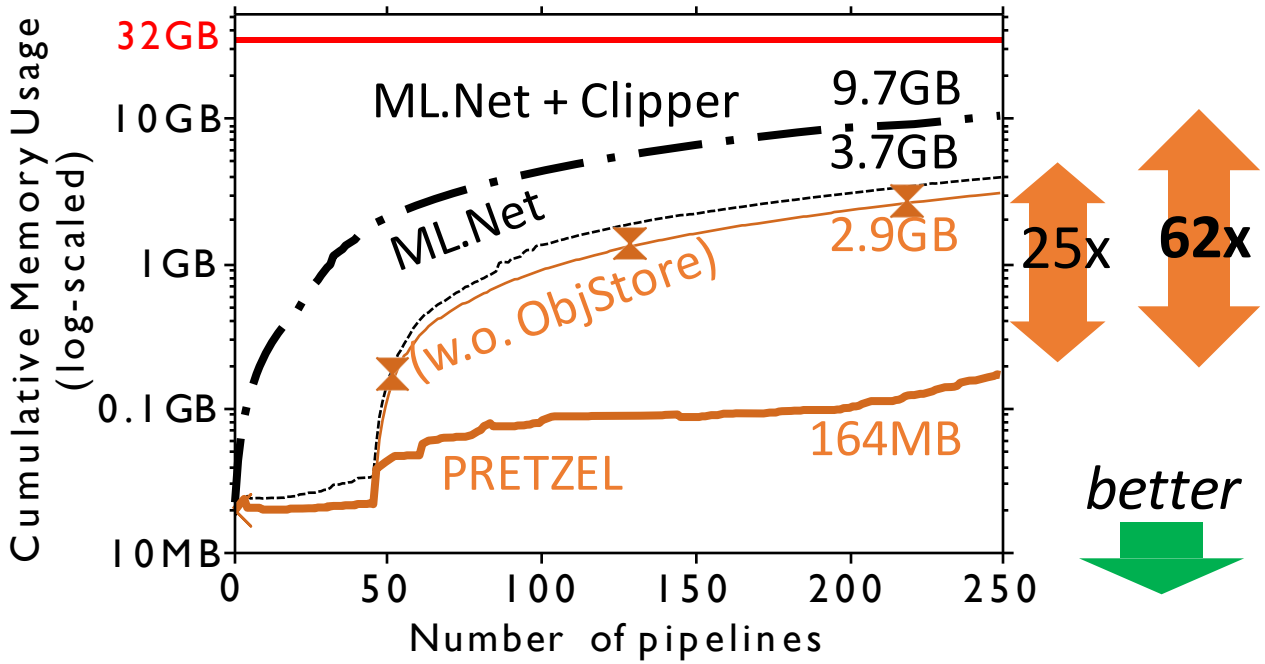
45x



Evaluation: Memory

- Measure Cumulative Memory Usage after loading 250 models
  - Attendee Count models (smaller size than Sentiment Analysis)
  - 4 settings for Comparison

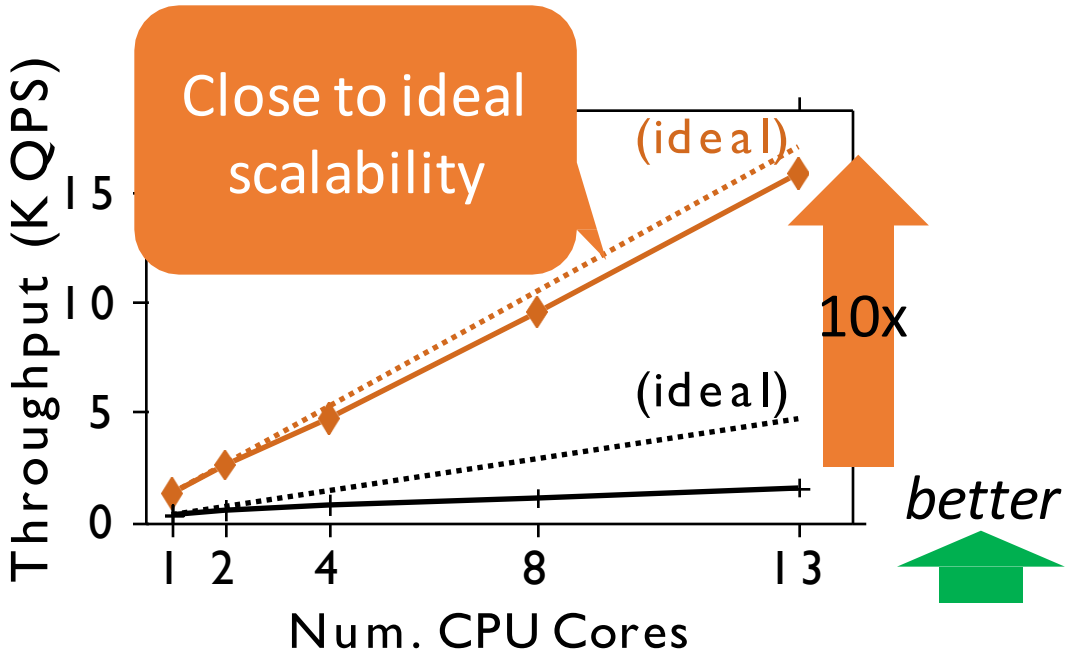
Settings	Shared Objects	Shared Runtime
ML.Net + Clipper		
ML.Net		✓
PRETZEL without ObjectStore		✓
PRETZEL	✓	✓



Evaluation: Throughput

- Micro-benchmark
  - Score 250 Attendee Count models 1000 times for each
  - Request 1000 queries in a batch
  - Compare ML.Net vs. PRETZEL

More results in the paper!



Conclusion

- PRETZEL is the first white-box prediction serving system for ML pipelines
- By using models' structural info, we enable two types of optimizations:
  - End-to-end optimizations generate efficient execution plans for a model
  - Multi-model optimizations let models share computation and memory resources
- Our evaluation shows that PRETZEL can improve performance compared to Black-box systems (e.g., ML.Net)
  - Decrease latency and memory footprint
  - Increase resource utilization and throughput

Conclusion

- PRETZEL casts prediction serving as a database problem and applies end-to-end and multi-query optimizations to maximize performance and resource utilization.

PRETZEL: a White-Box ML Prediction Serving System

Thank you!
Questions?

SEOUL
NATIONAL
UNIVERSITY

POLITECNICO
MILANO 1863

Microsoft