Hummingbird: A Tensor Compiler for Unified Machine Learning Prediction Serving

Supun Nakandala[u], Karla Saur[m], Gyeong-In Yu[s], Konstantinos Karanasos[m], Carlo Curino[m], Markus Weimer[m], Matteo Interlandi[m]

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Focus: Deep Learning (DL)

tvm TensorRT ONNX RUNTIME

Traditional Machine Learning in the Enterprises

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Powered By: Traditional Machine Learning

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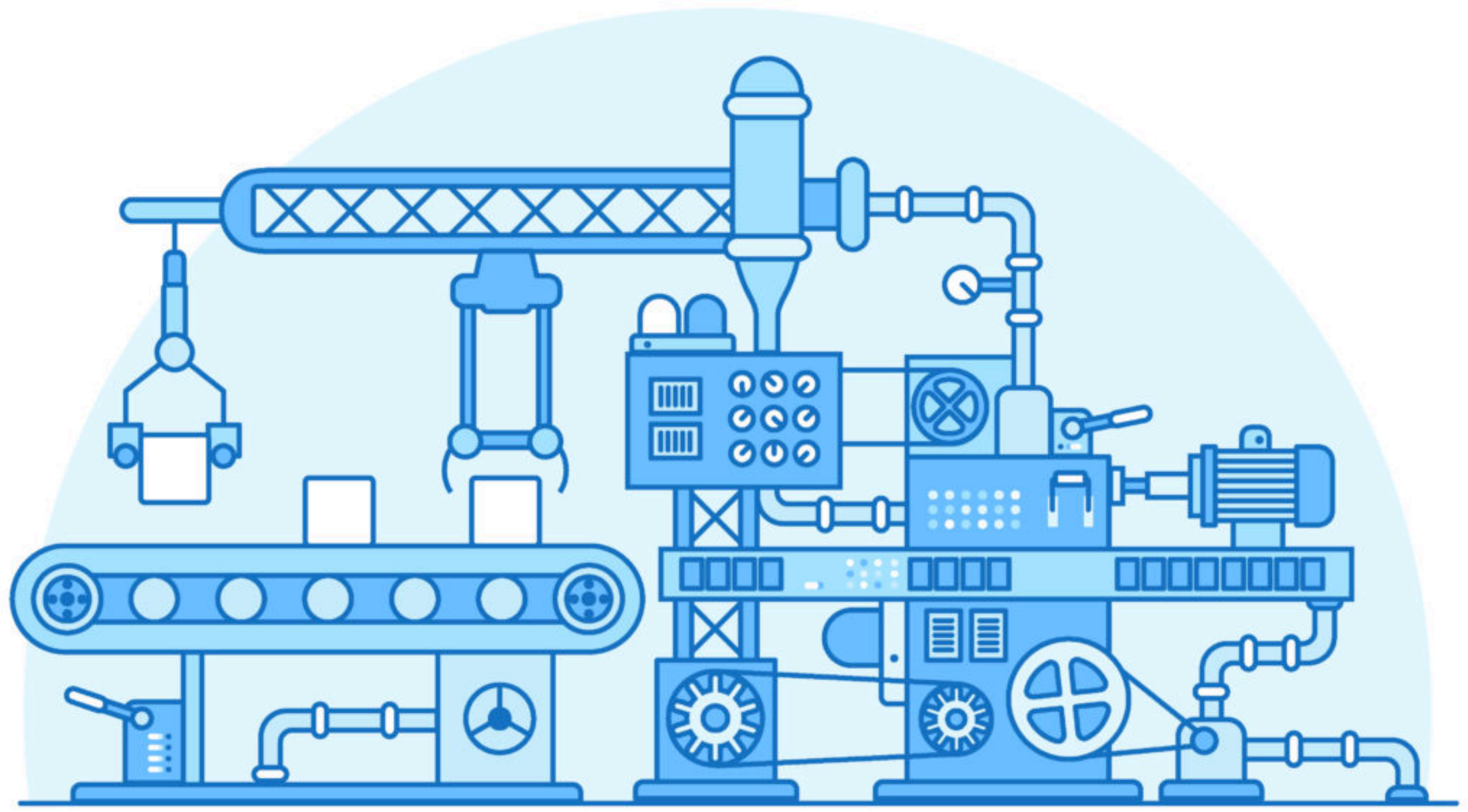

Predictive Maintenance

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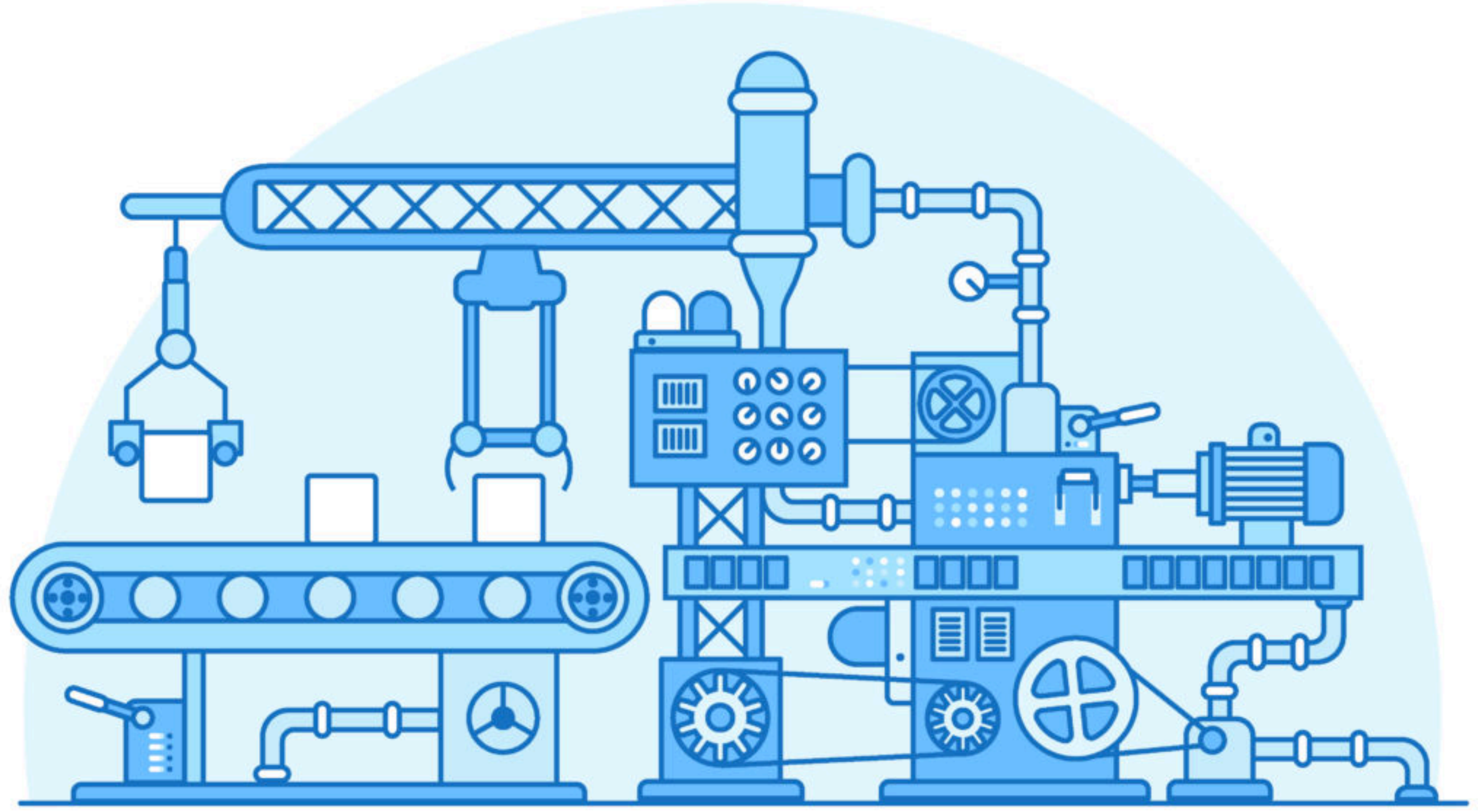

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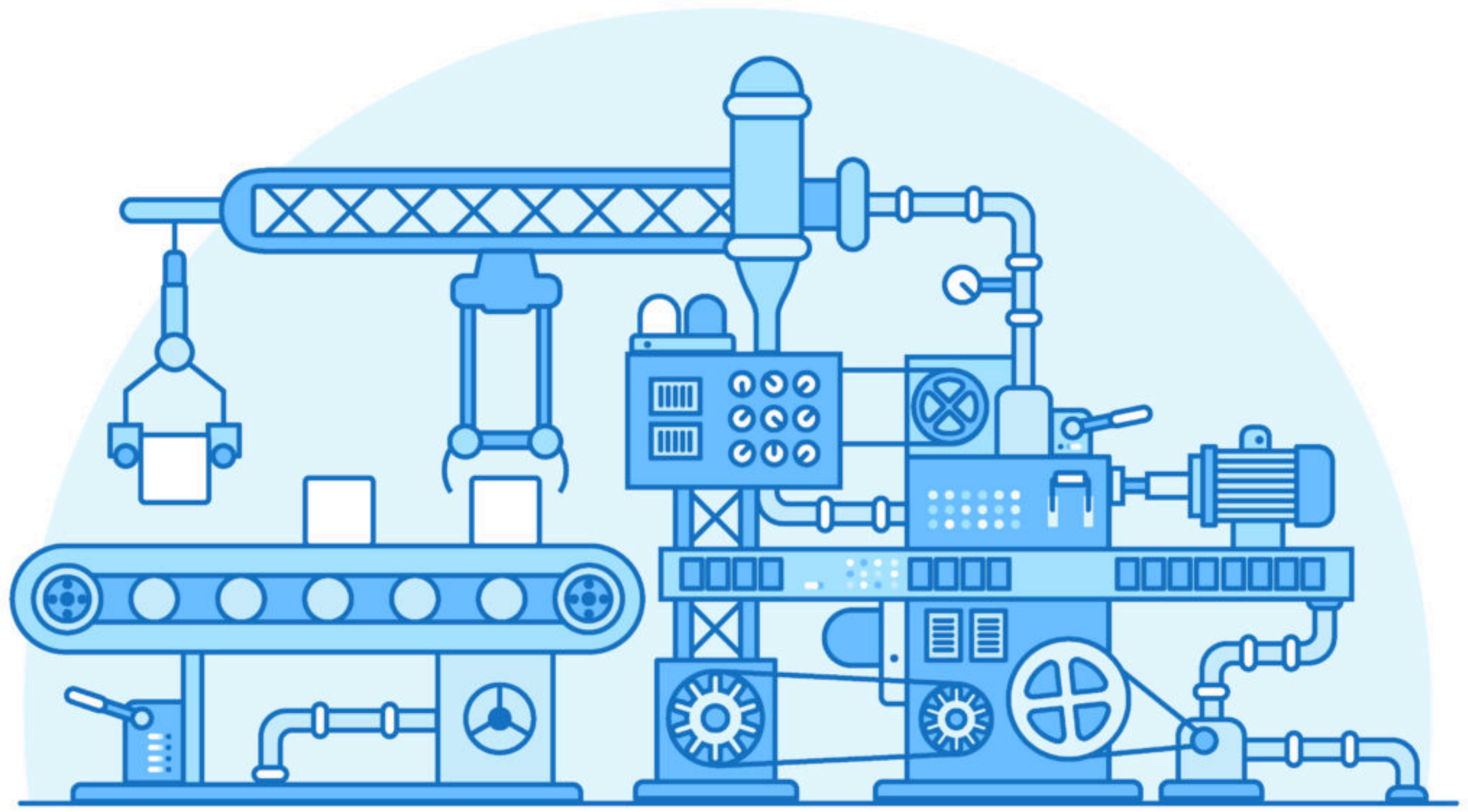

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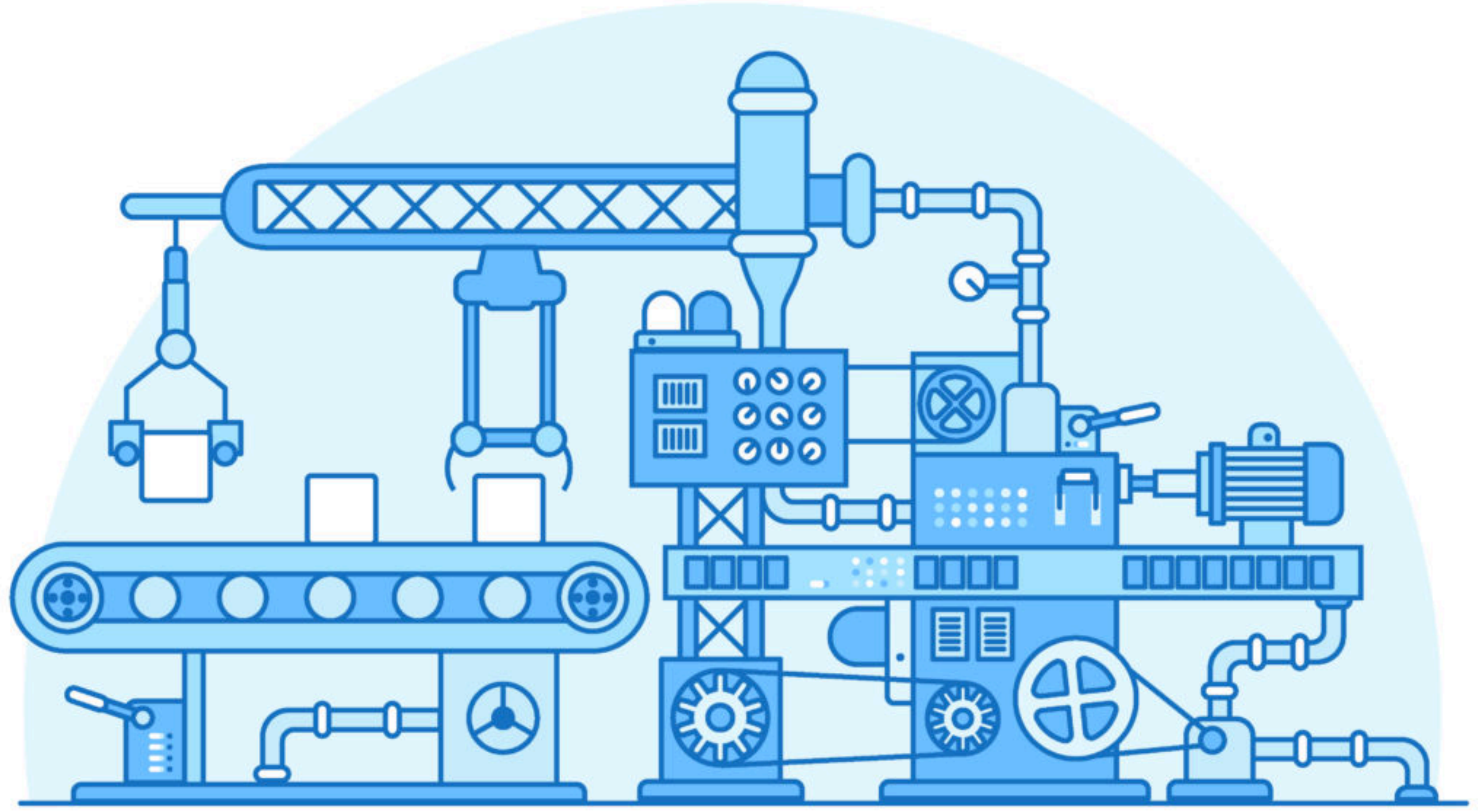

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50%-95% of all ML applications in an organization are based on Traditional ML

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Problem: Lack of Optimized Systems for Traditional ML Serving

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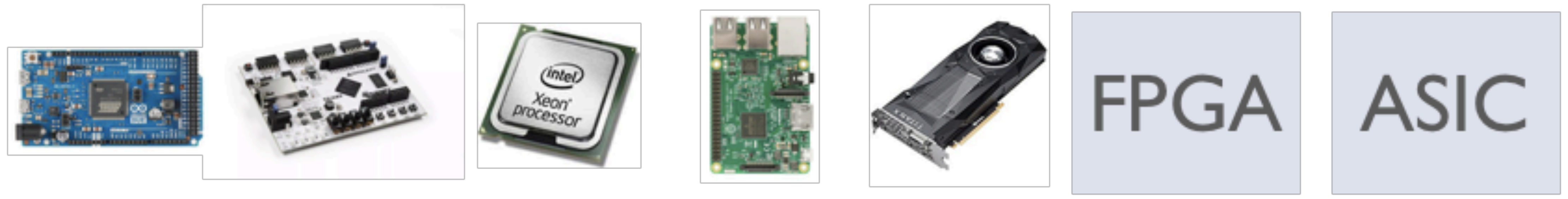

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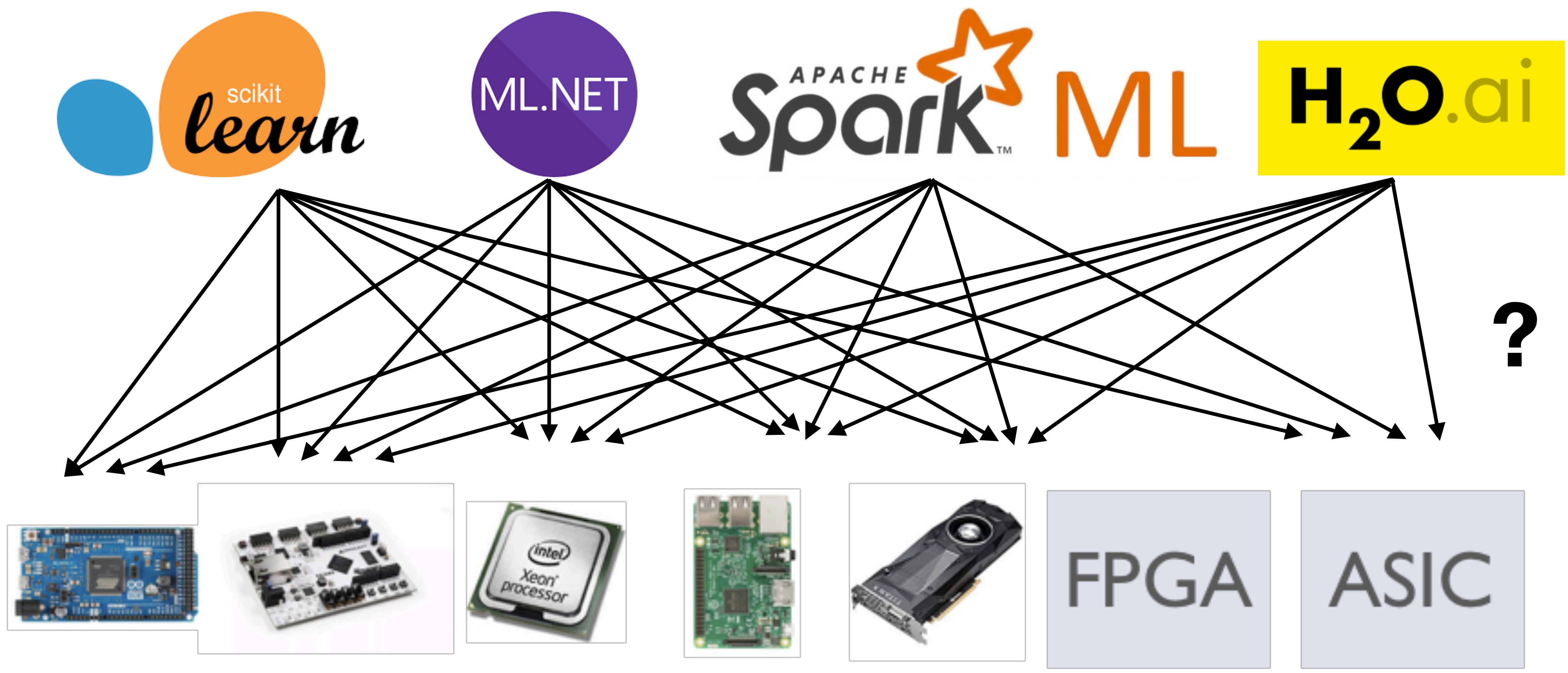

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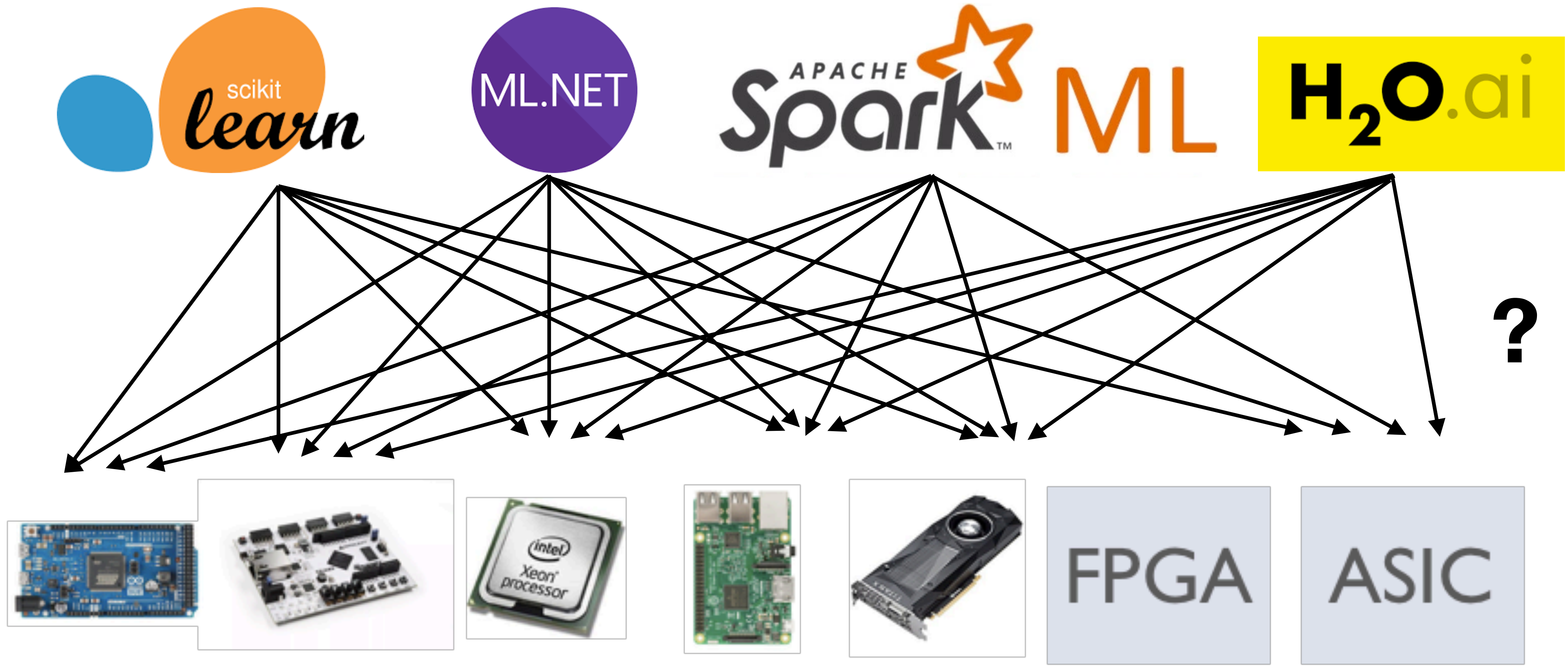

Highly complex solutions, amplified engineering costs, and reduced operational performance.

Proposed Approach: Reuse DL Prediction Serving Systems for Traditional ML Serving

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Outline

1. Background

   Traditional Machine Learning

   Deep Learning (DL) and Systems for DL Prediction Serving

2. Our System: Hummingbird

3. Experimental Evaluation

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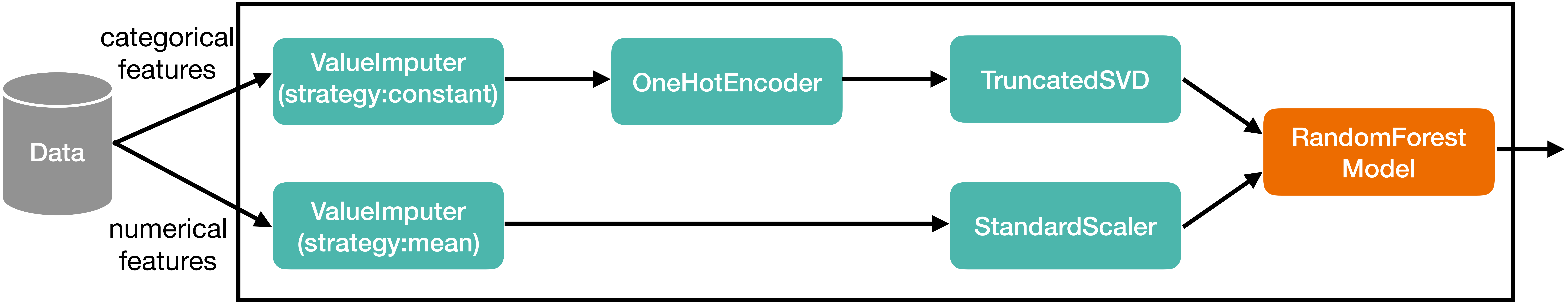

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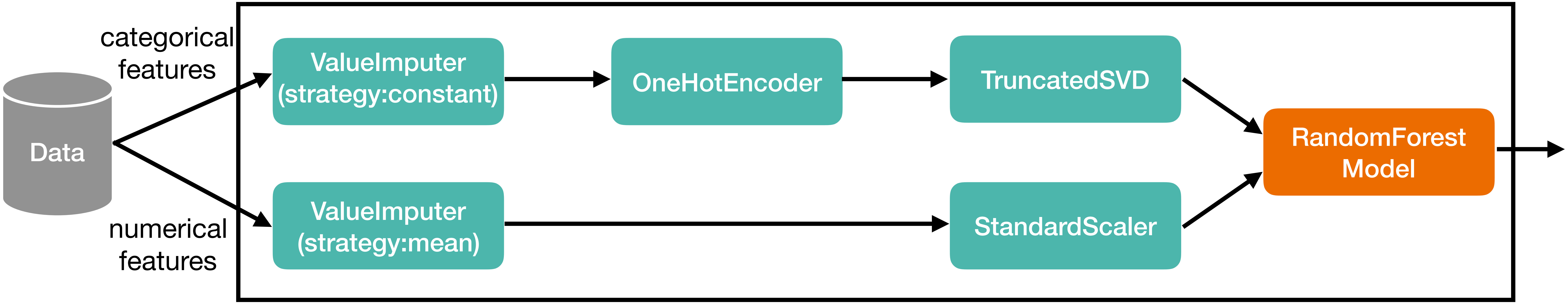

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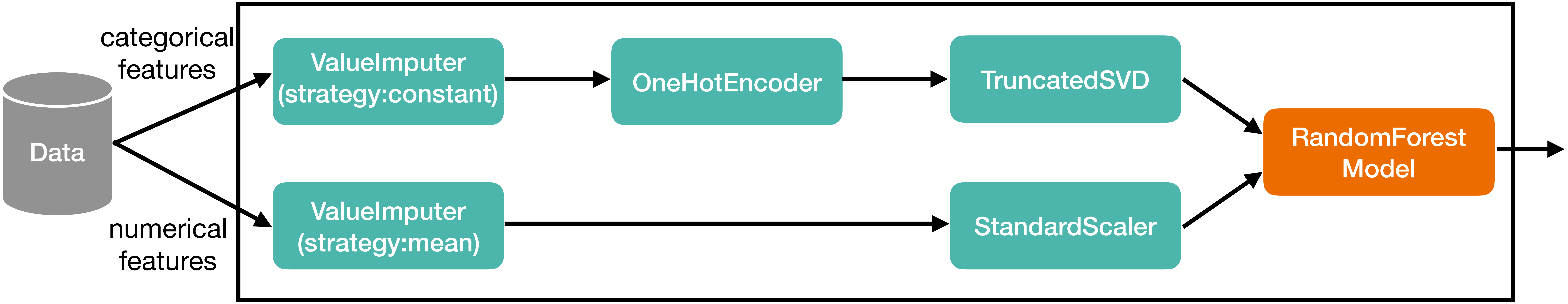

Operators are expressed using **imperative code.**

Can contain 10s of operators selected from 100s of potential featurization and model operators.

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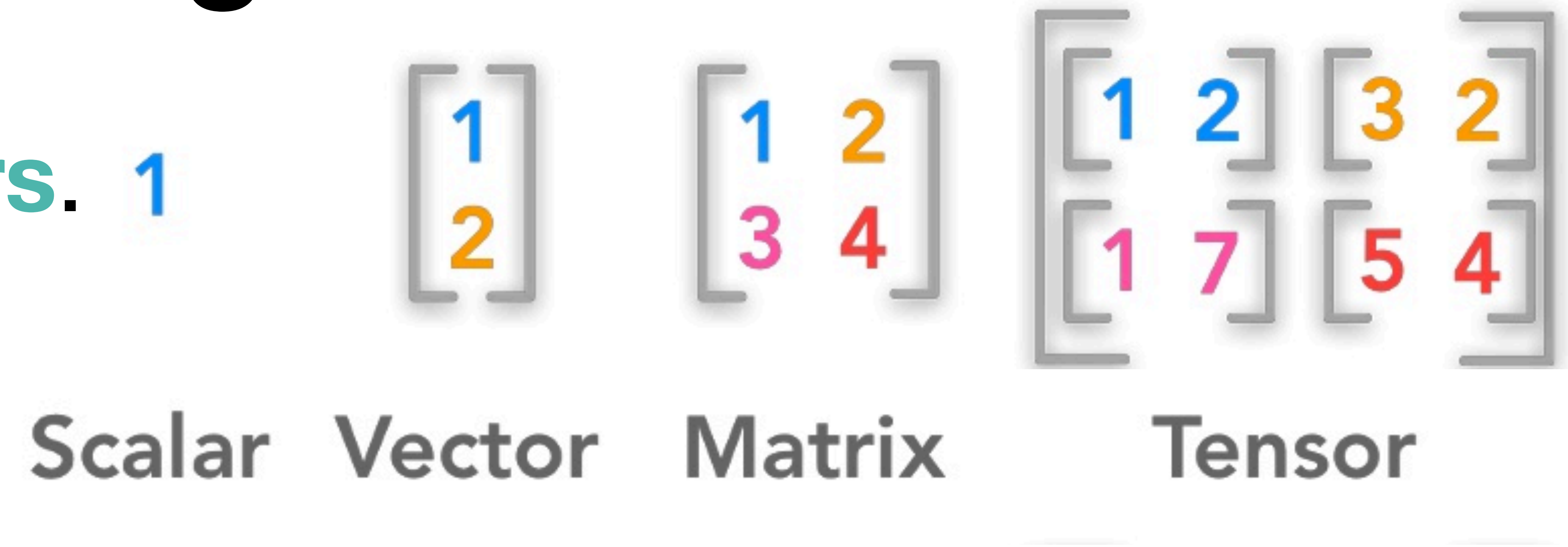
Primarily relies on the abstraction of **tensors**.



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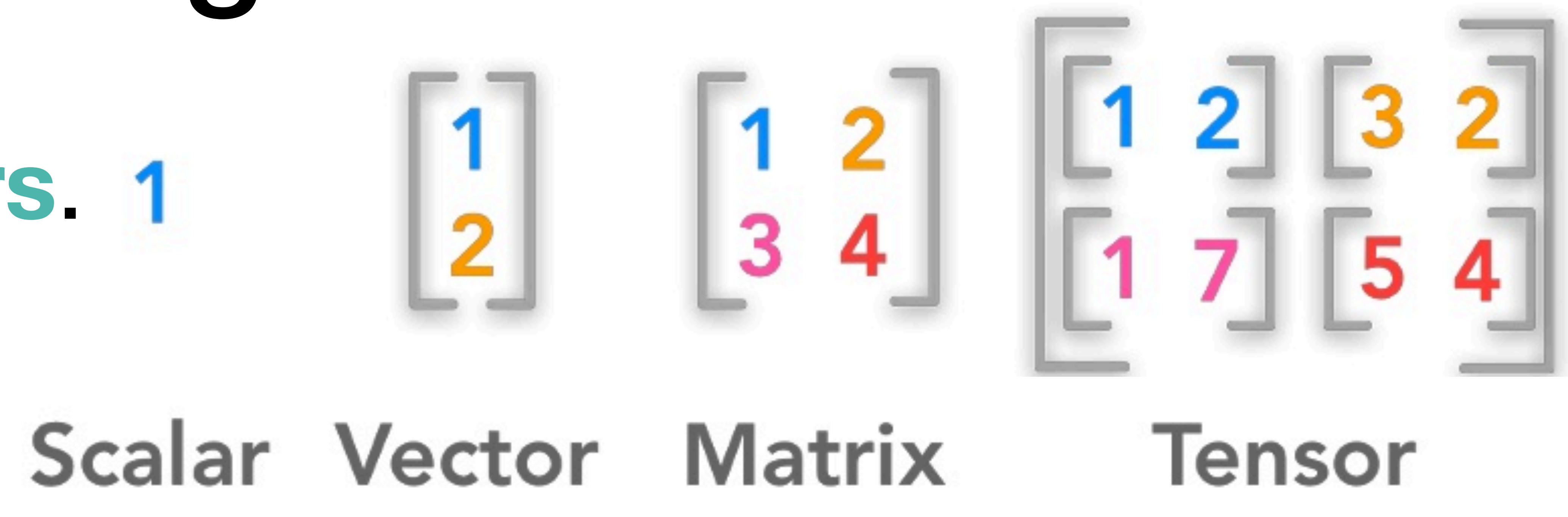
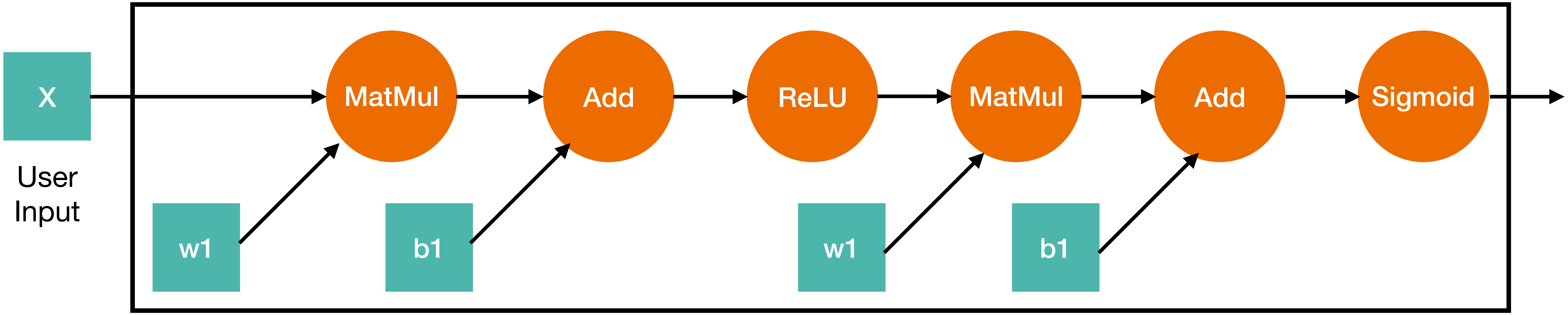


DL models are expressed as a DAG of **tensor operators**.



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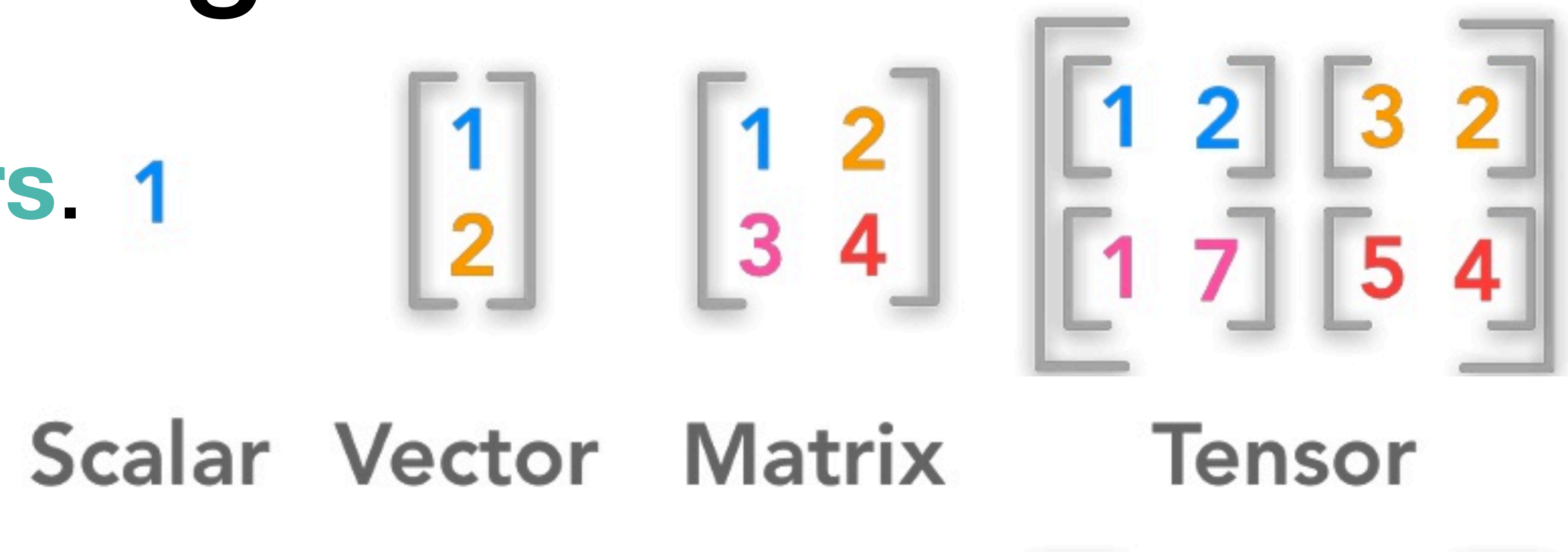

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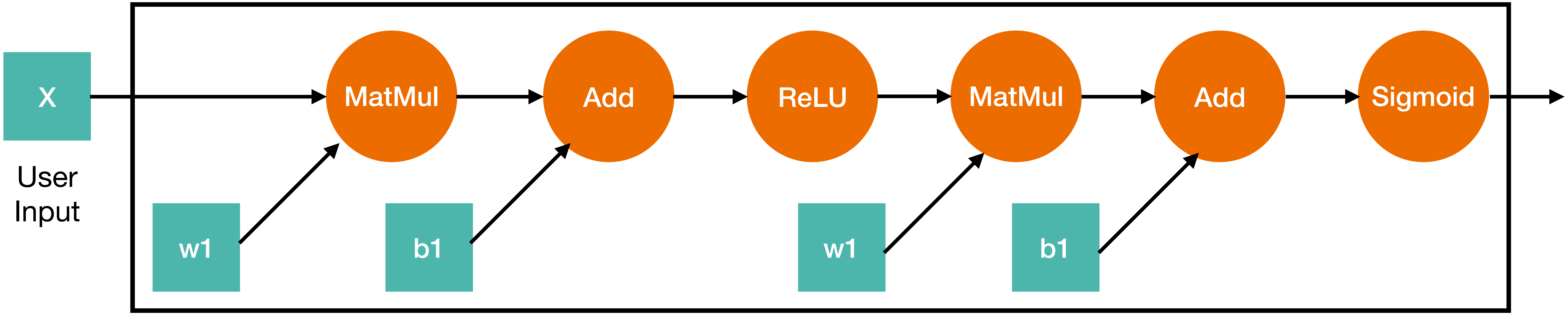

Can contain 100s of operators with often 10s of unique operator types.

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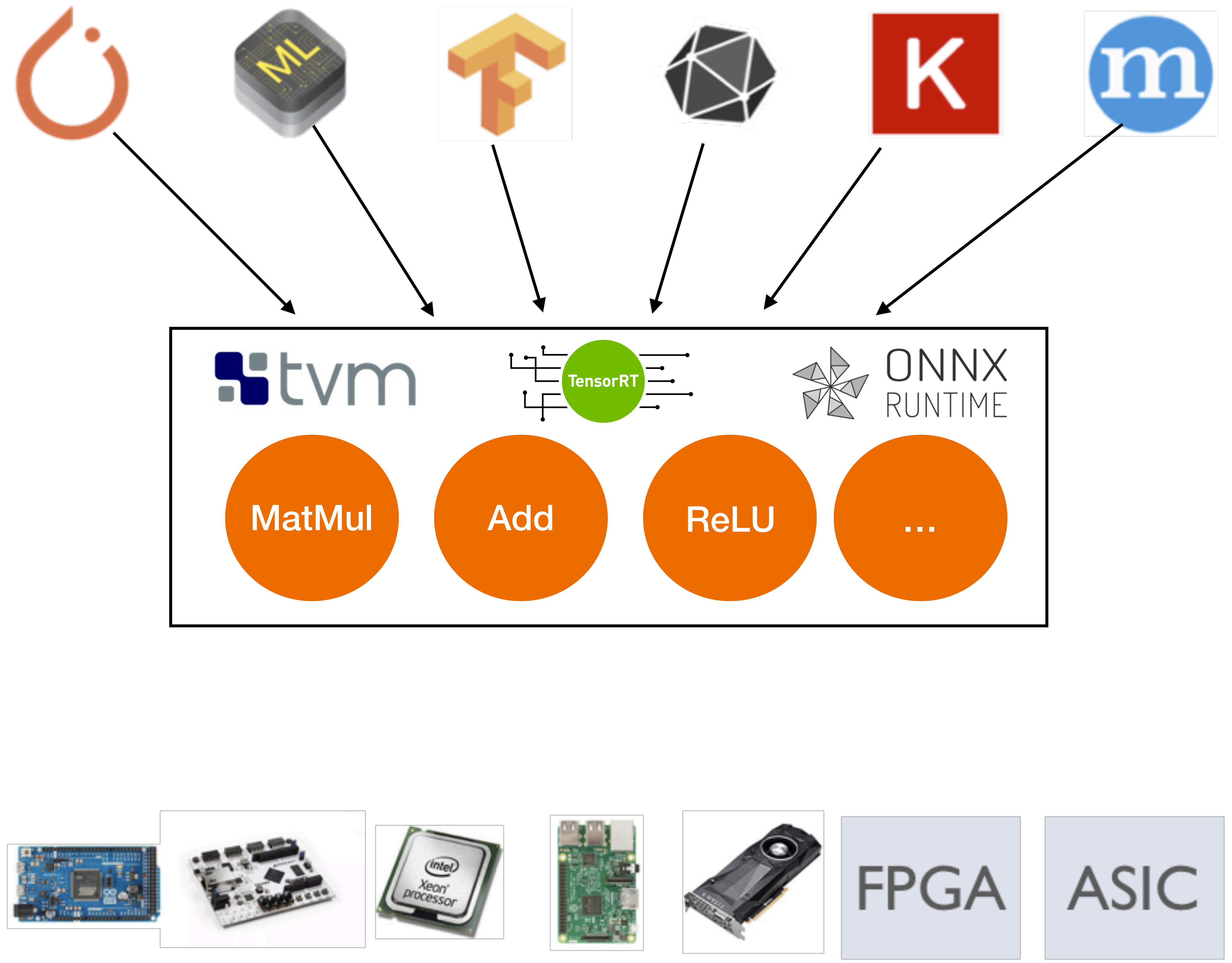

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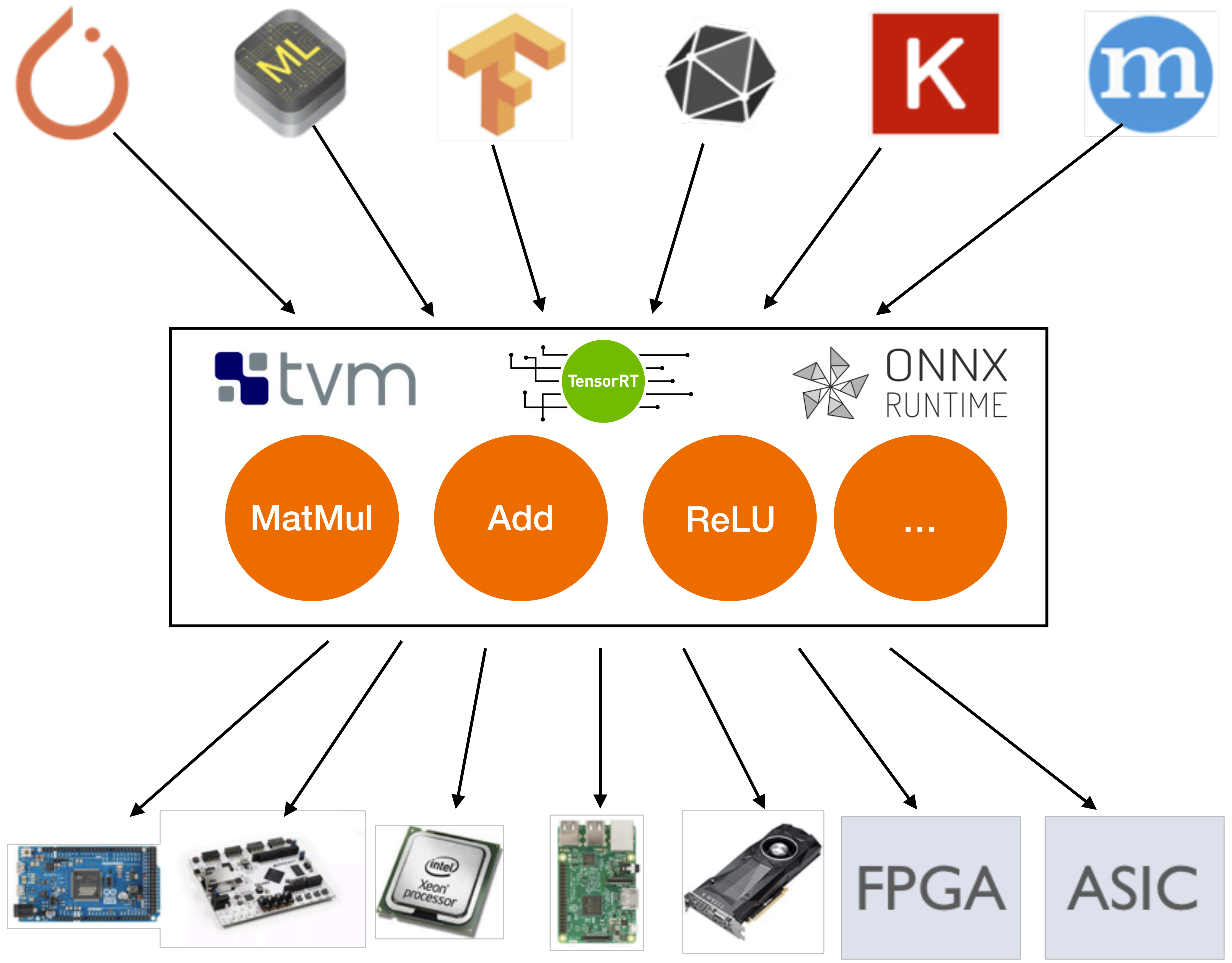

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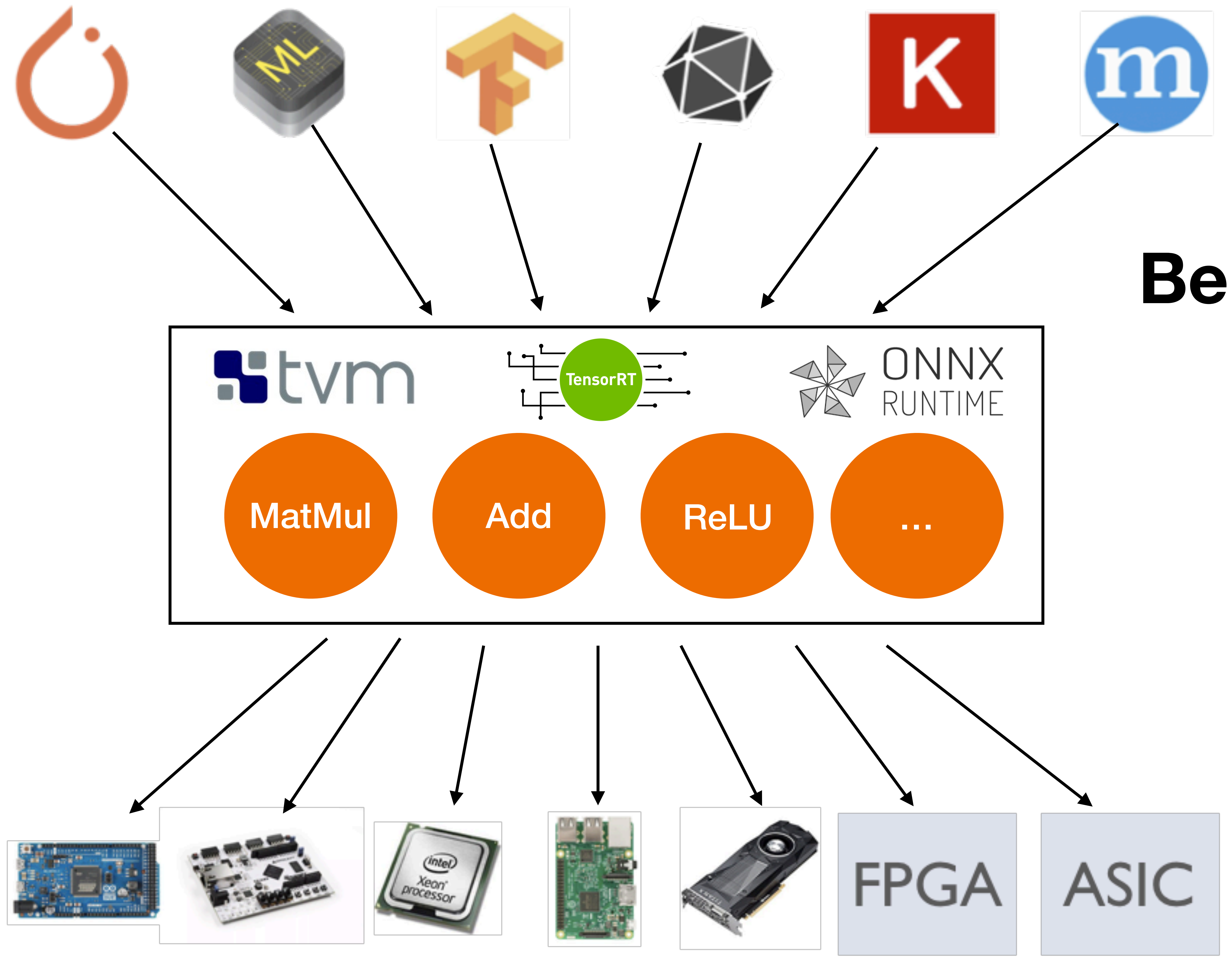

Benefits: Target-independent and target-dependent optimization in a single place.

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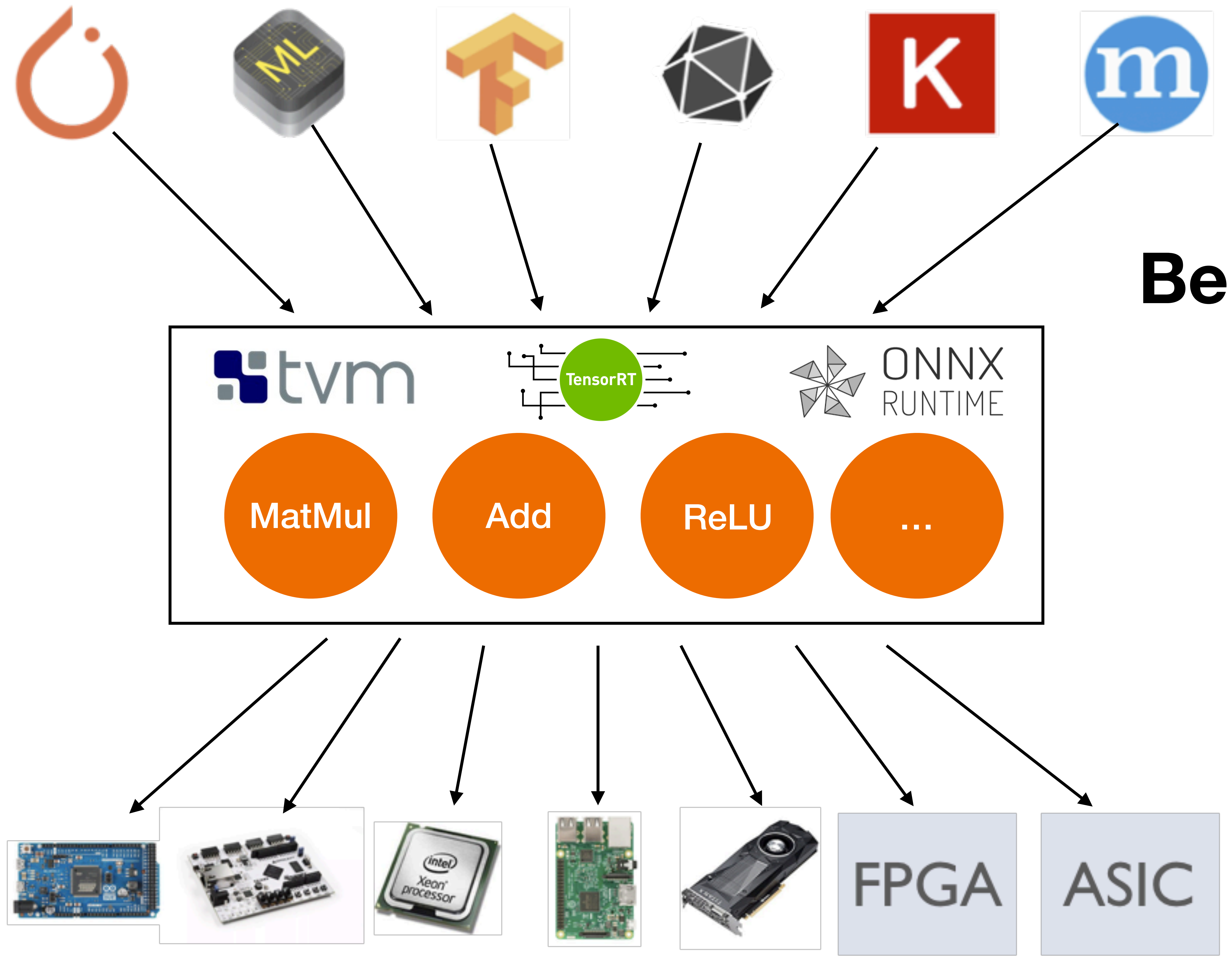

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   Main Idea: Compile Traditional ML Operators into Tensor Operators

   Example: Compiling Decision Tree-based Models

   High-level System Architecture

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Complex data access patterns and control-flow patterns!

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Our Solution: Introduce **redundancies**, both **computational** and **storage**, and make the data access patterns and control flow uniform for all inputs.

Depending on the level of redundancy introduced there can be more than one potential compilation approach.

Hummingbird picks the one that works best for the target setting.

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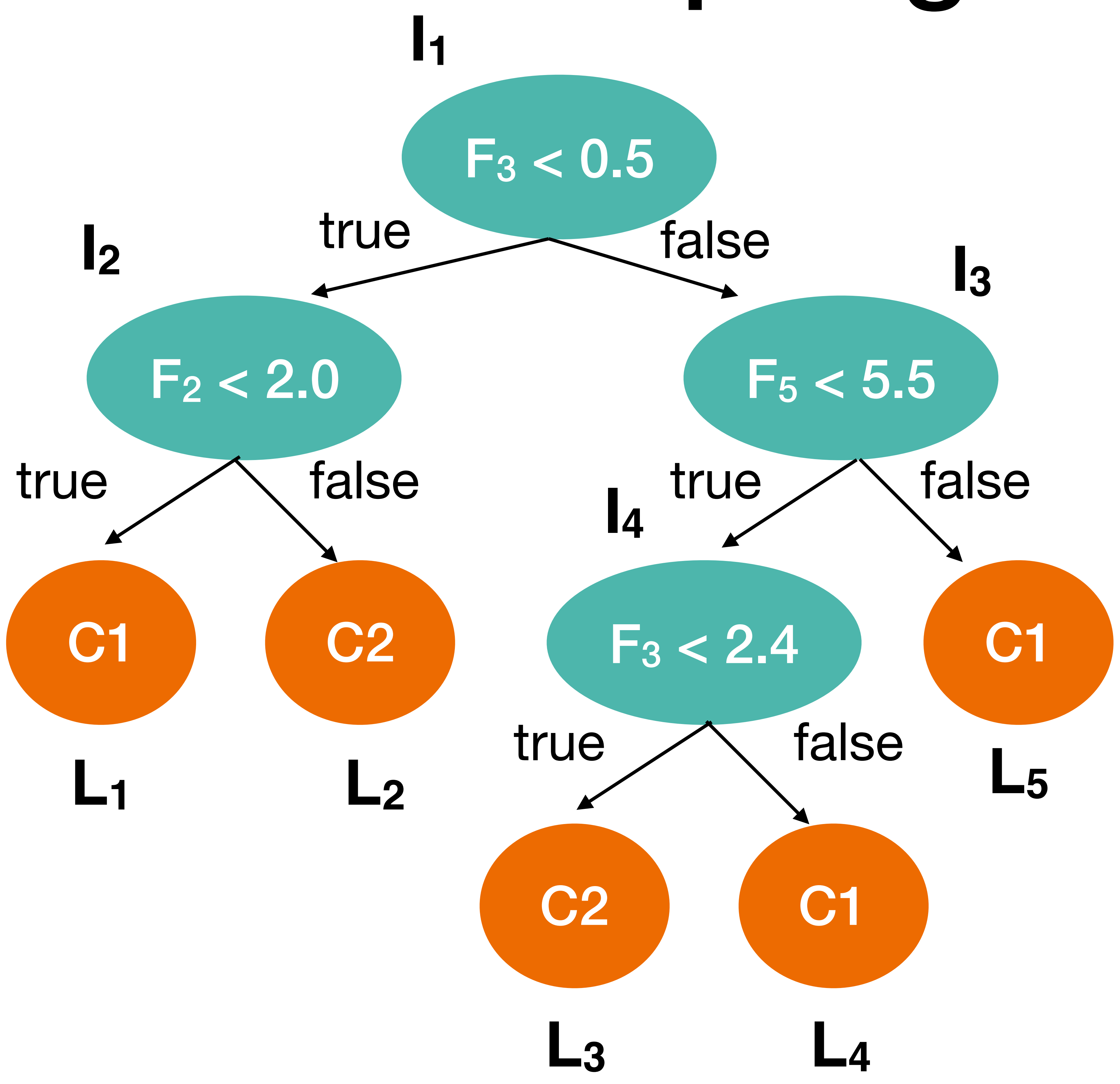
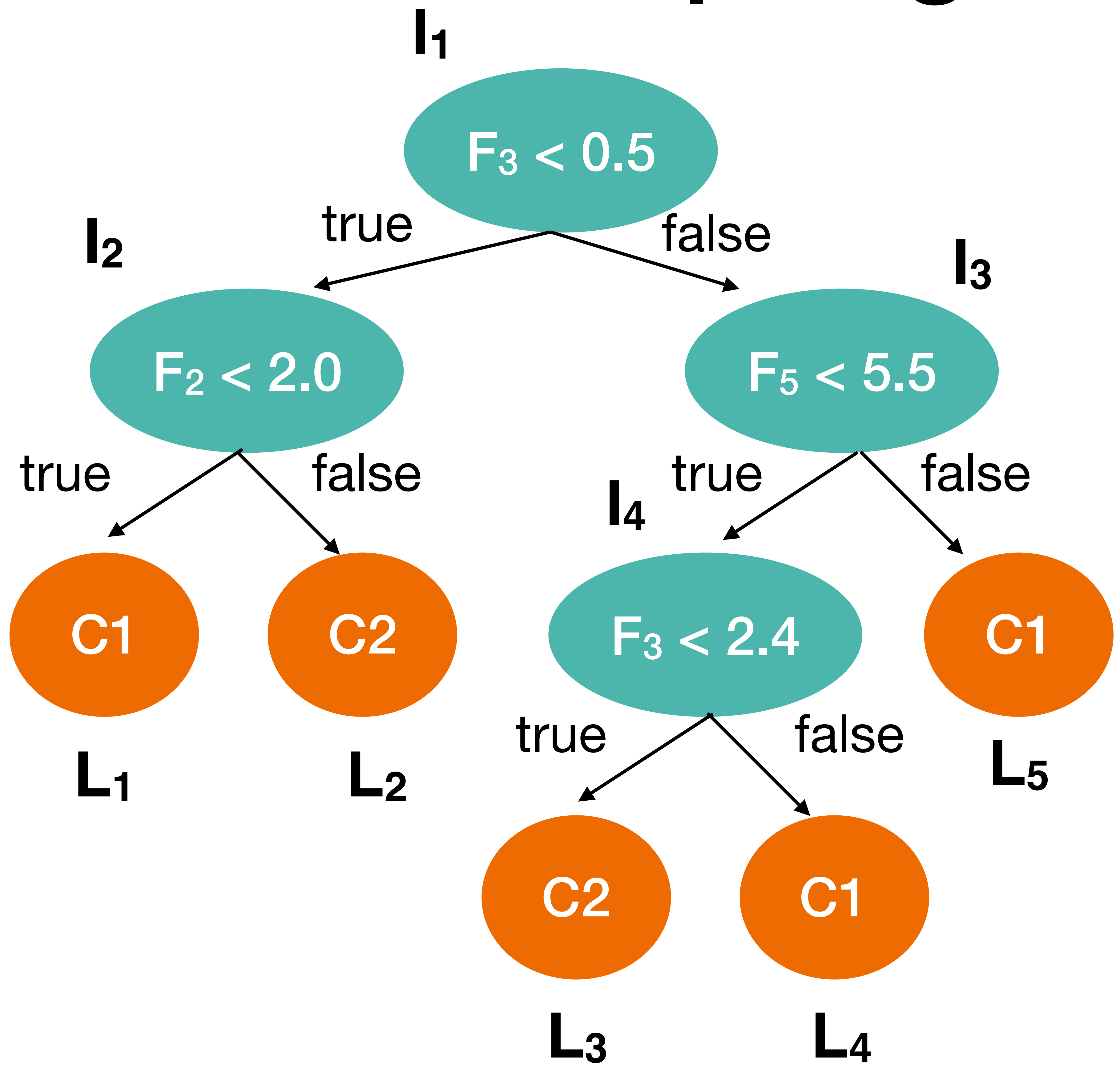


F_1	F_2	F_3	F_4	F_5
0.1	4.5	1.9	10.1	3.5

F (Feature Vector)

Compiling Decision Tree-based Models



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F (Feature Vector)

A

$$\begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

B

$$\begin{bmatrix} 0.5 & 2.0 & 5.5 & 2.4 \end{bmatrix}$$

$$A \in \mathbb{R}^{|F| \times |I|}$$

$$A_{i,j} = \begin{cases} 1, & I_j \textit{ evaluates } F_i \\ 0, & \textit{otherwise} \end{cases}$$

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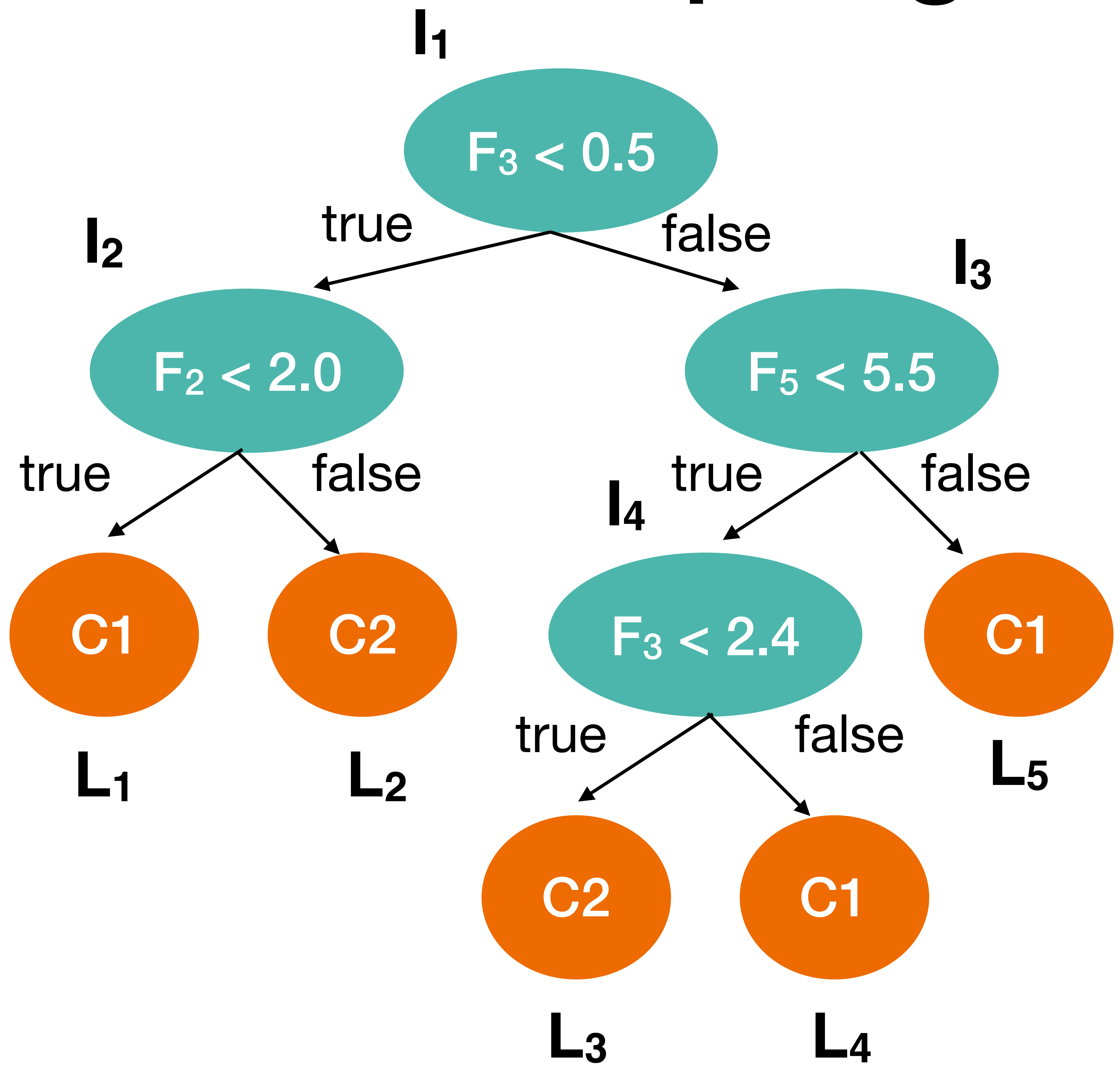

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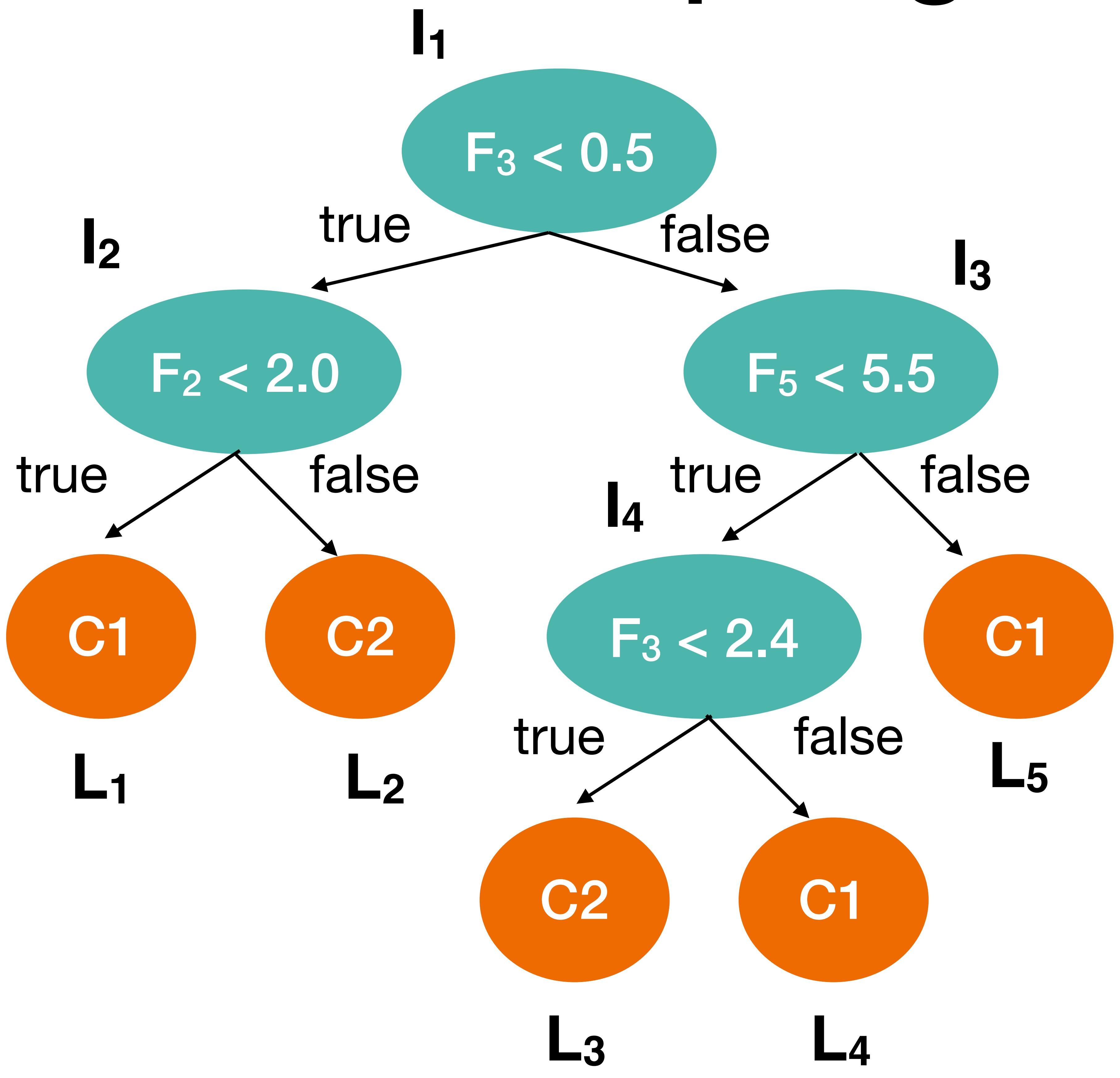

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F (Feature Vector)

C

1	1	-1	-1	-1
1	-1	0	0	0
0	0	1	1	-1
0	0	1	-1	0

$$C \in \mathbb{R}^{|I|\times|L|}$$

$$C_{i,j} = \begin{cases} -1, \ L_j \in \ RightSubTree(I_i) \\ 1, \ L_j \in \ LeftSubTree(I_i) \\ 0, \ otherwise \end{cases}$$

D

2	1	2	1	0

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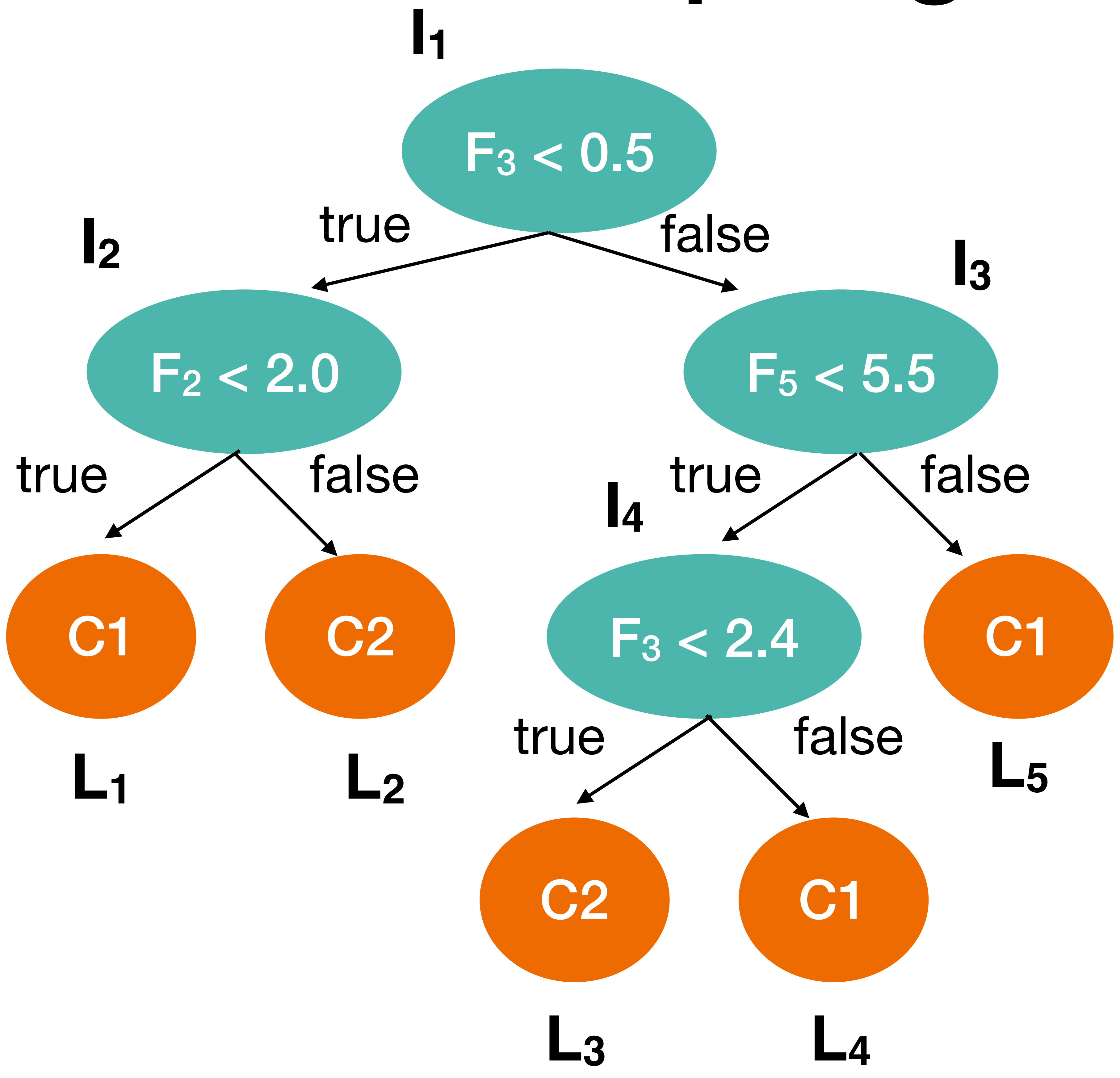

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$$D \in \mathbb{R}^{|L|}$$

$$D_j = \sum_{k \in L_j \xrightarrow{path} Root} \mathbf{1}(k == \ LeftChild(Parent(k)))$$

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Compiling Decision Tree-based Models

$$
\begin{bmatrix} 0 & 0 & 1 & 1 \end{bmatrix}
\times
\begin{bmatrix} 1 & 1 & -1 & -1 & -1 \\ 1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & -1 \\ 0 & 0 & 1 & -1 & 0 \end{bmatrix}
$$

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\begin{array}{cccc} I_1 & I_2 & I_3 & I_4 \\ \hline 0 & 0 & 1 & 1 \end{array}
\times
\overset{C}{\begin{bmatrix} 1 & 1 & -1 & -1 & -1 \\ 1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & -1 \\ 0 & 0 & 1 & -1 & 0 \end{bmatrix}}
=
\begin{bmatrix} 0 & 0 & 1 & 1 & -1 \end{bmatrix}
$$

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$$\begin{array}{cccc} I_1 & I_2 & I_3 & I_4 \end{array}$$

$$\begin{bmatrix} 0 & 0 & 1 & 1 \end{bmatrix} \times \underbrace{\begin{bmatrix} 1 & 1 & -1 & -1 & -1 \\ 1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & -1 \\ 0 & 0 & 1 & -1 & 0 \end{bmatrix}}_{\text{ }}^{} = \begin{bmatrix} 0 & 0 & 1 & 1 & -1 \end{bmatrix}$$

C

D

$$\begin{bmatrix} 0 & 0 & 1 & 1 & -1 \end{bmatrix} == \begin{bmatrix} 2 & 1 & 2 & 1 & 0 \end{bmatrix}$$

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$$
\begin{array}{cccc} I_1 & I_2 & I_3 & I_4 \\ \end{array}
\qquad
C
$$

$$
\begin{bmatrix} 0 & 0 & 1 & 1 \end{bmatrix}
\times
\begin{bmatrix} 1 & 1 & -1 & -1 & -1 \\ 1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & -1 \\ 0 & 0 & 1 & -1 & 0 \end{bmatrix}
=
\begin{bmatrix} 0 & 0 & 1 & 1 & -1 \end{bmatrix}
$$

$$
\begin{array}{c} \\ \begin{bmatrix} 0 & 0 & 1 & 1 & -1 \end{bmatrix} \end{array}
==
\begin{array}{c} D \\ \begin{bmatrix} 2 & 1 & 2 & 1 & 0 \end{bmatrix} \end{array}
$$

$$
= \begin{array}{ccccc} L_1 & L_2 & L_3 & L_4 & L_5 \\ \hline 0 & 0 & 0 & 1 & 0 \end{array}
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\begin{array}{cccc} I_1 & I_2 & I_3 & I_4 \\ \hline 0 & 0 & 1 & 1 \end{array}
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\overset{\textbf{C}}{\begin{bmatrix} 1 & 1 & -1 & -1 & -1 \\ 1 & -1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & -1 \\ 0 & 0 & 1 & -1 & 0 \end{bmatrix}}
\;=\;
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$$
= \begin{array}{ccccc} L_1 & L_2 & L_3 & L_4 & L_5 \\ \hline 0 & 0 & 0 & 1 & 0 \end{array}
$$

This technique can be easily adopted for tree-ensembles by batching individual tensors for each tree.

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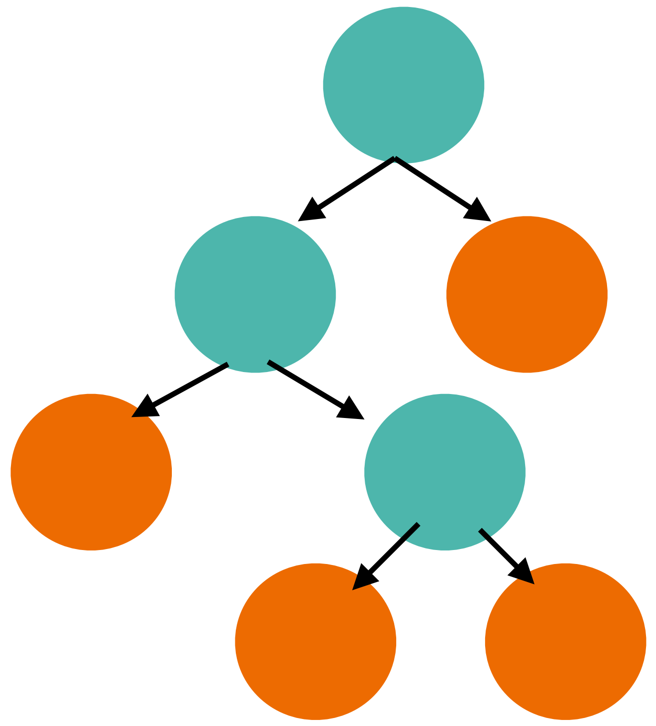
Two other tree traversal-based methods that exploit the tree structure.

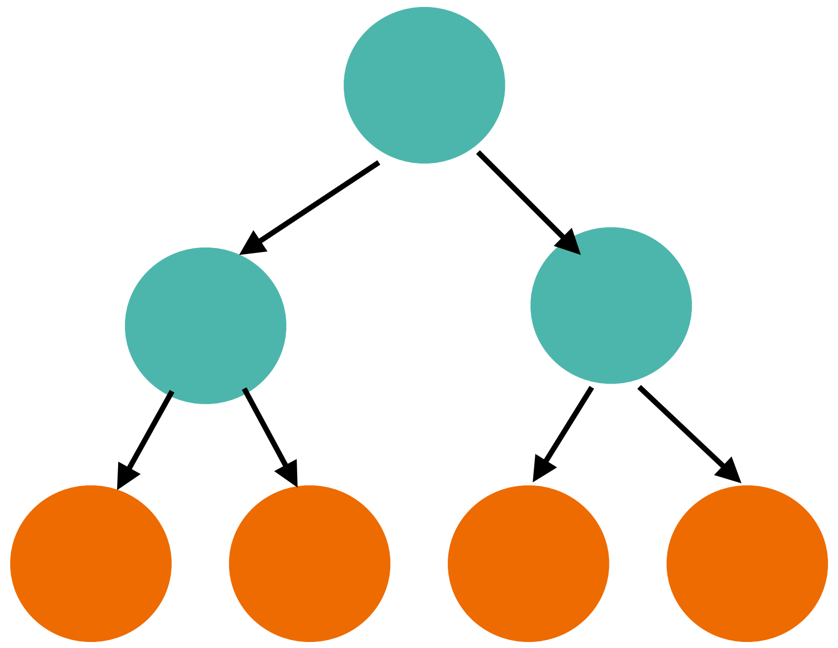
TreeTraversal

For tall trees (e.g., LightGBM)



PerfectTreeTraversal

For bushy trees (e.g., XGBoost)



Compiling Decision Tree-based Models

Above approach (**GEMM** approach) essentially evaluates all paths in a decision tree model: **computation redundancy**.

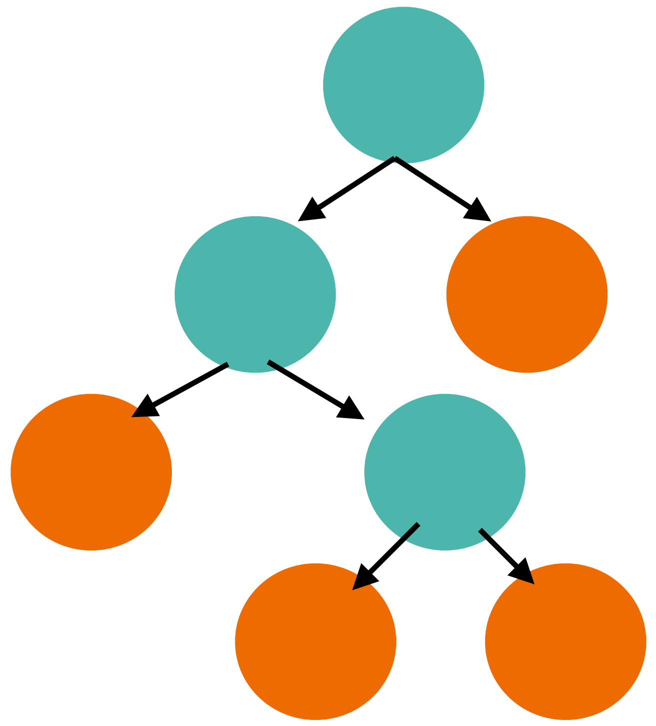
Encoding tree structure using tensors introduce **storage redundancy**.

Works surprisingly well on modern hardware for many cases!

Two other tree traversal-based methods that exploit the tree structure.

TreeTraversal

For tall trees (e.g., LightGBM)



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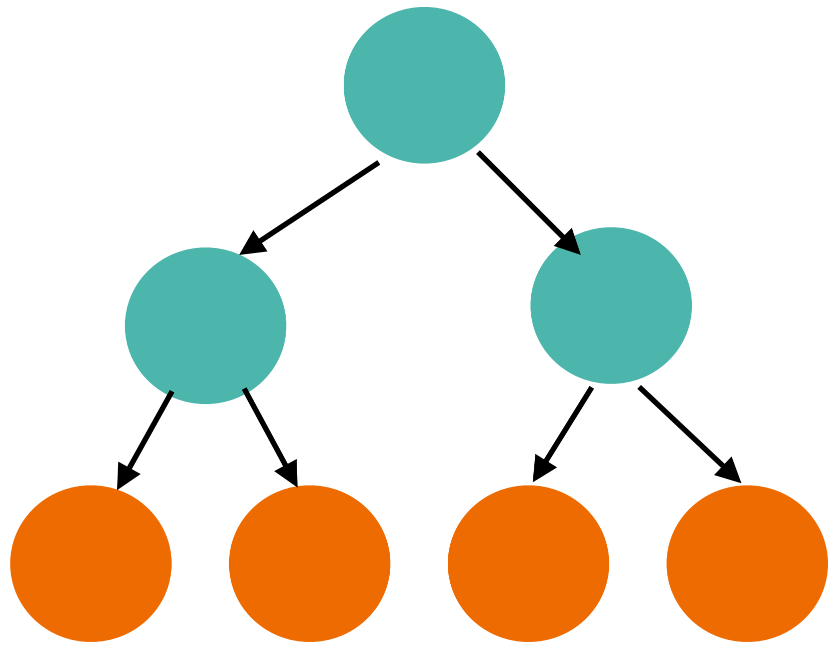


More details about these methods and a summary of techniques used to compile 40+ Scikit-Learn ops can be found in our paper.

Outline

1. Background

2. Our System: Hummingbird

    Main Idea: Compile Traditional ML Operators into Tensor Operators

    Example: Compiling Decision Tree-based Models

    High-level System Architecture

3. Experimental Evaluation

High-level System Architecture

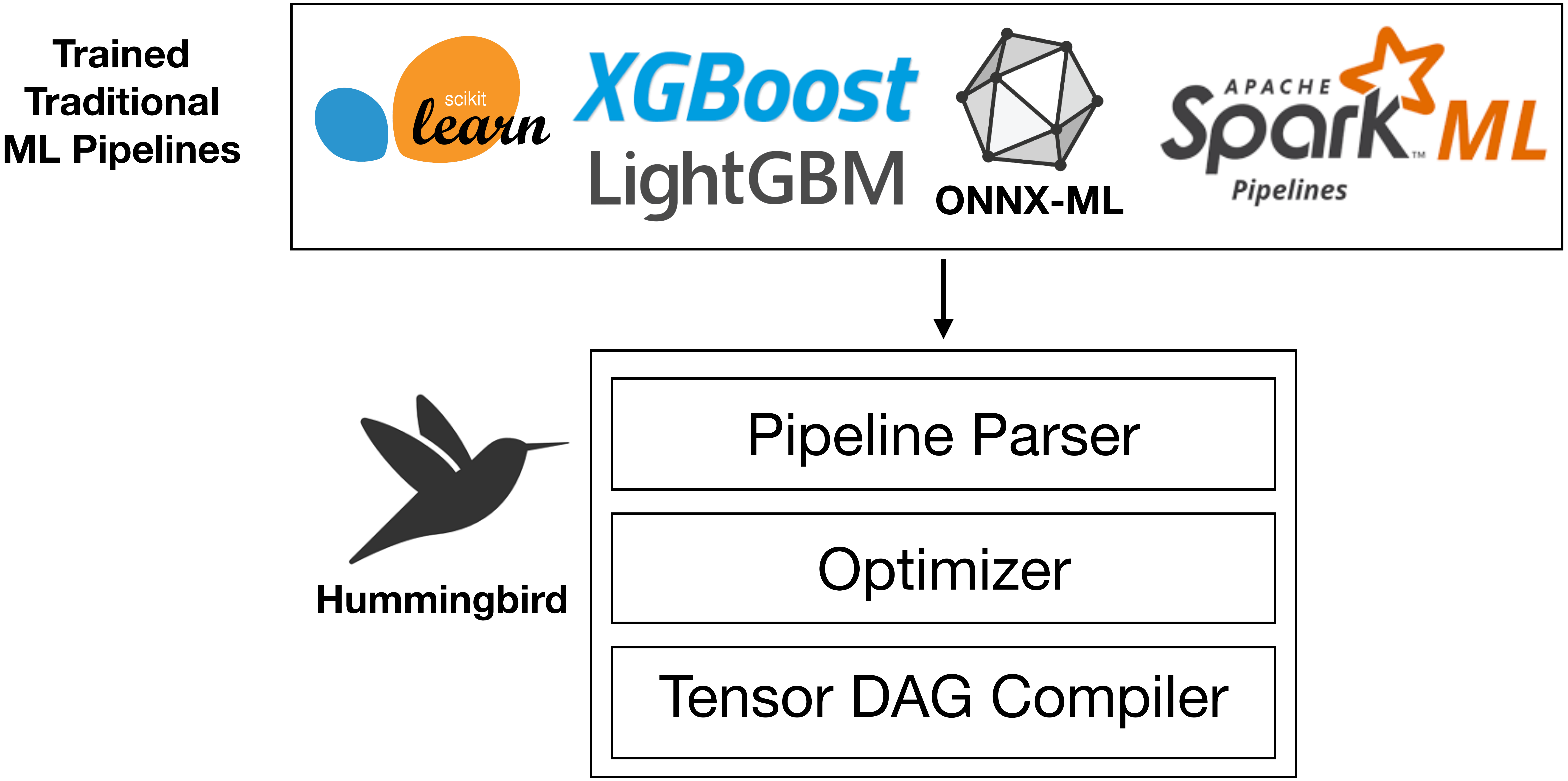
Hummingbird

Pipeline Parser

Optimizer

Tensor DAG Compiler

High-level System Architecture



High-level System Architecture

Trained Traditional ML Pipelines

scikit learn | XGBoost | LightGBM | ONNX-ML | APACHE Spark ML Pipelines

↓

Hummingbird

- Pipeline Parser
- Optimizer
- Tensor DAG Compiler

Optimizations:

Heuristics-based strategy selection

Feature selection push-down

Algebraic rewrites

Batching stacked models

(More details in our paper)

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DL Prediction Serving Systems

tvm | ONNX RUNTIME | PyTorch/TorchScript

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tvm · ONNX RUNTIME · PyTorch/TorchScript · TensorRT · TF XLA

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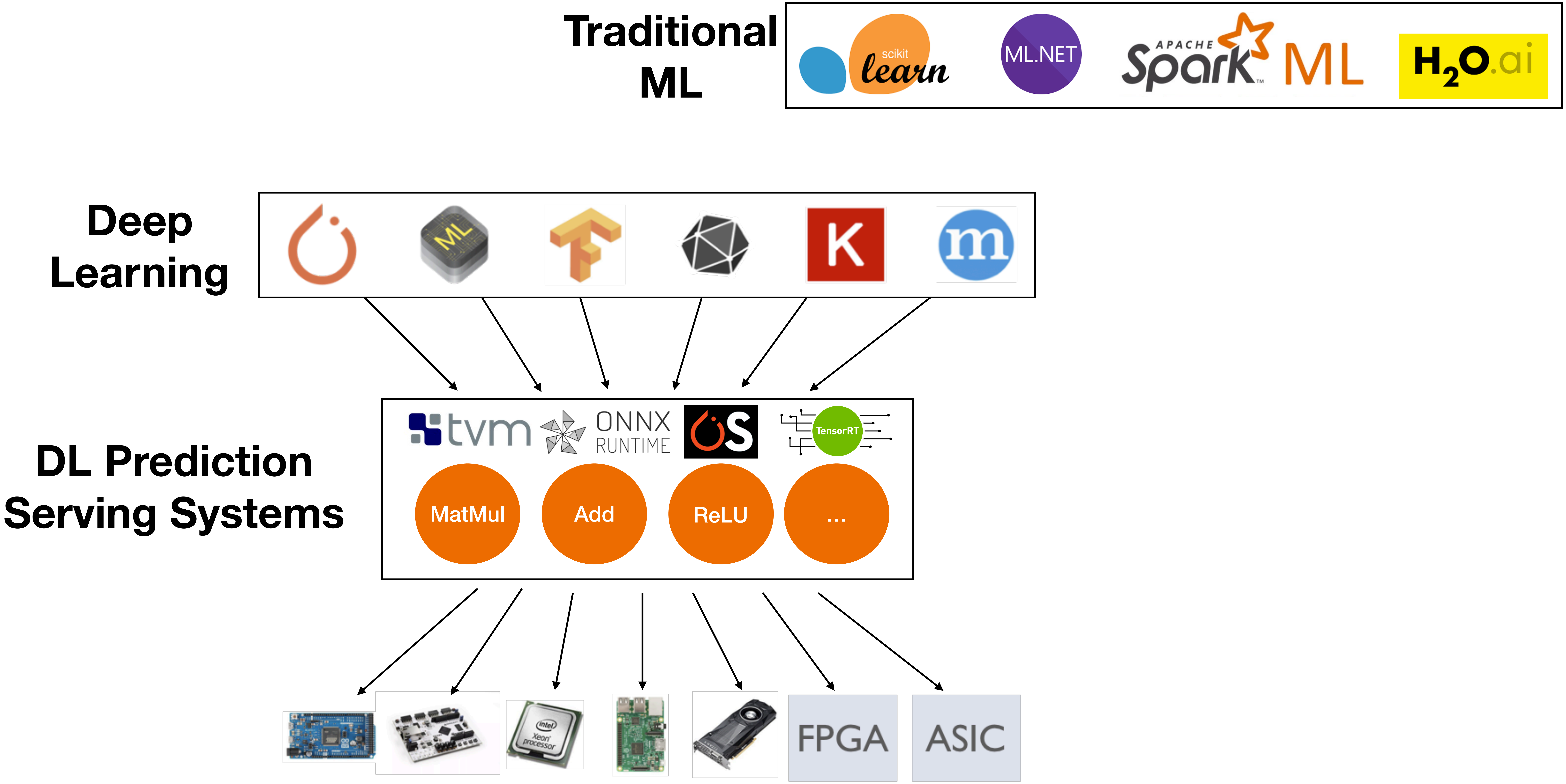
Traditional ML
scikit learn
ML.NET
APACHE Spark ML
H2O.ai
Deep Learning
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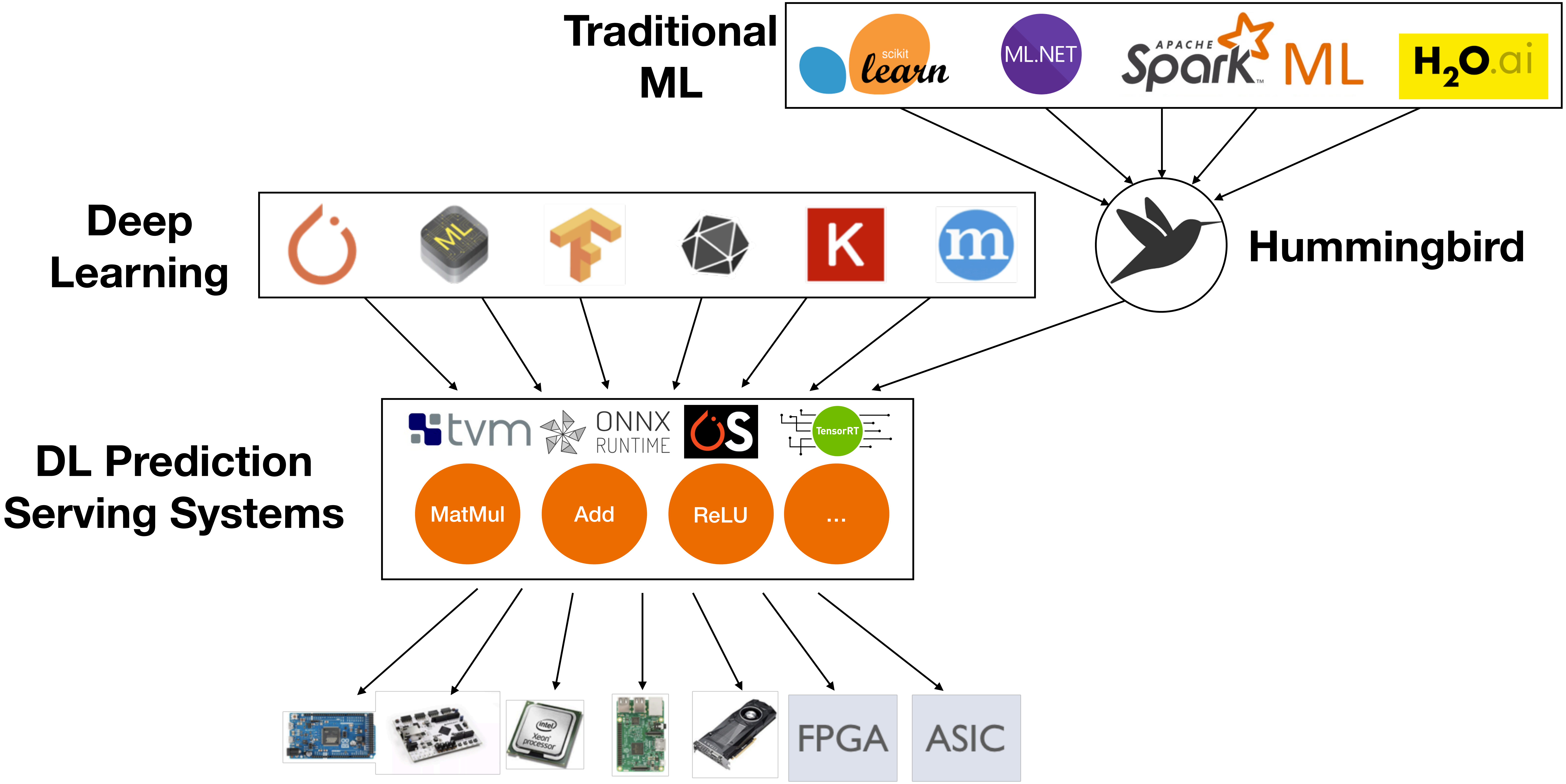
MatMul
Add
ReLU
...
FPGA
ASIC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Outline

1. Background

2. Our System: Hummingbird

3. Experimental Evaluation

End-to-End Pipeline Evaluation

Hardware Setup

Azure NC6 v2 machine

Intel Xeon E5-2690 v4@ 2.6GHz (6 cores)

112 GB RAM

Nvidia P100

Ubuntu 18.04,
PyTorch 1.3, TVM 0.6, CUDA 10,
RAPIDS 0.9

End-to-End Pipeline Evaluation

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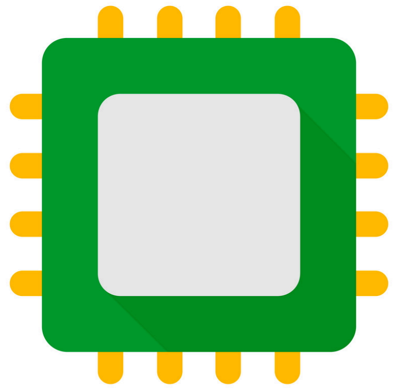

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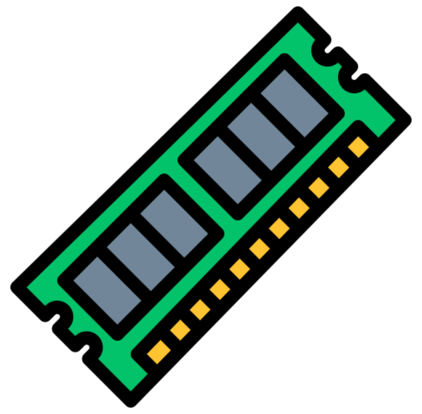

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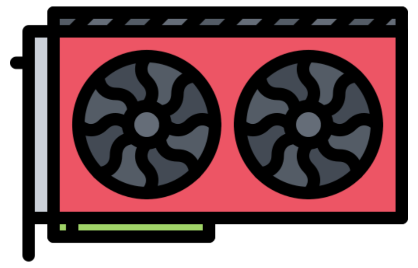

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Experimental Workload

Scikit-Learn pipelines for OpenML-CC18 benchmark which has 72 datasets.

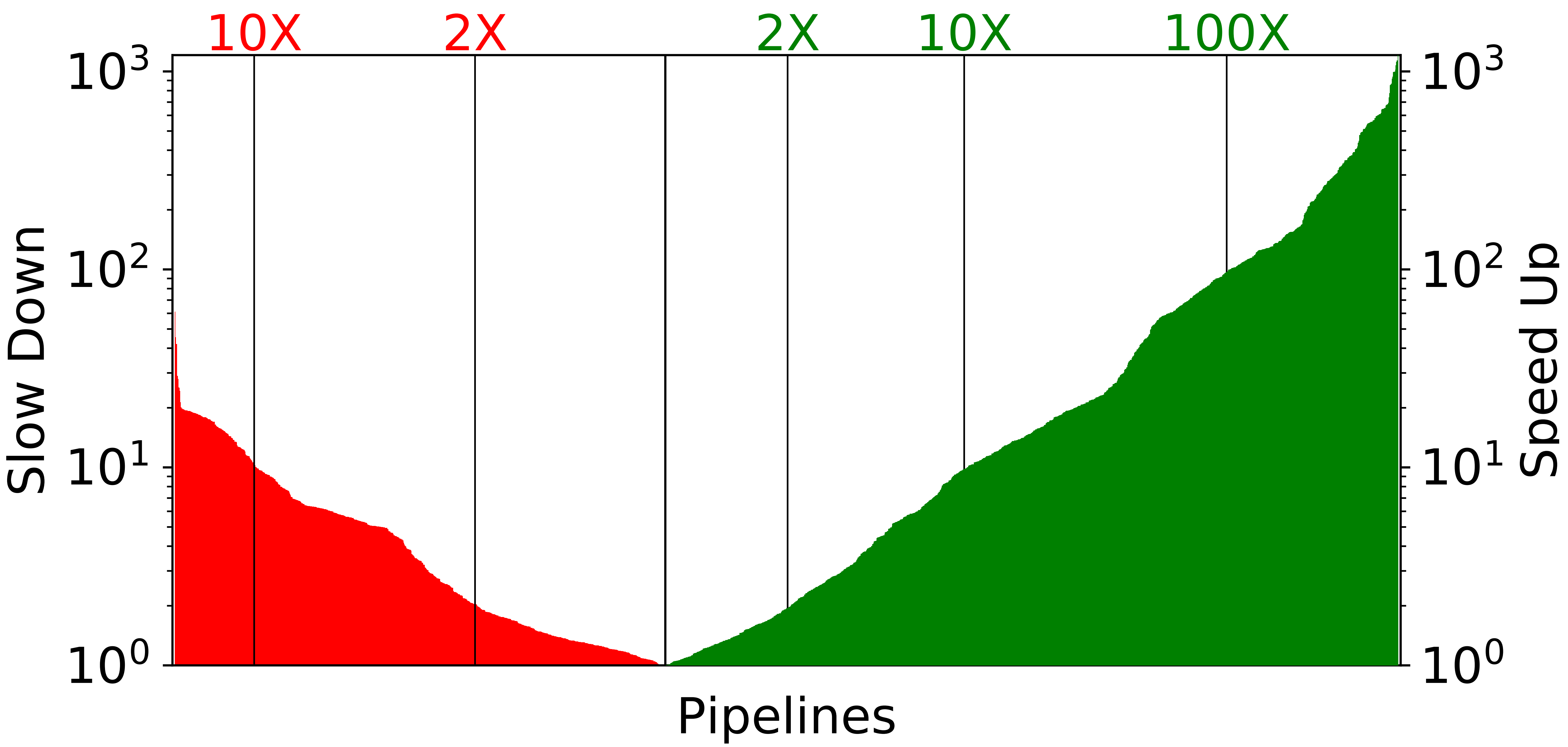
Hummingbird can translate 2328 pipelines (88%).

Perform inference on 20% of the dataset.

TorchScript as the backend for Hummingbird.

End-to-End Pipeline Evaluation

CPU



End-to-End Pipeline Evaluation

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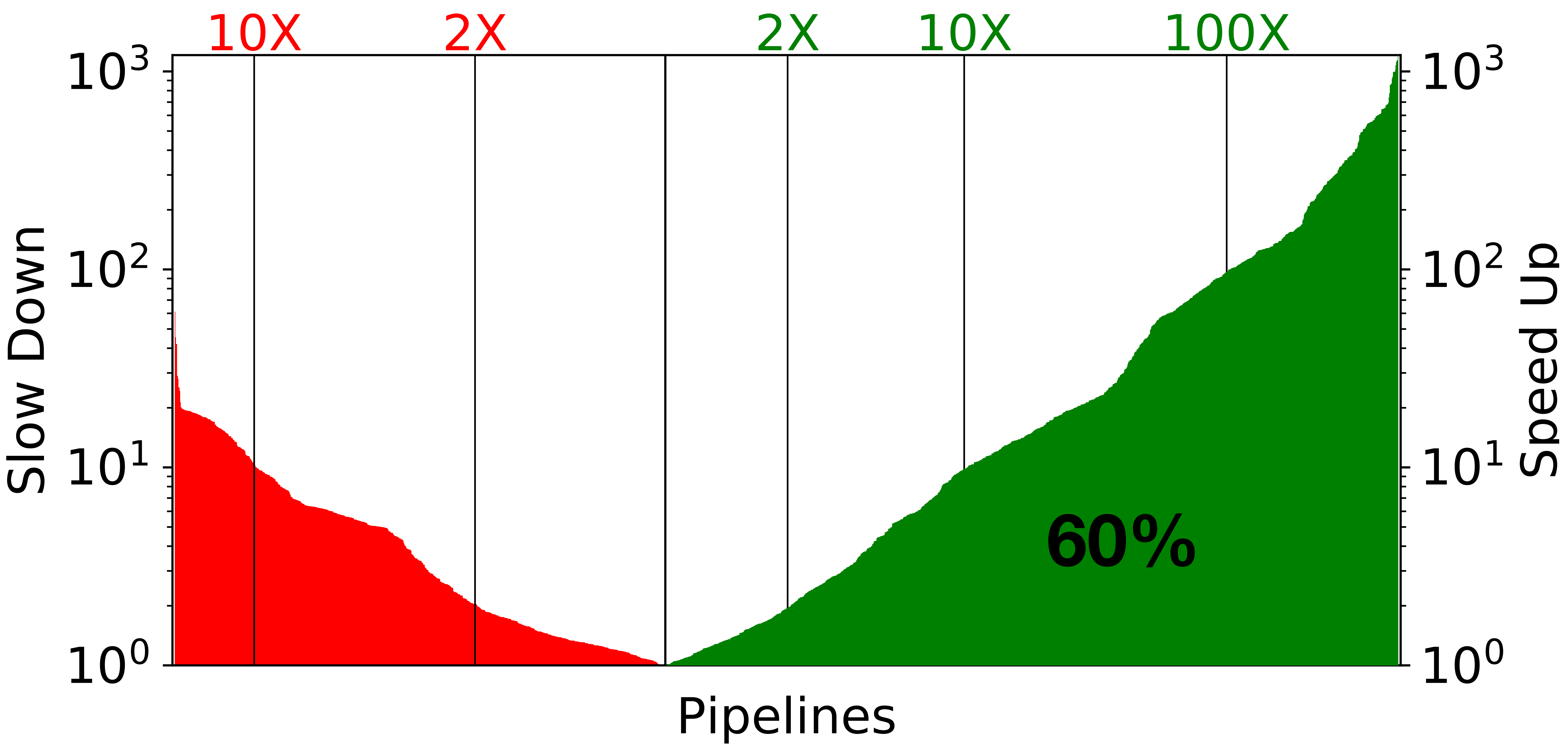

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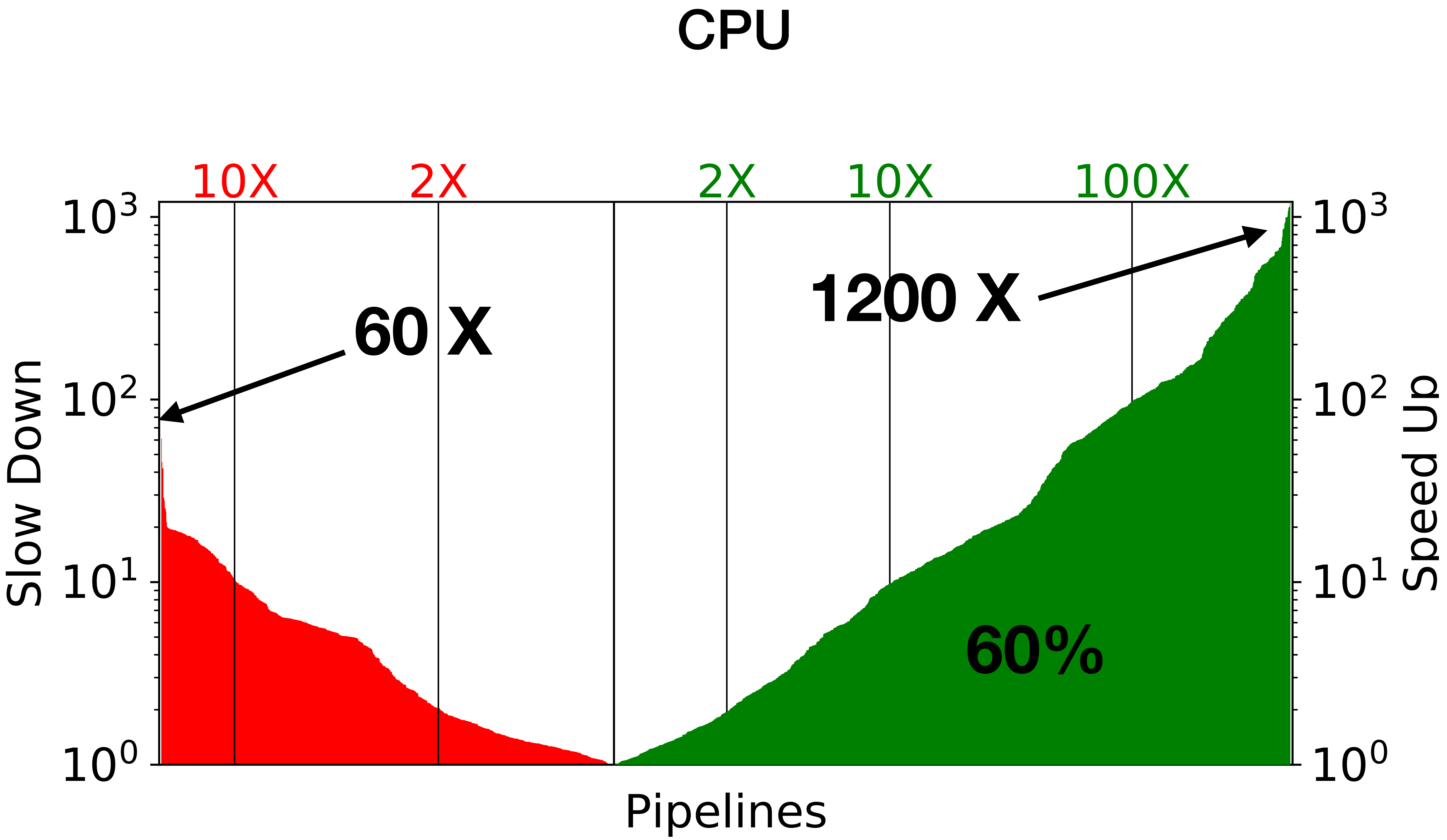

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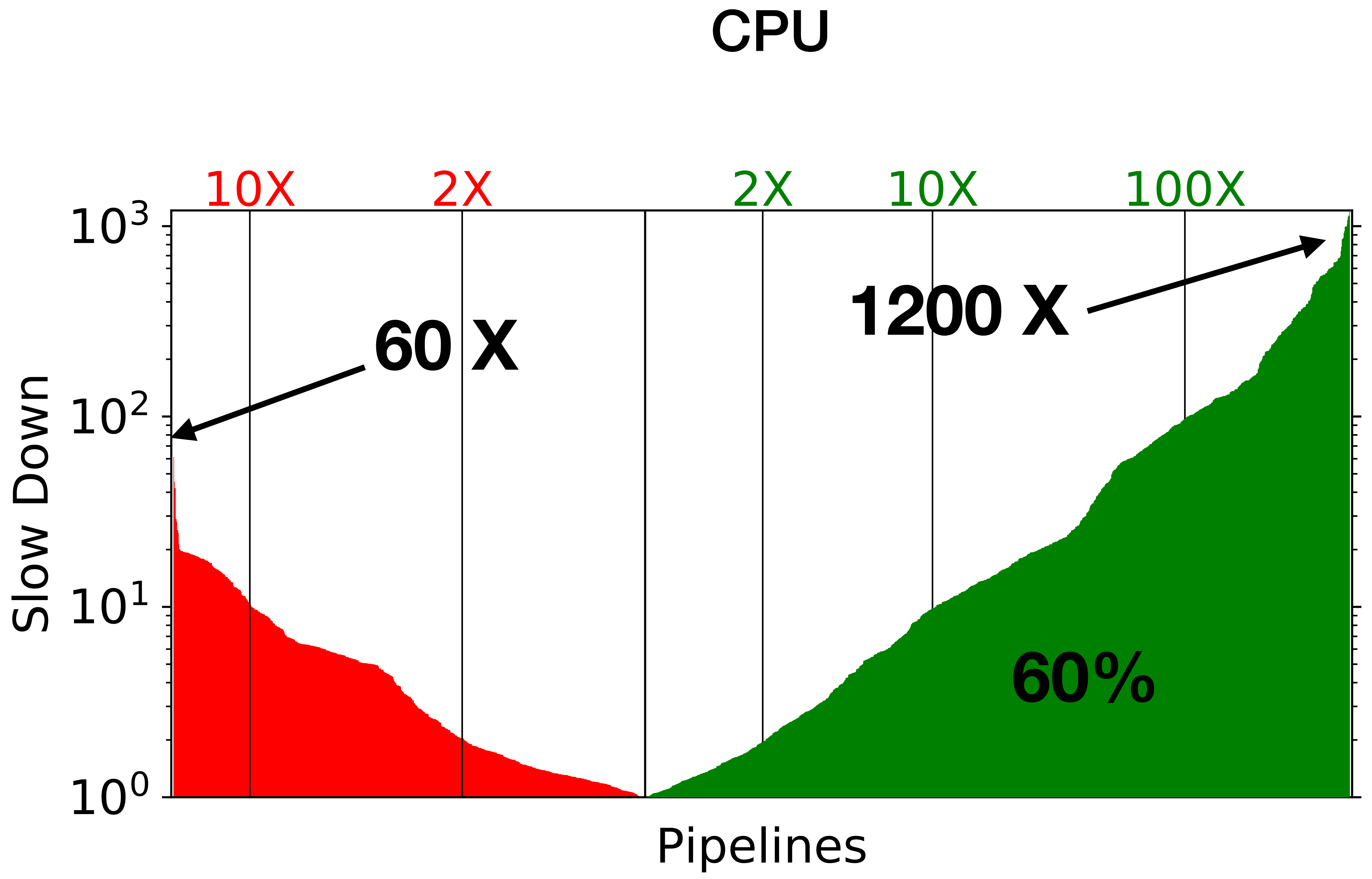

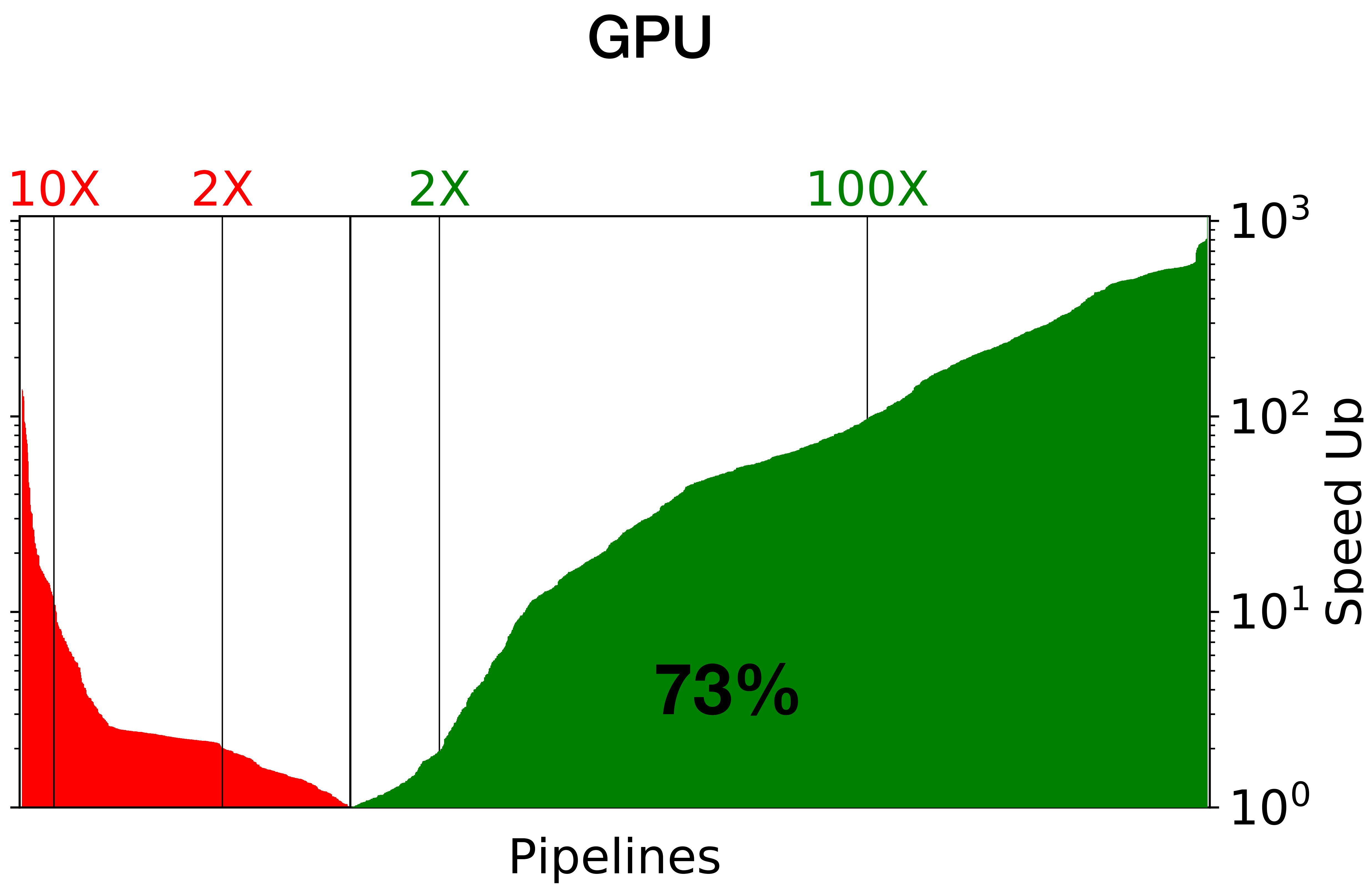

End-to-End Pipeline Evaluation

End-to-End Pipeline Evaluation

Main reasons for slowdowns: Sparse input data, small inference datasets.

Tree-Models Microbenchmark

Experimental Workload: Nvidia Gradient Boosting Algorithm Benchmark*

Dataset	Rows	#Features	Task
Fraud	285k	28	BinaryClass
Year	512k	90	Regression
Covtype	581k	54	MultiClass
Epsilon	500k	2000	BinaryClass

(* https://github.com/NVIDIA/gbm-bench)

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3 Models: RandomForest, XGBoost, LightGBM.

80/20 train/test split.

Batch inference (batch size 10k w/ and w/o GPU.

(* https://github.com/NVIDIA/gbm-bench)

Tree-Models Microbenchmark

Algorithm	Dataset	Sklearn (CPU Baseline)	Hummingbird (CPU)		RAPIDS (GPU Baseline)	Hummingbird (GPU)	
			TorchScript	TVM		TorchScript	TVM
Rand. Forest	Fraud						
	Year						
	Covtype						
	Epsilon						
LightGBM	Fraud						
	Year						
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(All runtimes are reported in seconds. More datasets and experimental results in the paper.)

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Rand. Forest	Fraud	**2.5**	7.8	3.0			
	Year	1.9	7.7	**1.4**			
	Covtype	**5.9**	16.5	6.8			
	Epsilon	9.8	13.9	**6.6**			
LightGBM	Fraud	3.4	7.6	**1.7**			
	Year	5.0	7.6	**1.6**			
	Covtype	51.1	79.5	**27.2**			
	Epsilon	10.5	14.5	**4.0**			
XGBoost	Fraud	1.9	7.6	**1.6**			
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LightGBM	Fraud	3.4	7.6	**1.7**	**0.014**	0.044	**0.014**
	Year	5.0	7.6	**1.6**	**0.023**	0.045	0.025
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Summary

Hummingbird: A Tensor Compiler for Unified Machine Learning Prediction Serving.

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Thank You!

https://github.com/microsoft/hummingbird

hummingbird-dev@microsoft.com

ARTIFACT EVALUATED usenix ASSOCIATION AVAILABLE

ARTIFACT EVALUATED usenix ASSOCIATION FUNCTIONAL

ARTIFACT EVALUATED usenix ASSOCIATION REPRODUCED