Arc

An MLIR Dialect for Data Analytics

PLDS' 20 Workshop
March 5, 2020

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- Outline
    - **Introduction & Problem**
    - **Related Work**
    - **Arc & MLIR**
    - **Summary**

Introduction & Problem

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[Q1]: What does a programming language for **data analytics** definitely need?

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[Q2]: Which **data types**?

Introduction & Problem

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[A2]: Tables, **Arrays, Streams, Graphs, …**

Introduction & Problem

[Q1]: What does a programming language for **data analytics** definitely need?
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[Q2]: Which **data types**?
[A2]: Tables, **Arrays, Streams, Graphs, …**

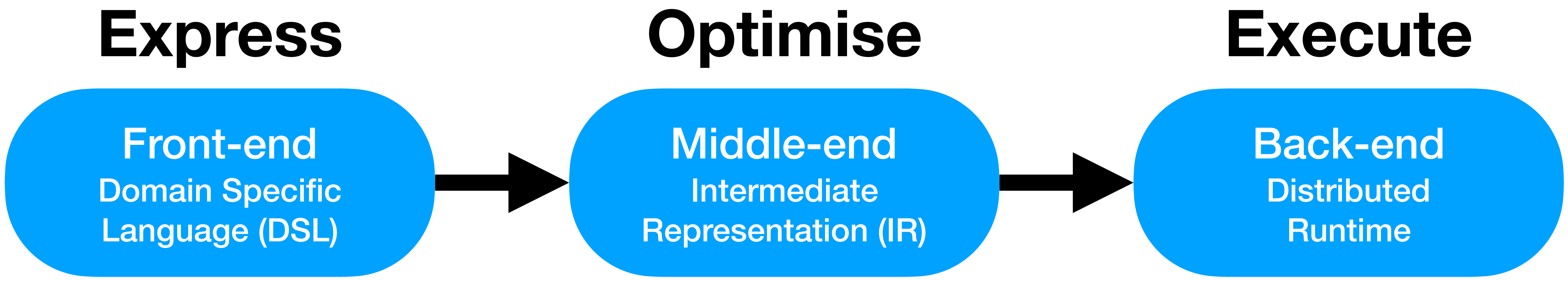
[Q3]: Can **[A1]** be "combined" under one **system** and **programming model**?

Introduction & Problem

Introduction & Problem

Express **Optimise** **Execute**

Introduction & Problem



Introduction & Problem

Express

Front-end
Domain Specific Language (DSL)

Challenges:

Optimise

Middle-end
Intermediate Representation (IR)

Challenges:

Execute

Back-end
Distributed Runtime

Challenges:

Introduction & Problem

Express	Optimise	Execute
Front-end Domain Specific Language (DSL)	**Middle-end** Intermediate Representation (IR)	**Back-end** Distributed Runtime

Challenges:
- Abstraction level
- Syntax & type system
- Tooling & Integration

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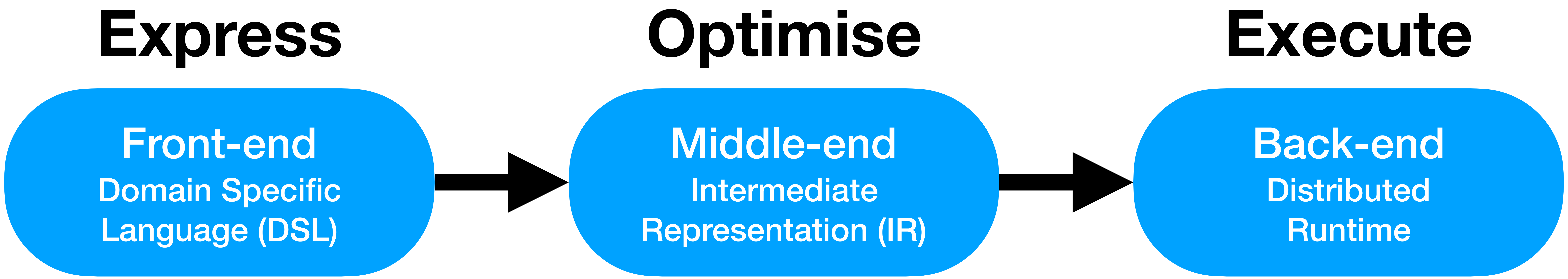
Introduction & Problem



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Challenges:
- Progressive lowering
- Algebraic simplification
- Instruction selection
- Cost model

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Challenges:
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Challenges:
- State management
- Scheduling
- Failure recovery
- Profiling & Debugging

Related Work

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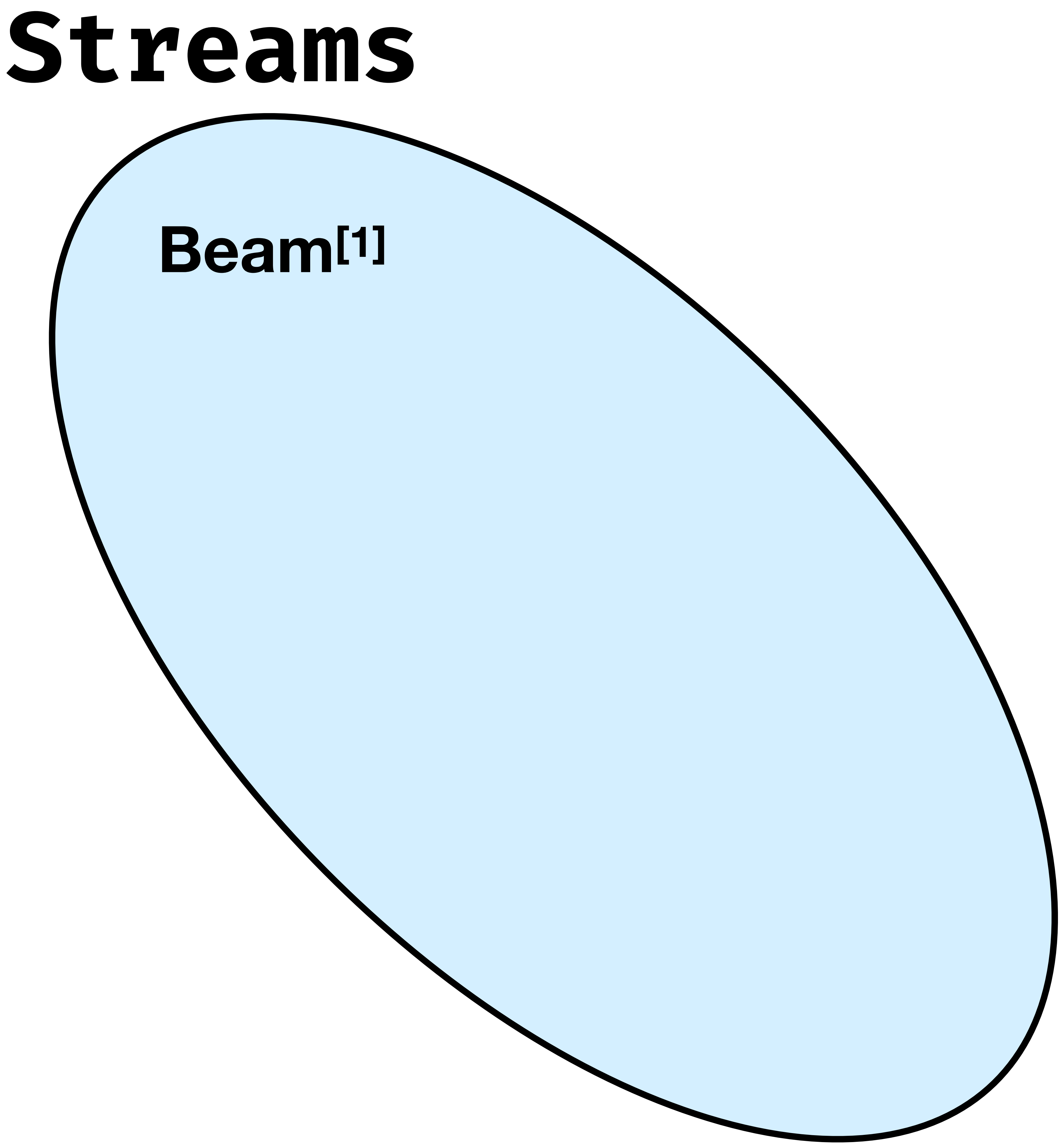

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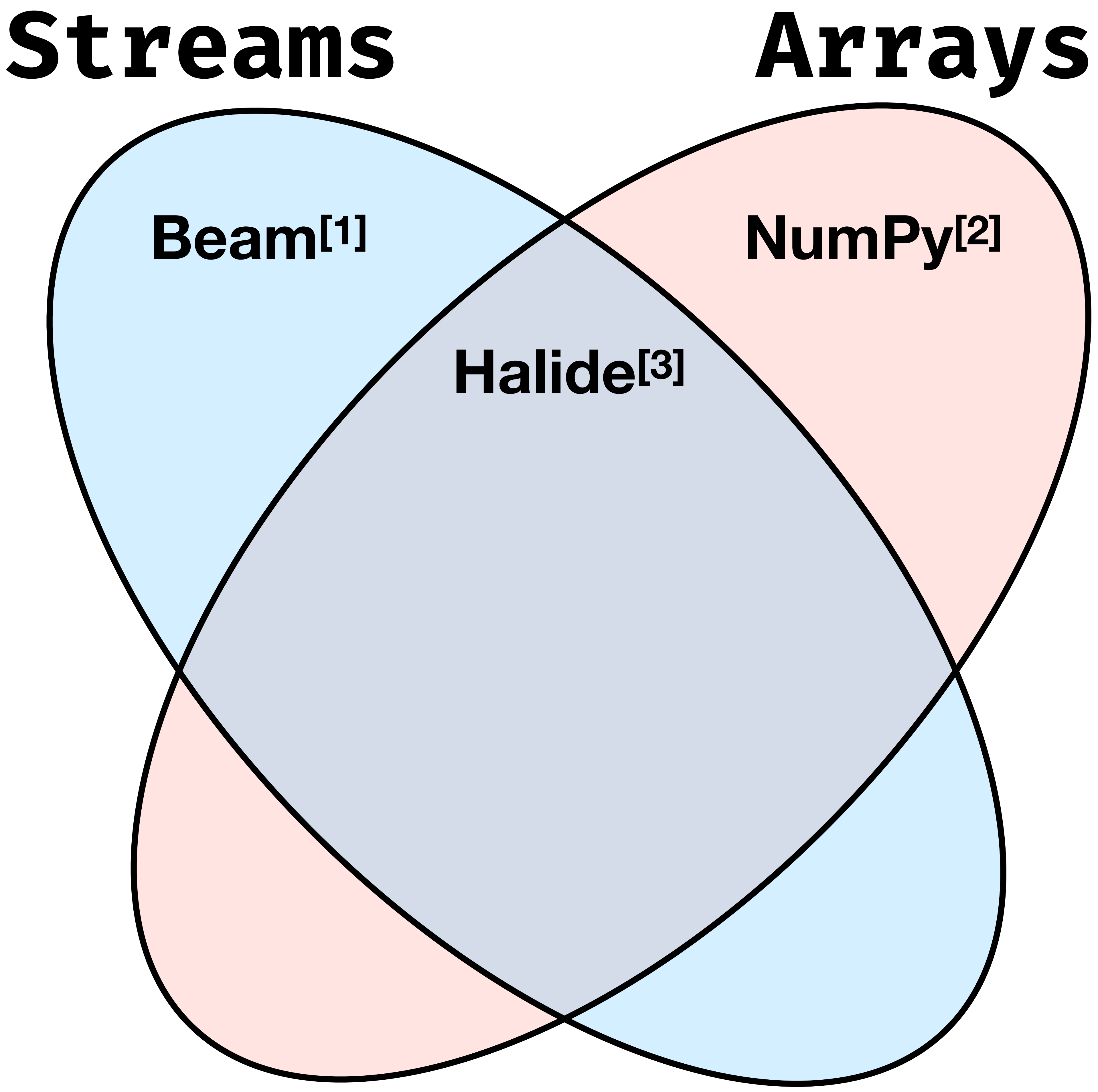

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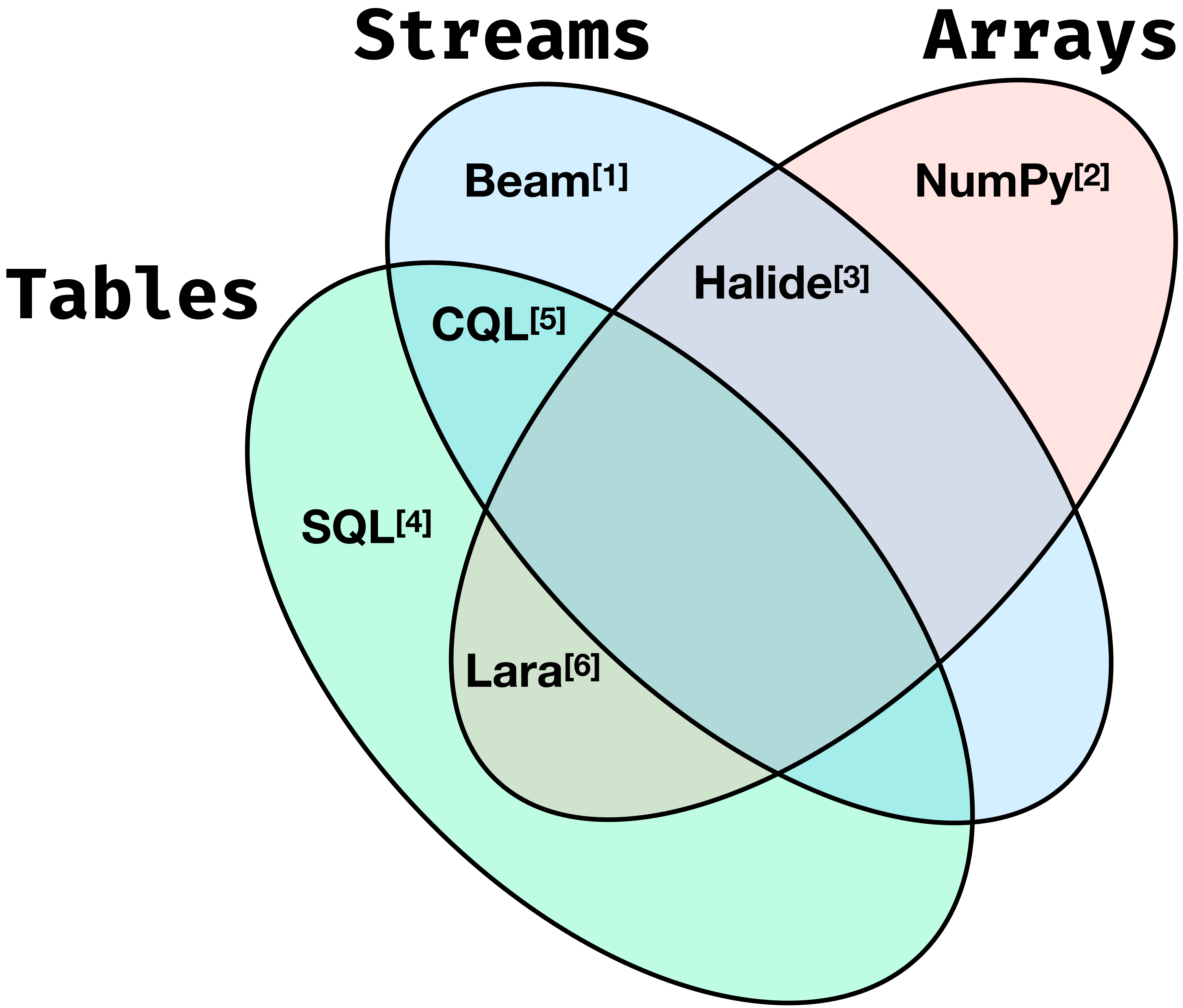

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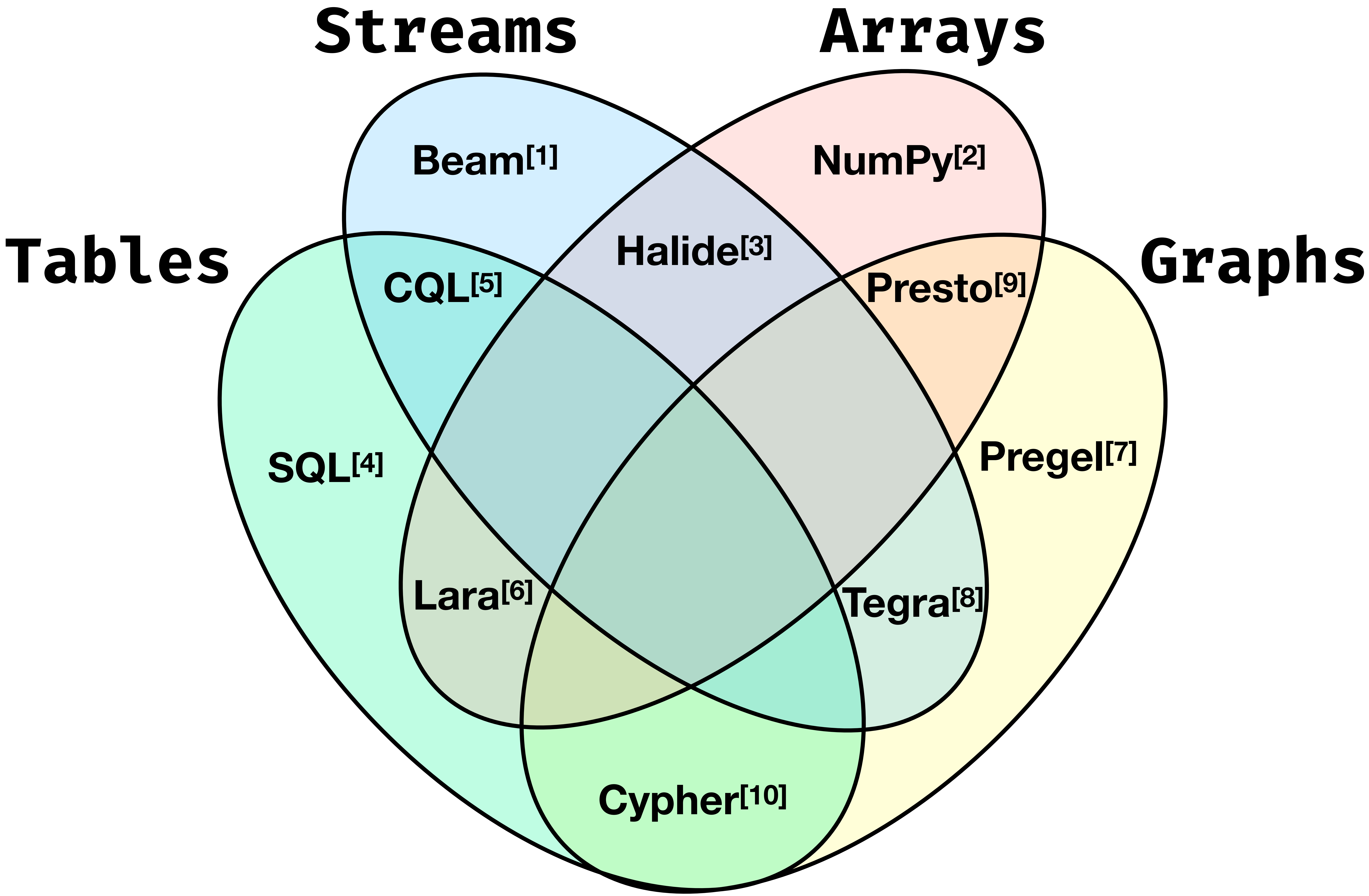

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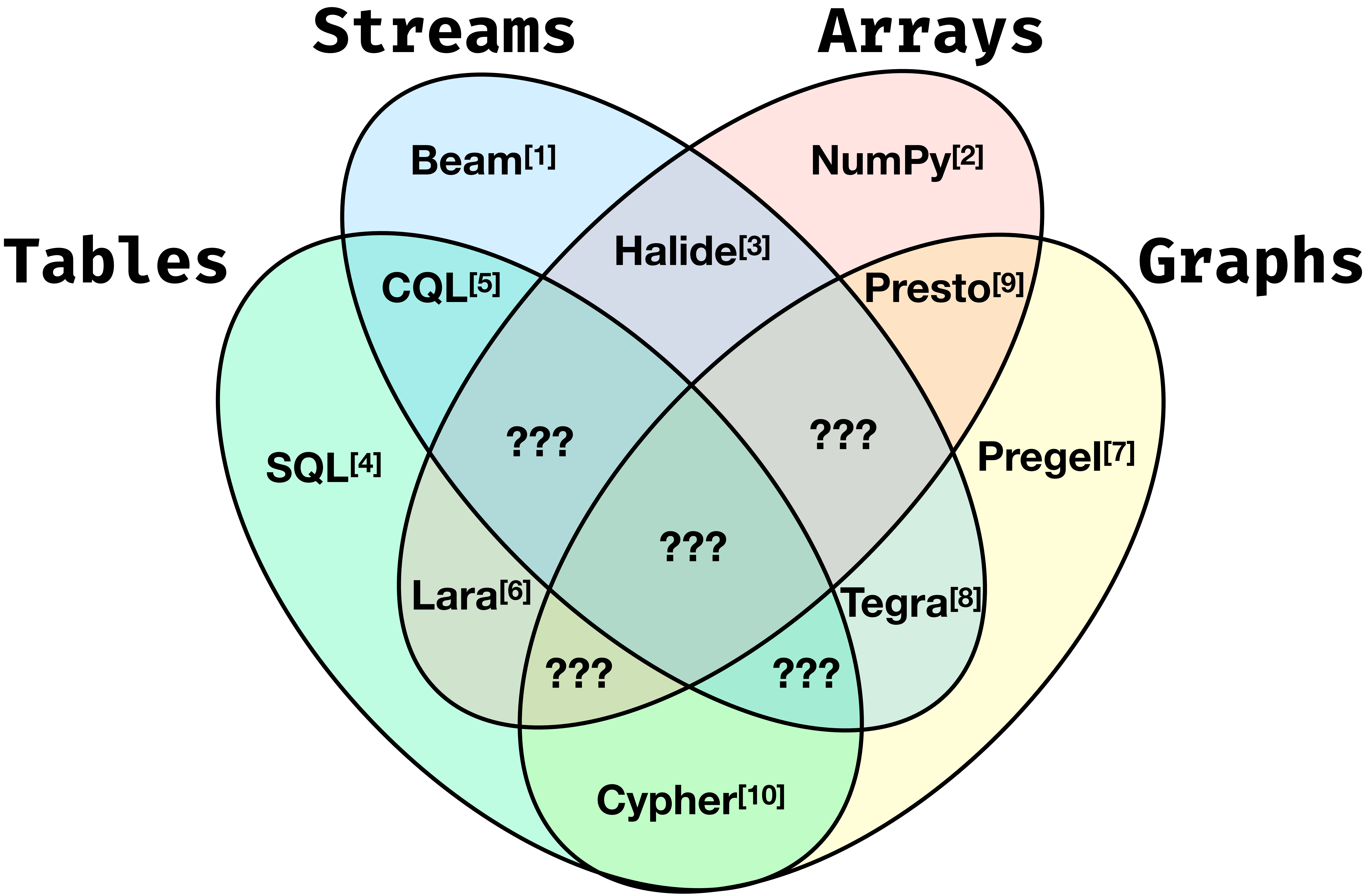

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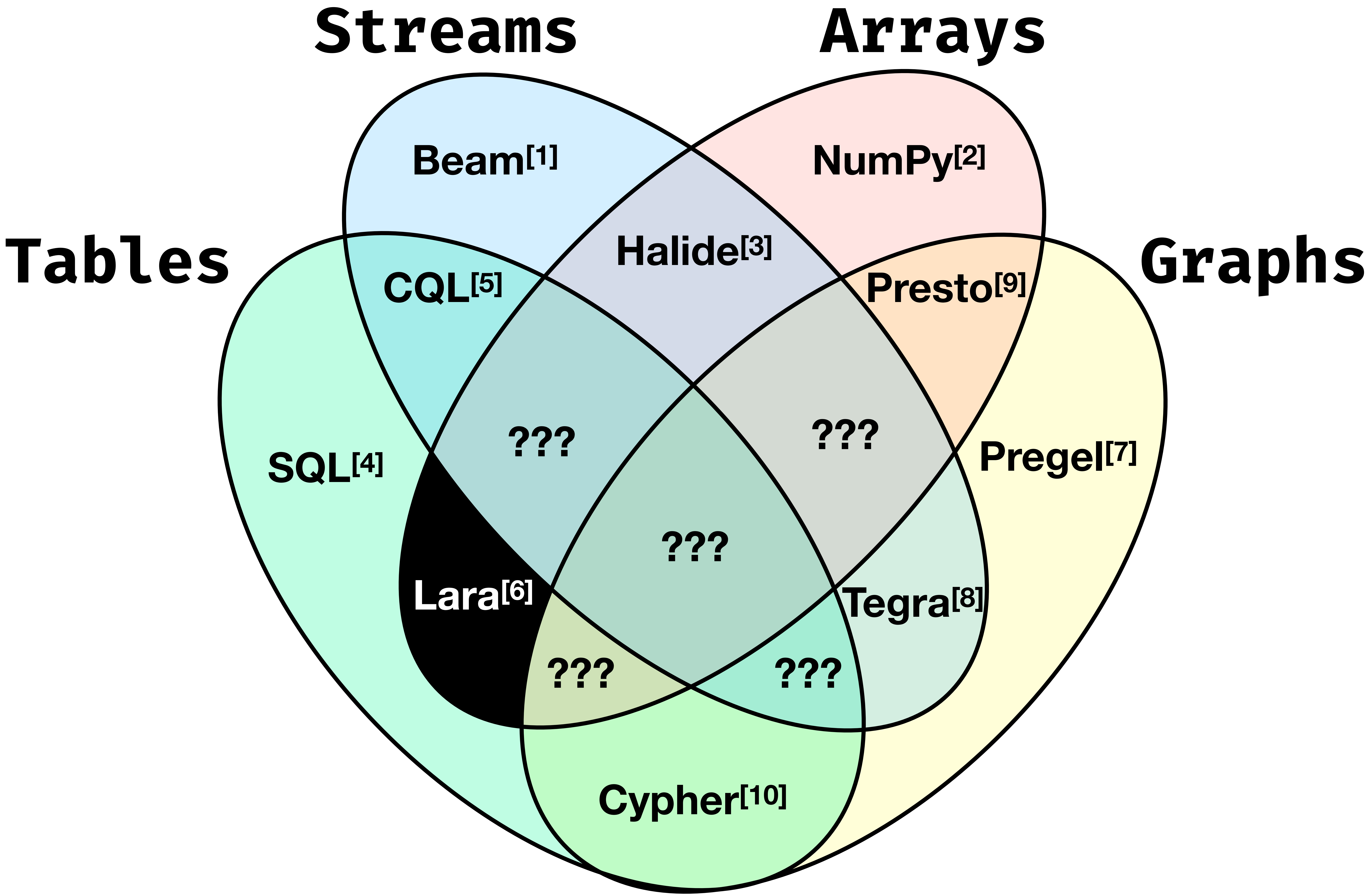

What is Lara?

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An Intermediate Representation for Optimizing Machine Learning Pipelines

Andreas Kunft[*] Asterios Katsifodimos[**] Sebastian Schelter[†]
Sebastian Breß[‡*] Tilmann Rabl[+] Volker Markl[‡*]

[*]TU Berlin [**]Delft University of Technology [†]New York University [‡]DFKI [+]HPI, Universität Potsdam

Where did Lara come from?

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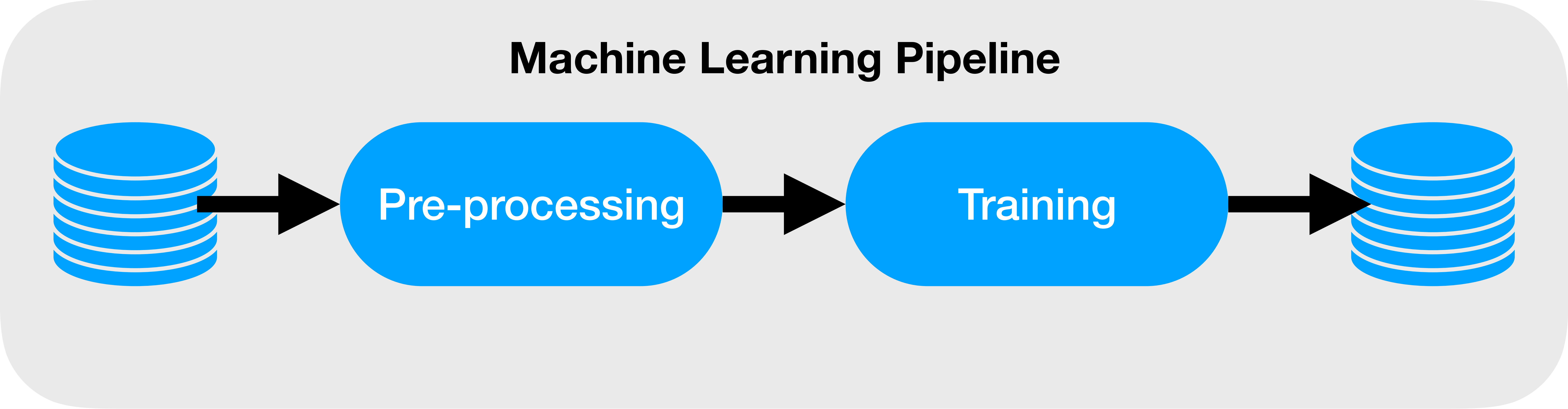

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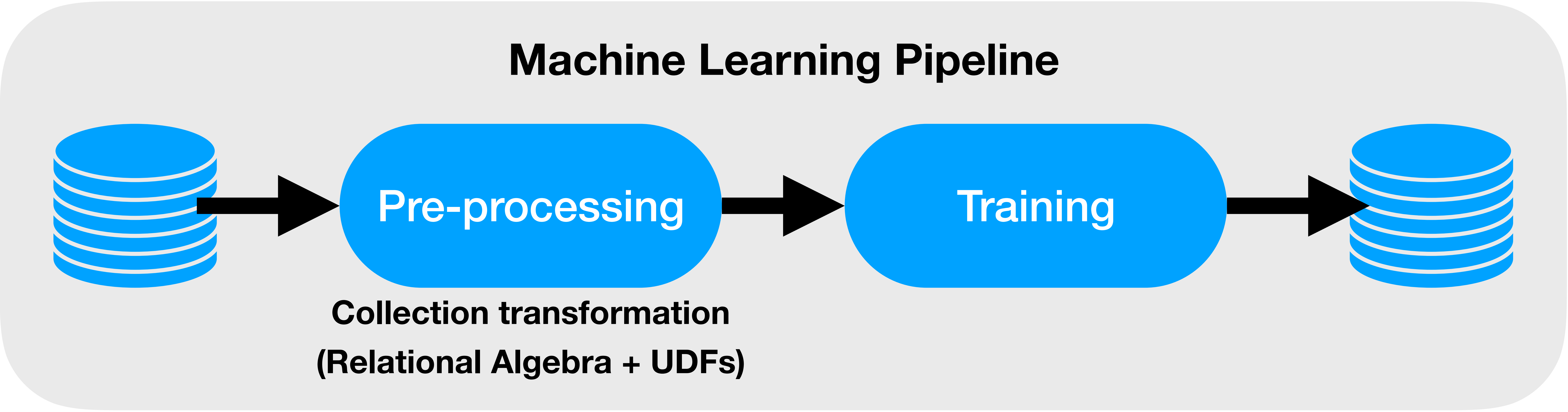

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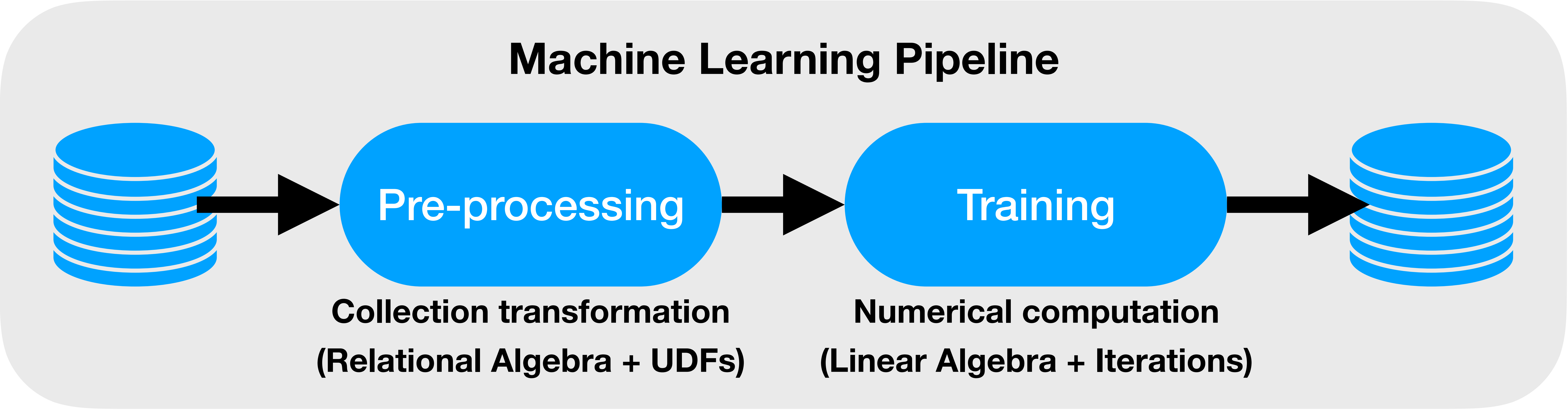

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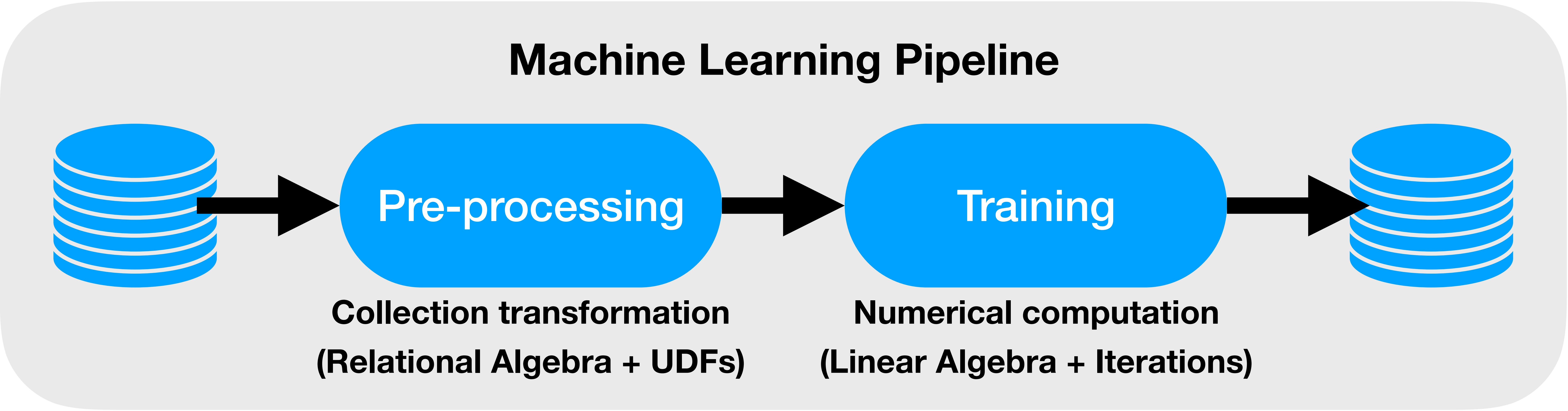

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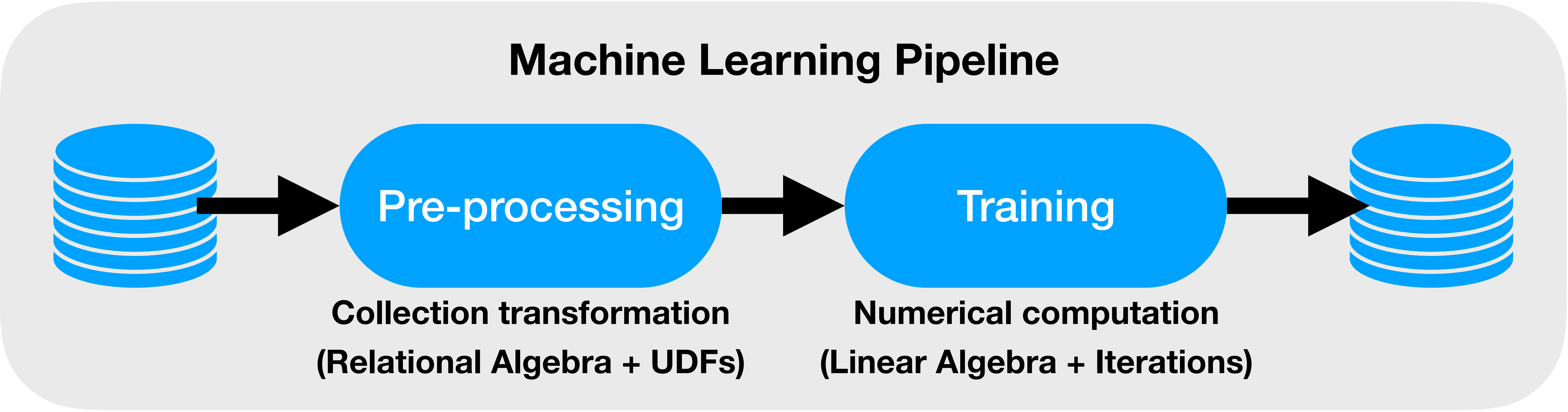

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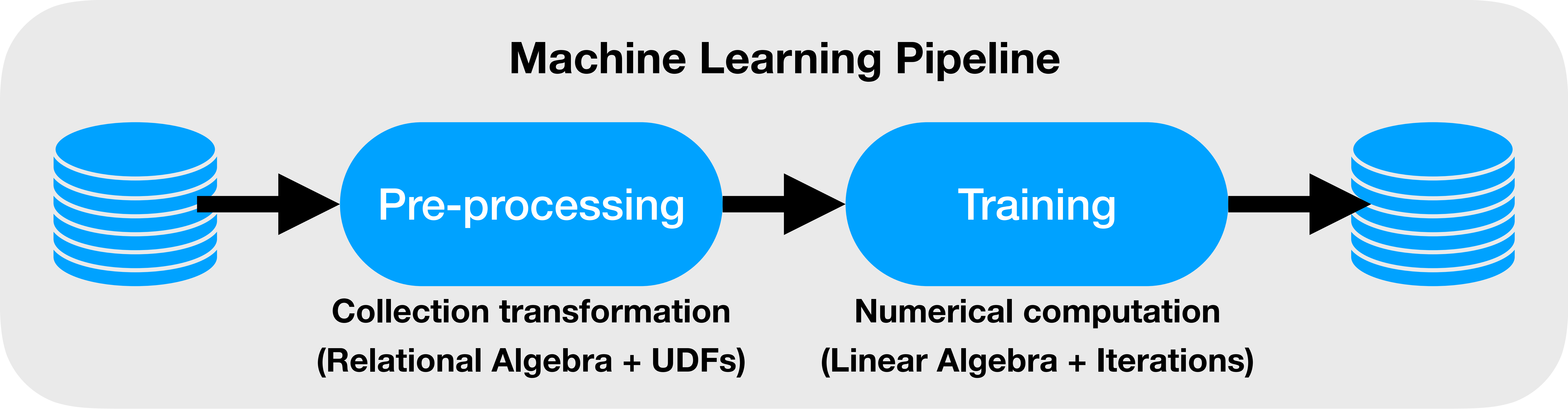

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Solution? Lara: A language for **L**inear **A**lgebra and **R**elational **A**lgebra

How does Lara work?

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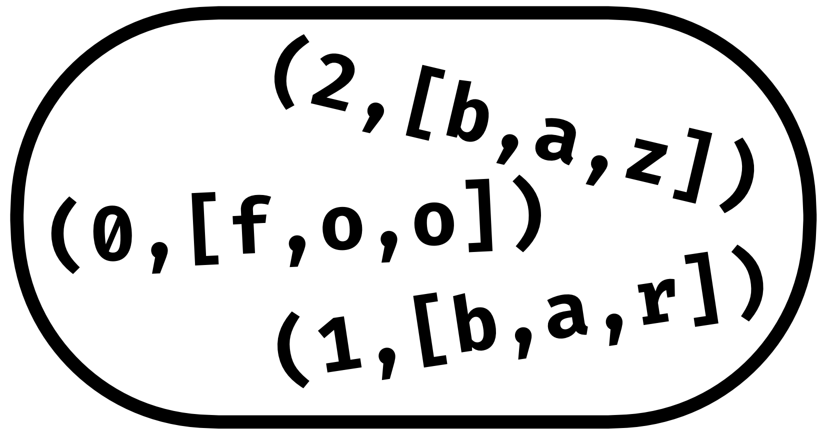

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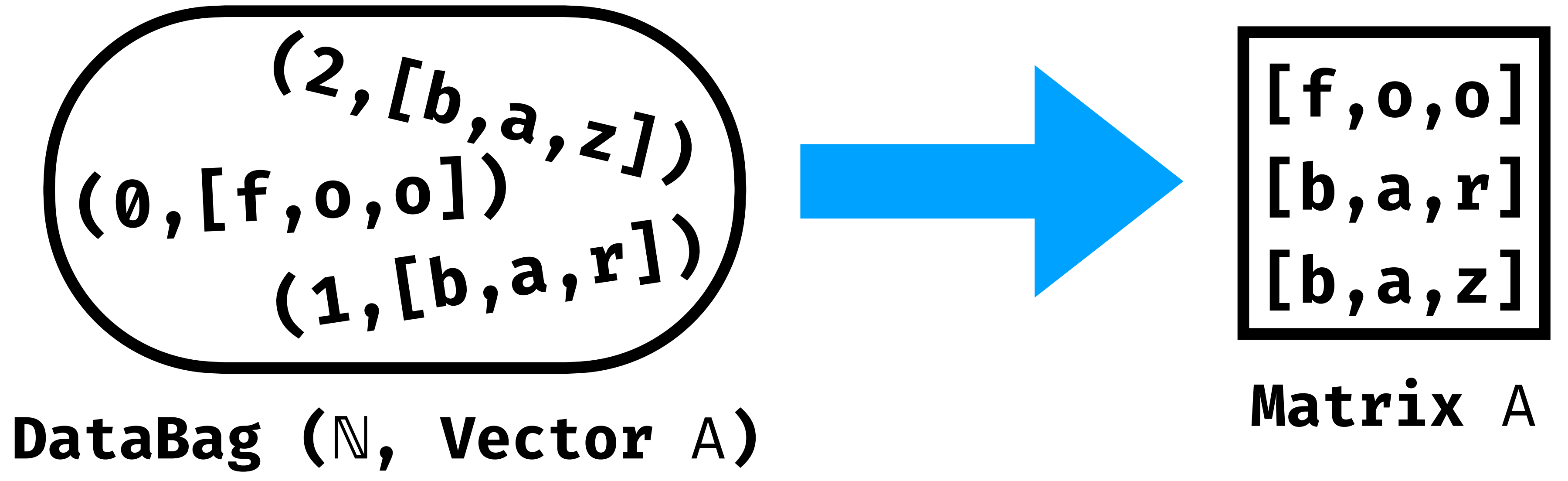

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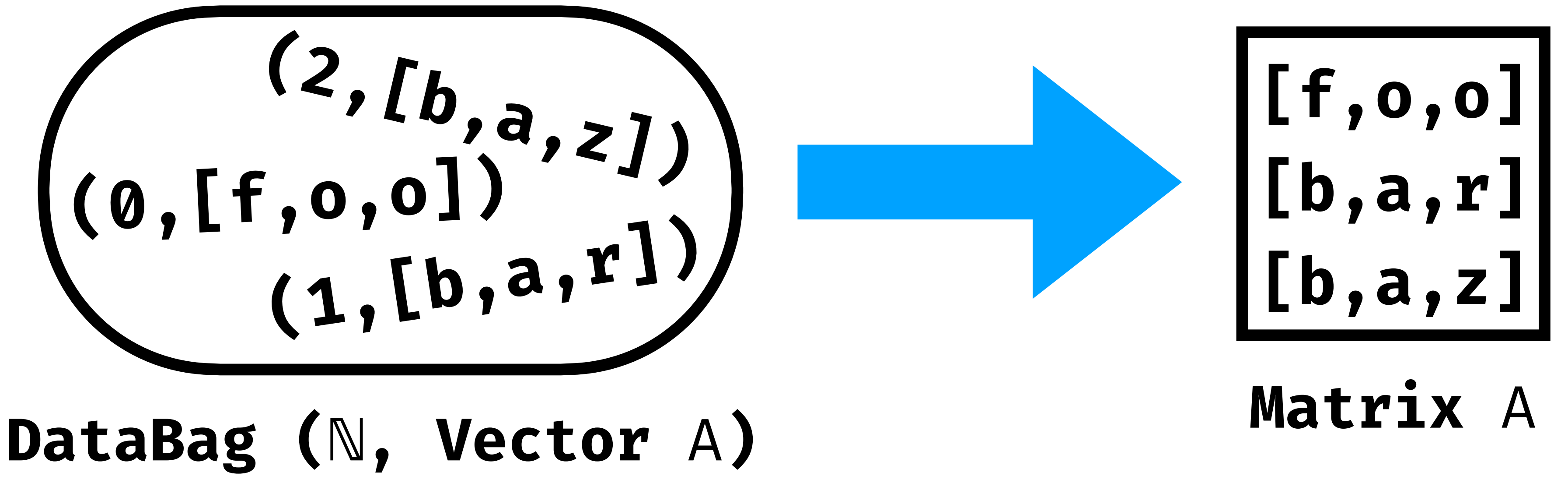

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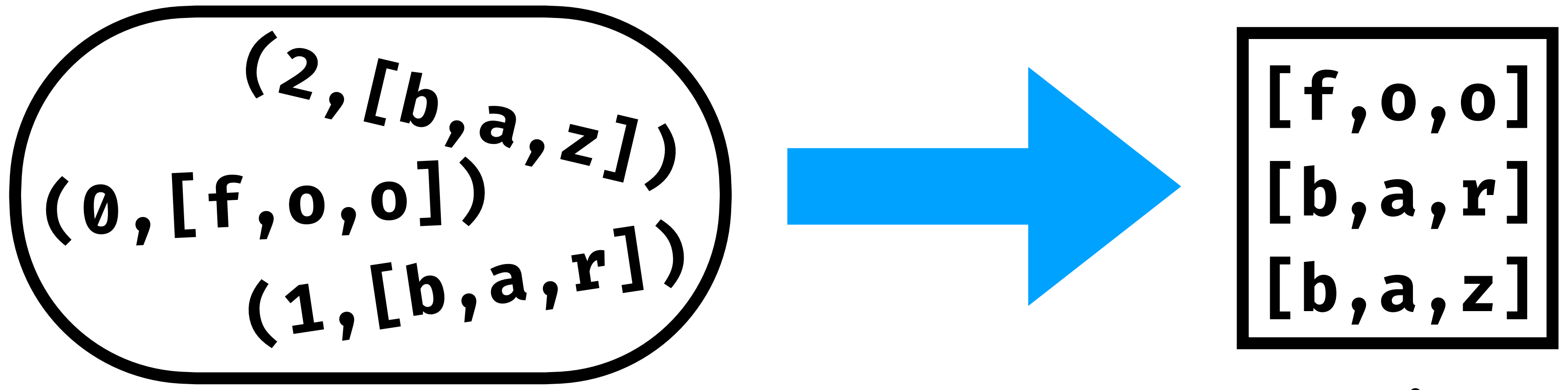

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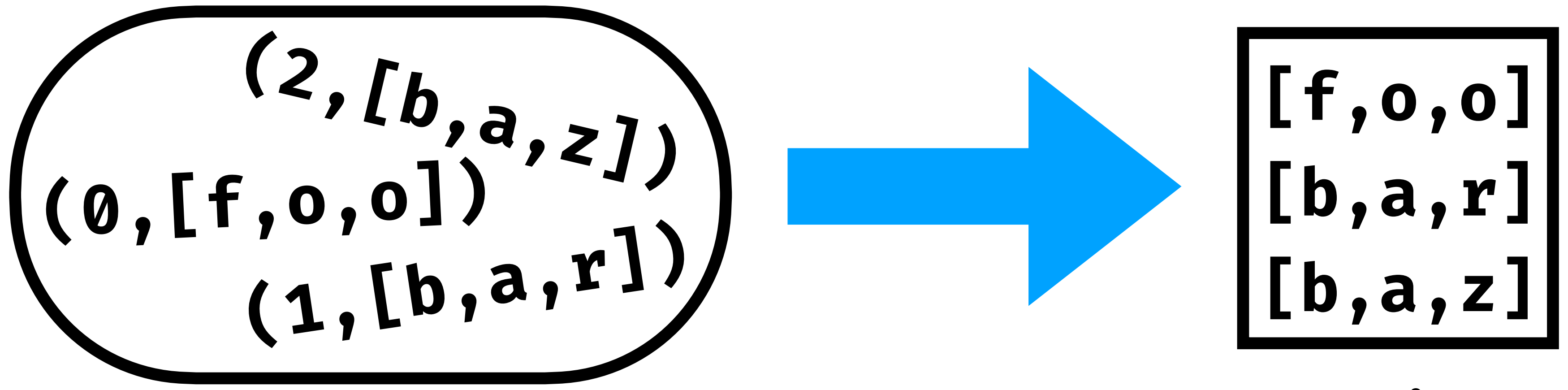

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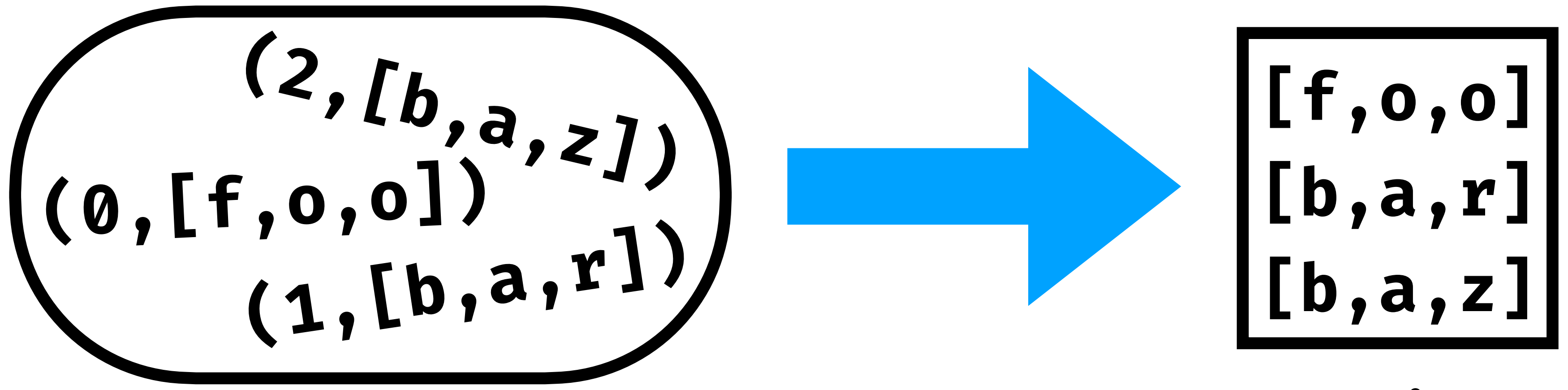

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$$\mathbf{x} + \mathbf{y}$$

Element-wise
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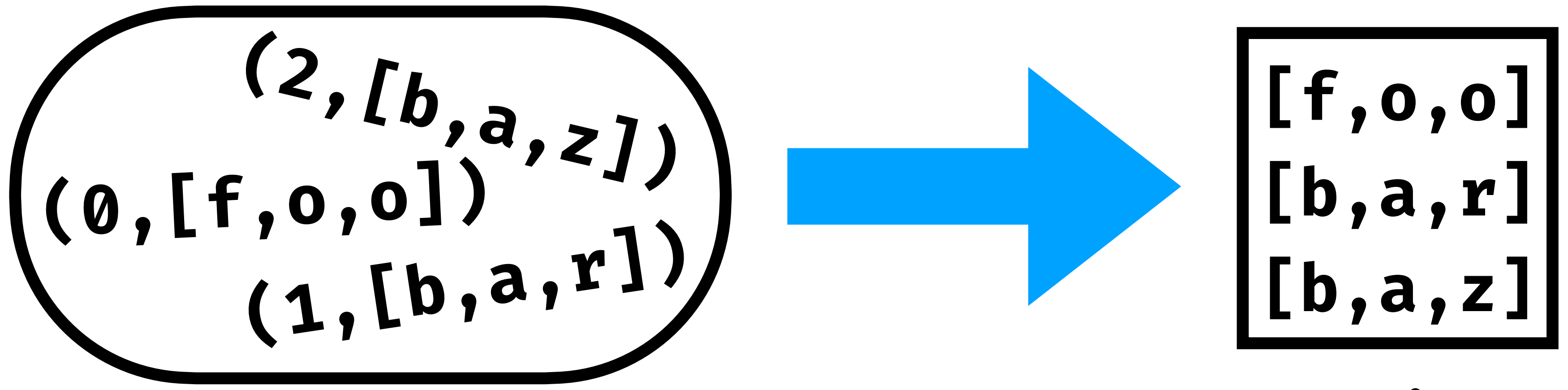

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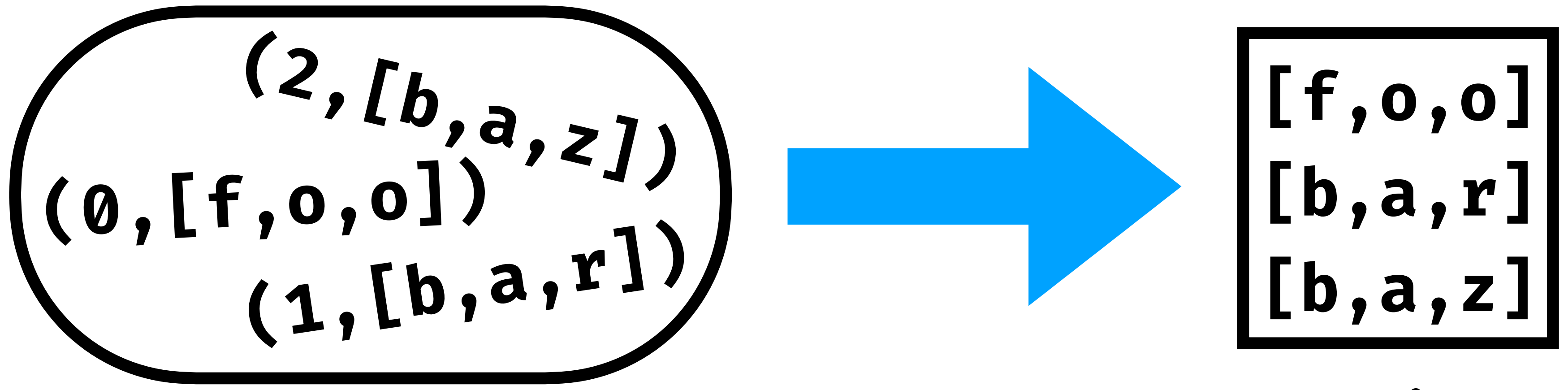

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```
for {
  (idx_x, val_x) ← x
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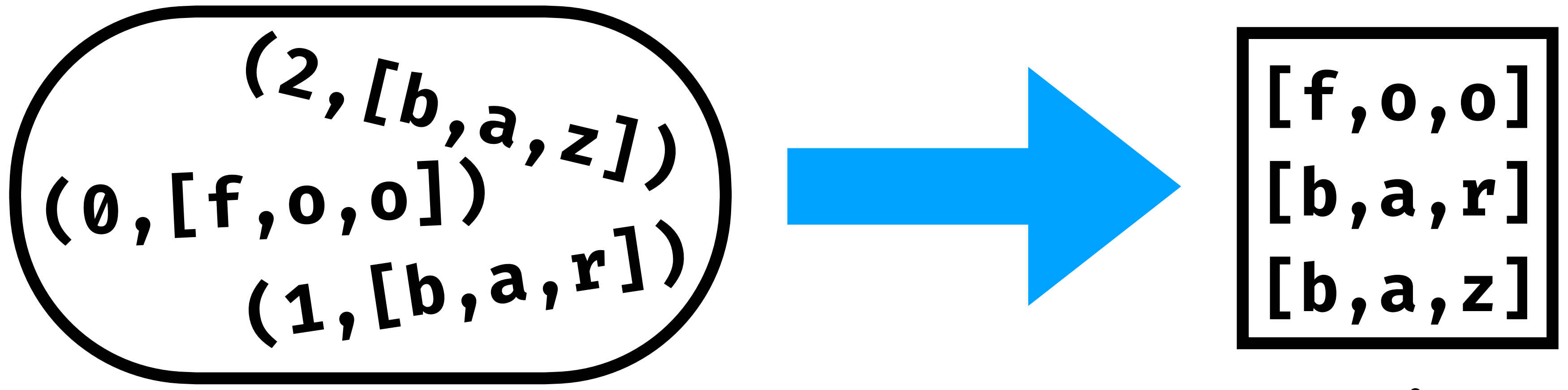

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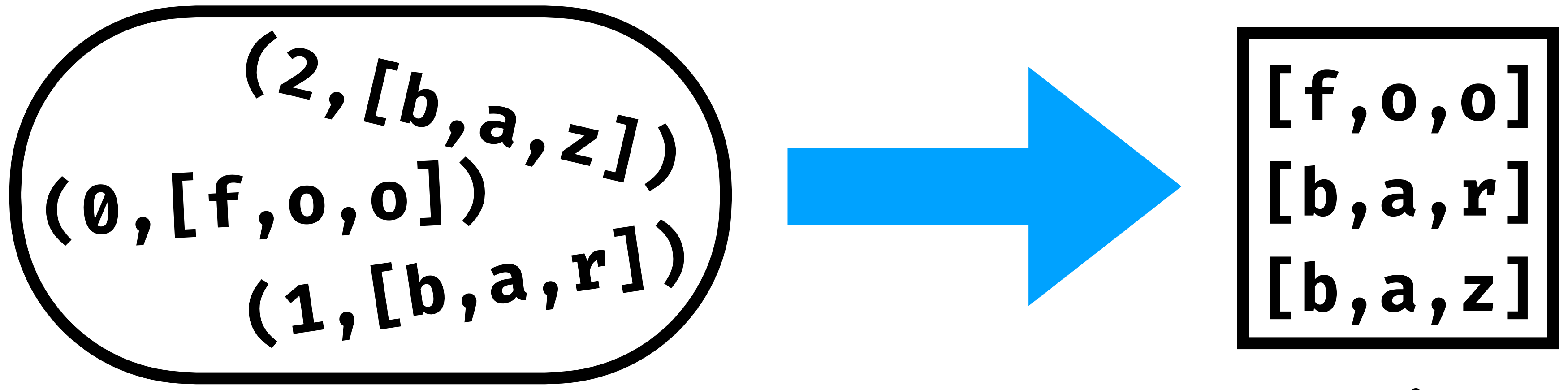

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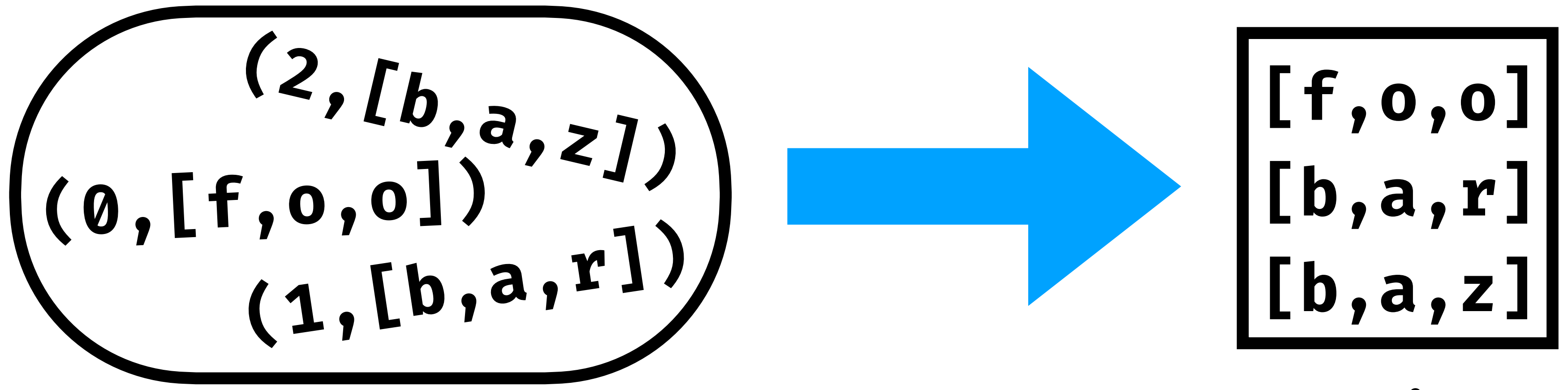

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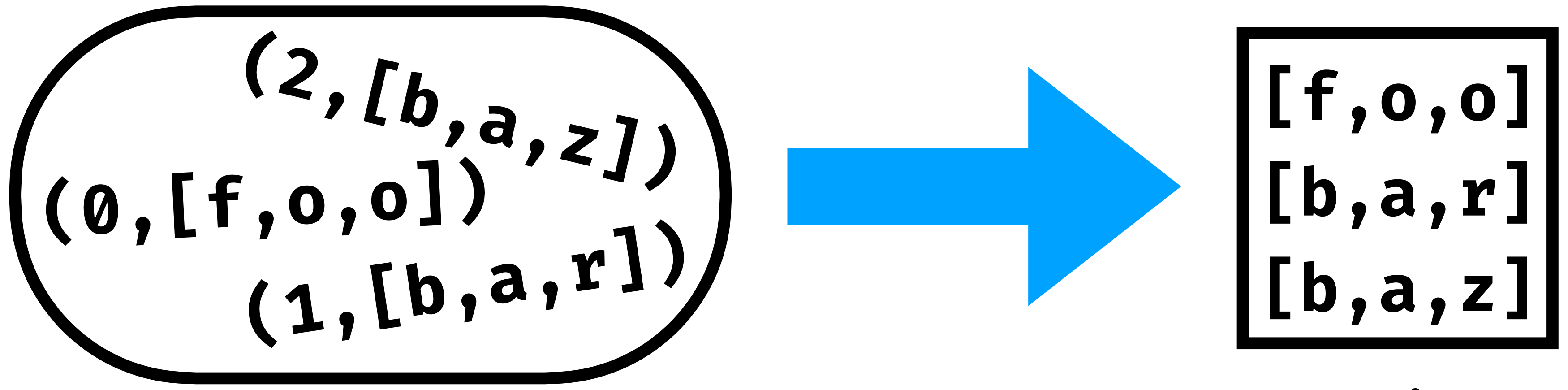

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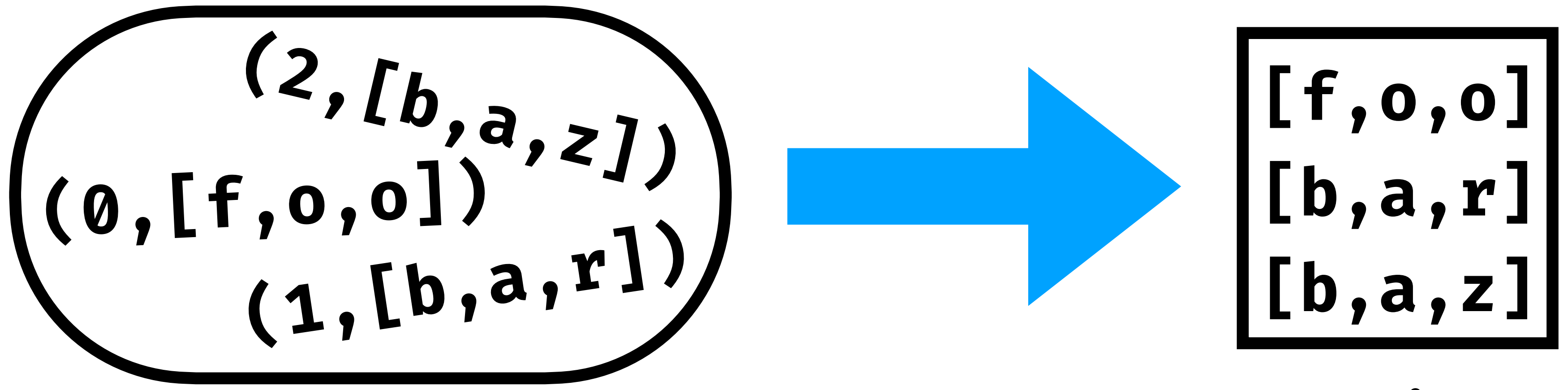

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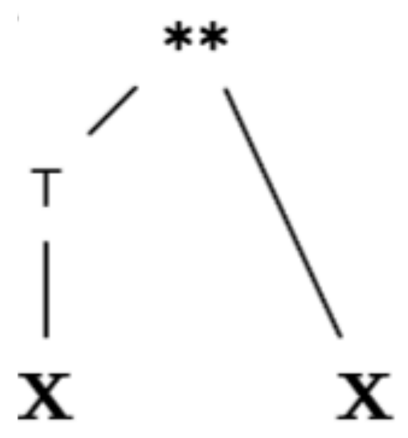

Gram matrix calculation

Operator tree

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Types (Monads):

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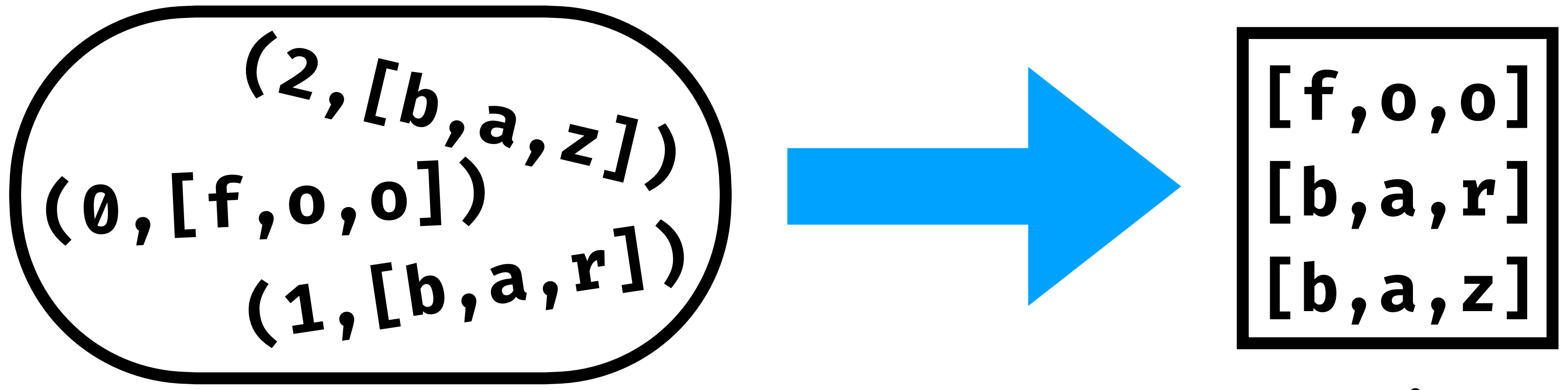

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$$\mathbf{x} + \mathbf{y}$$

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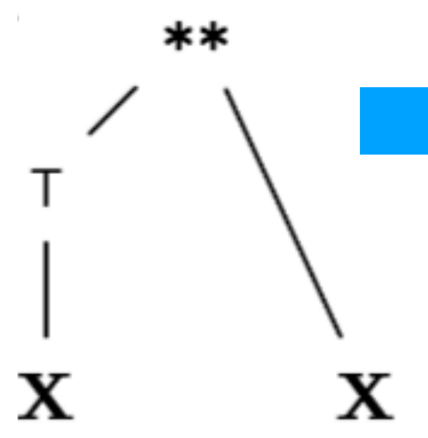

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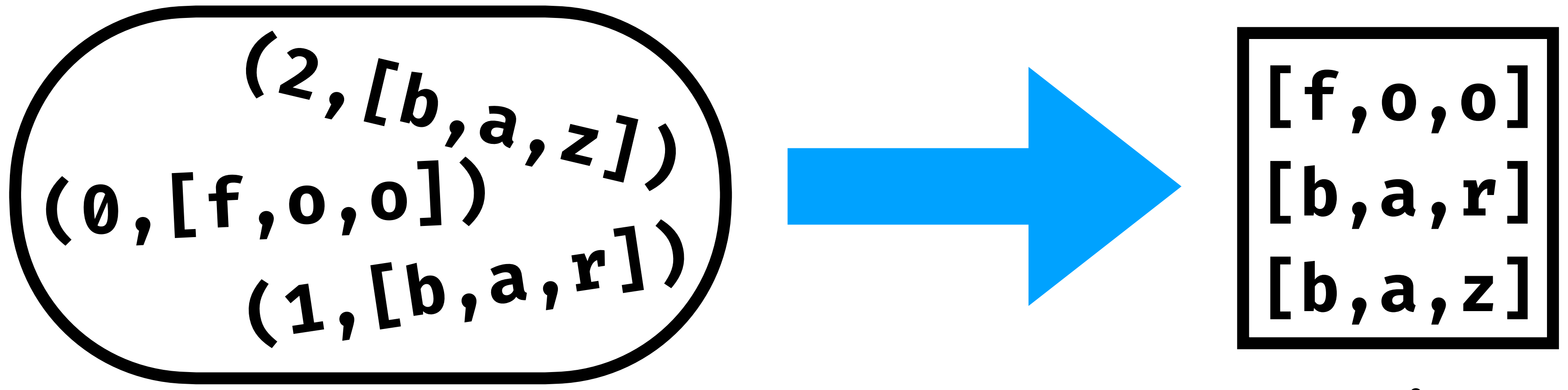

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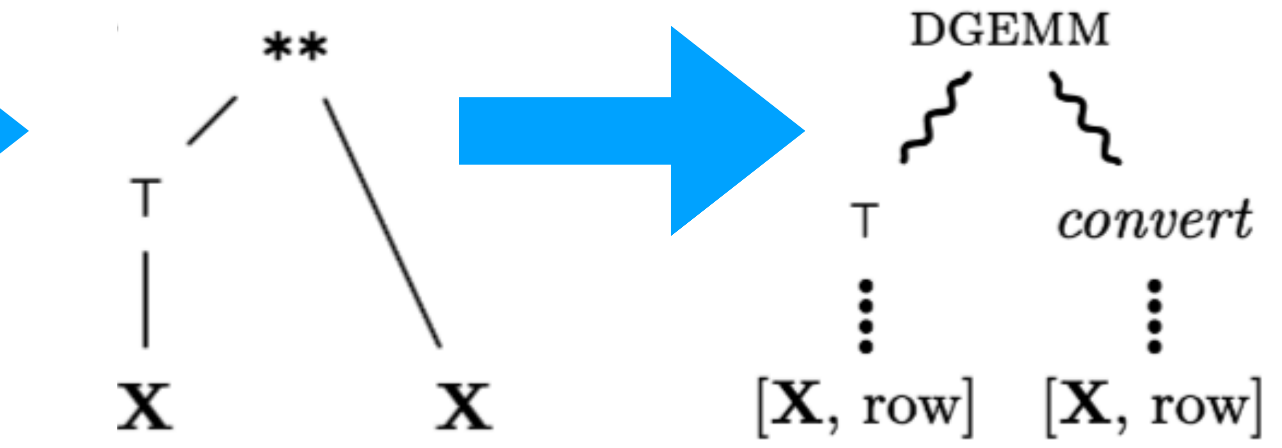

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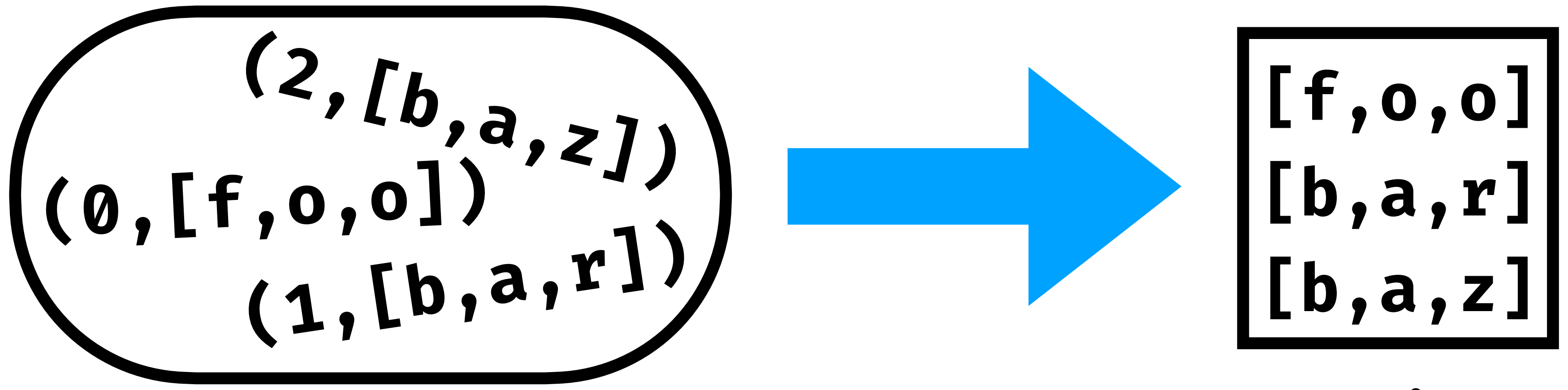

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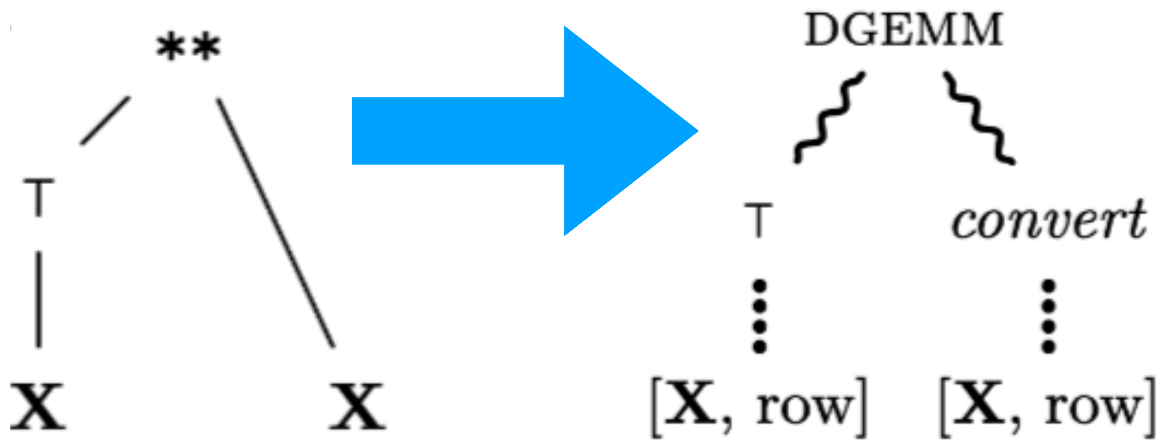

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Arc - Compiler Approach

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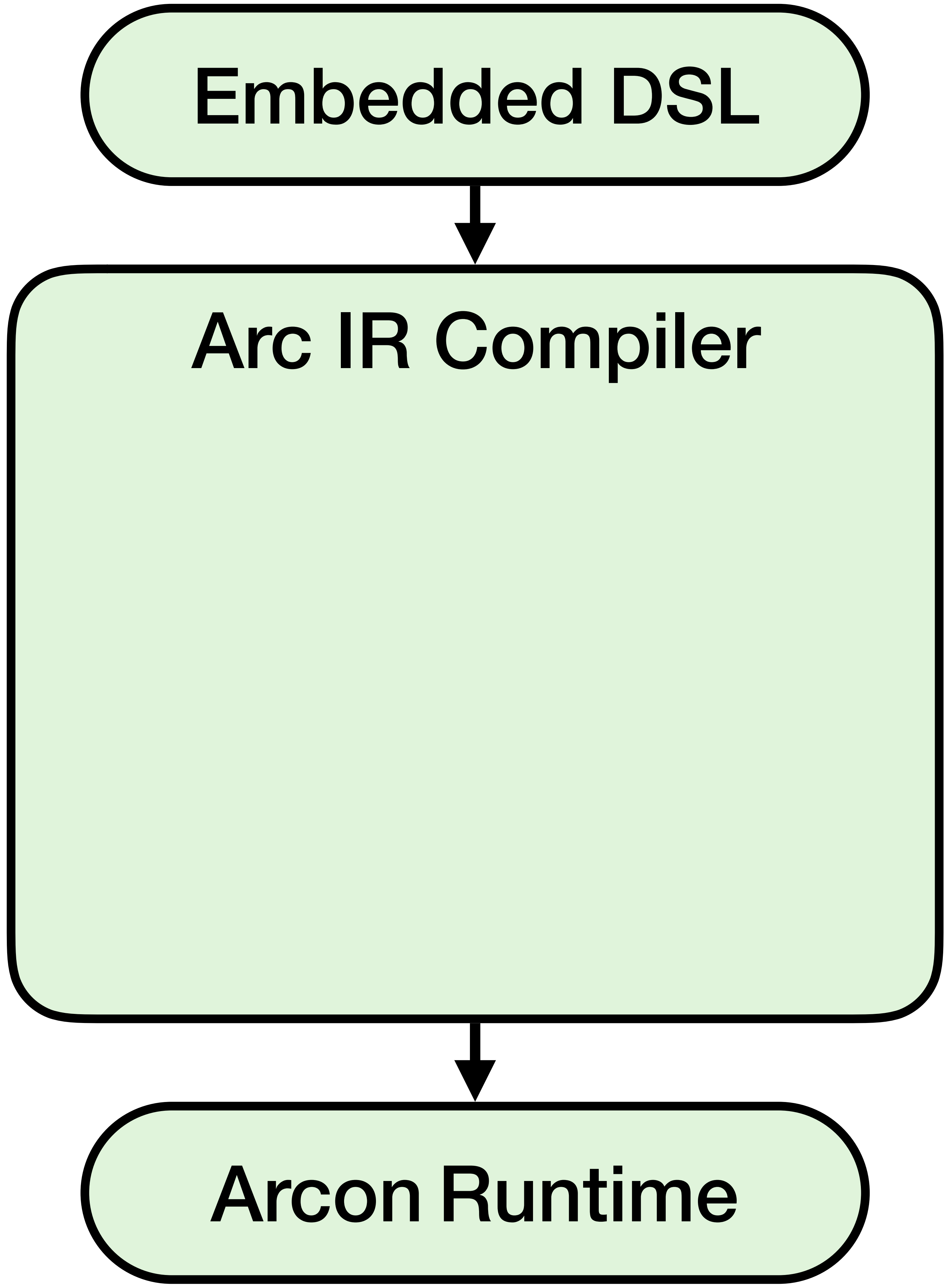
Original approach



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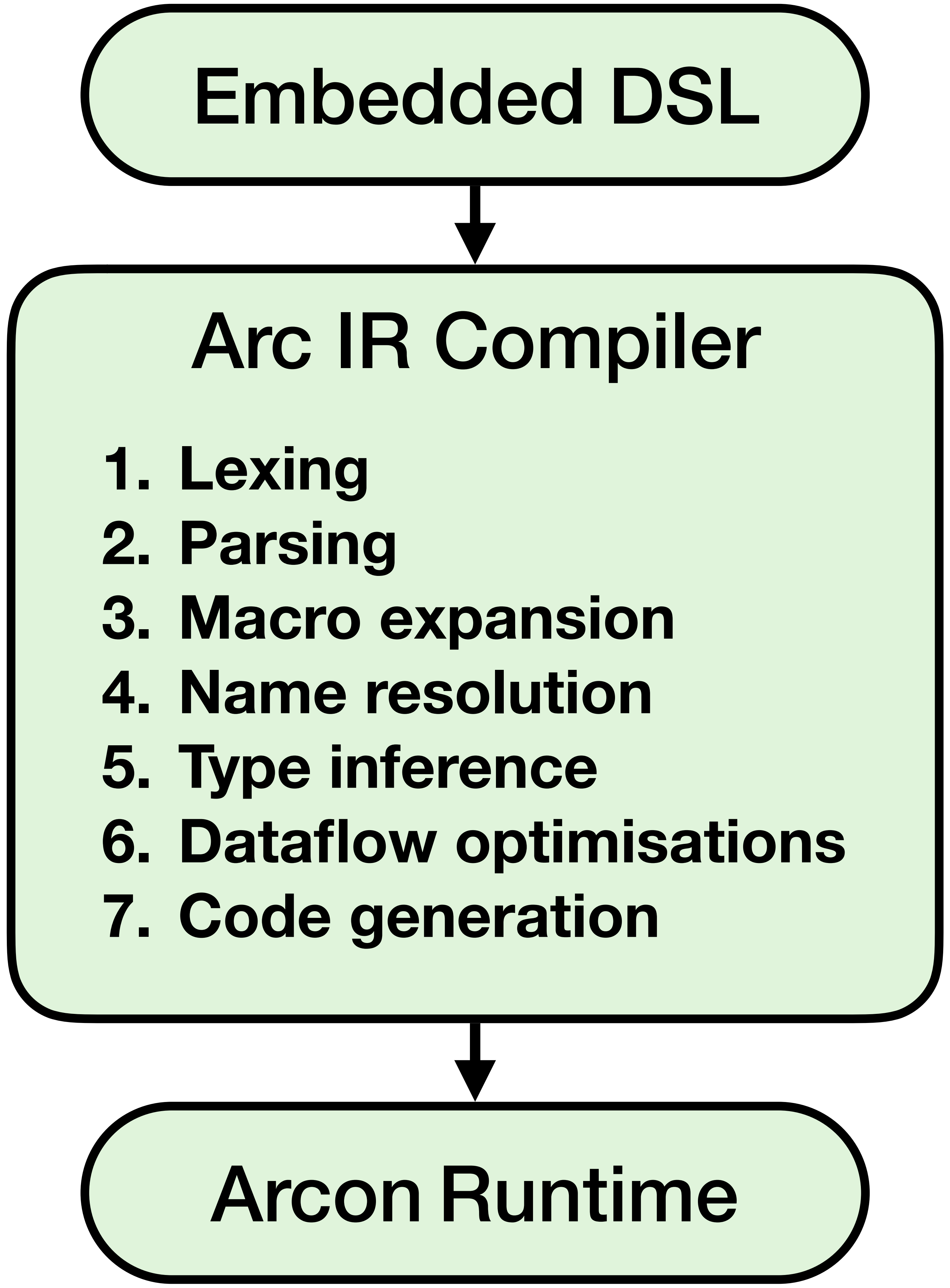

Arc - Compiler Approach

Original approach

Embedded DSL

↓

Arc IR Compiler

1. **Lexing**
2. **Parsing**
3. **Macro expansion**
4. **Name resolution**
5. **Type inference**
6. **Dataflow optimisations**
7. **Code generation**

↓

Arcon Runtime

Current approach

Embedded DSL

↓

MLIR (Multi-Level IR)

? ? ? ? ?

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↓

Arcon Runtime

What is MLIR (Multi-Level IR)?

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MLIR: A Compiler Infrastructure for the End of Moore's Law

Chris Lattner * — Google
Mehdi Amini — Google
Uday Bondhugula — IISc
Albert Cohen — Google
Andy Davis — Google

Jacques Pienaar — Google
River Riddle — Google
Tatiana Shpeisman — Google
Nicolas Vasilache — Google

Oleksandr Zinenko — Google

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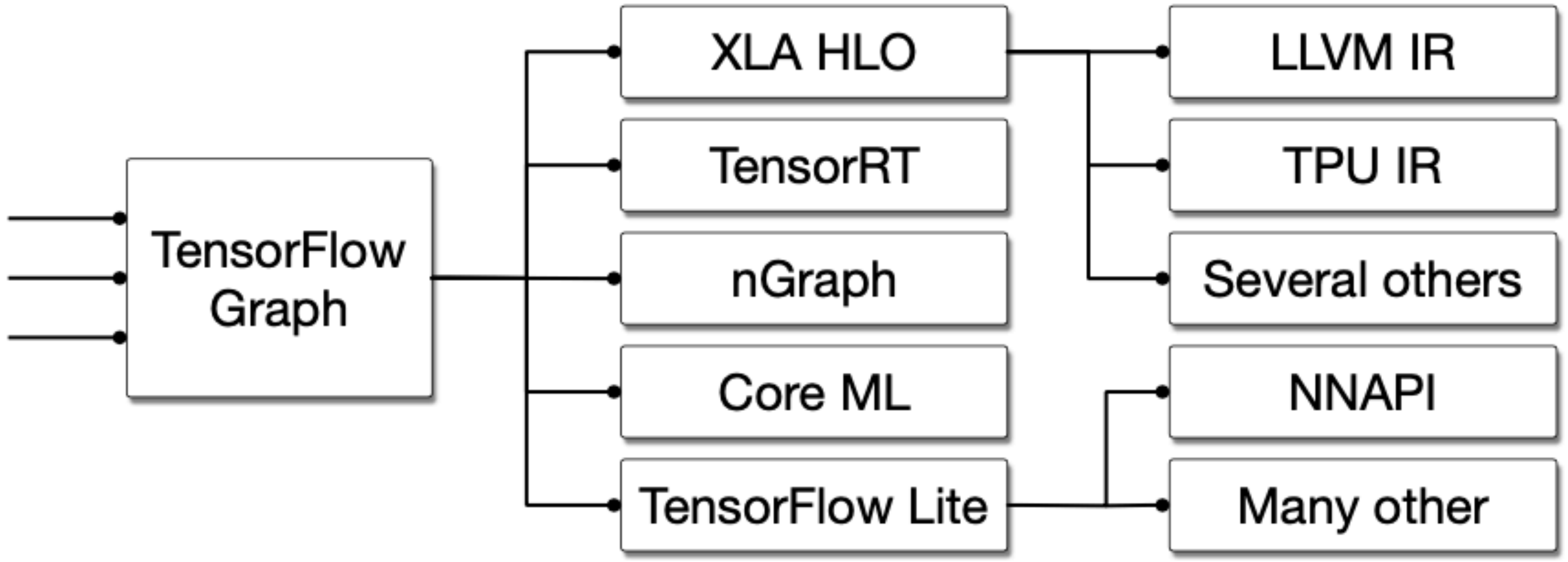

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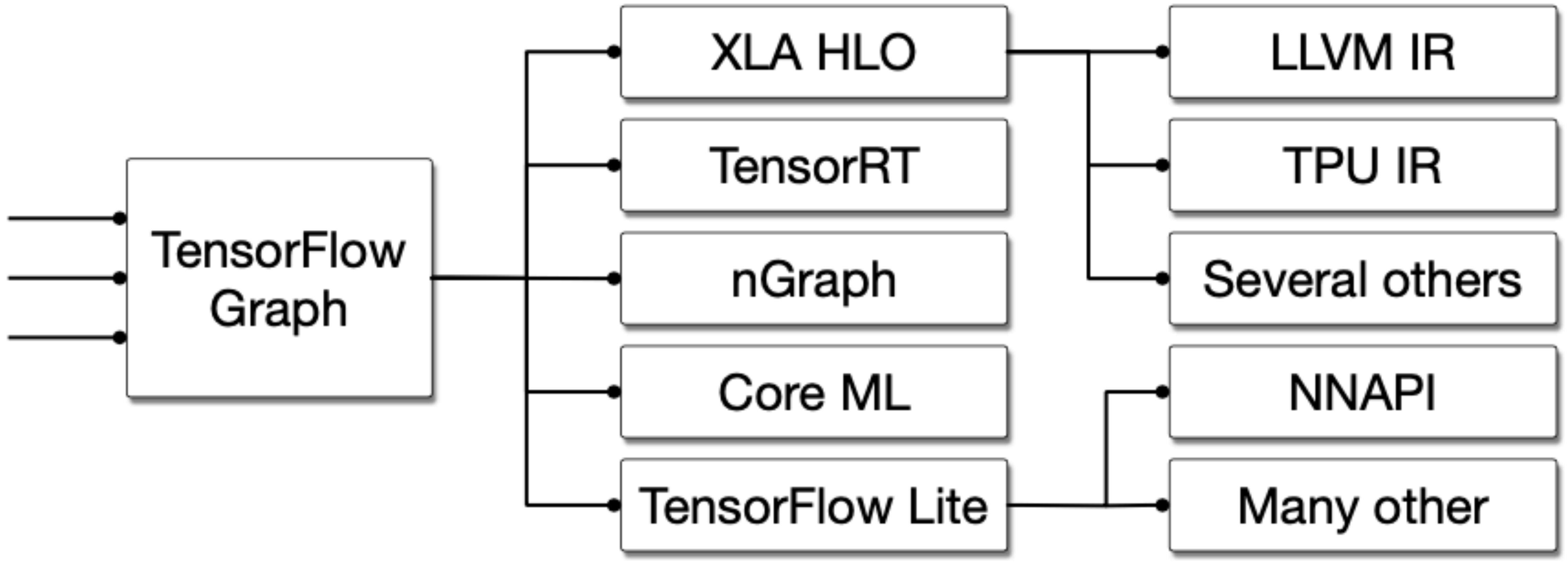

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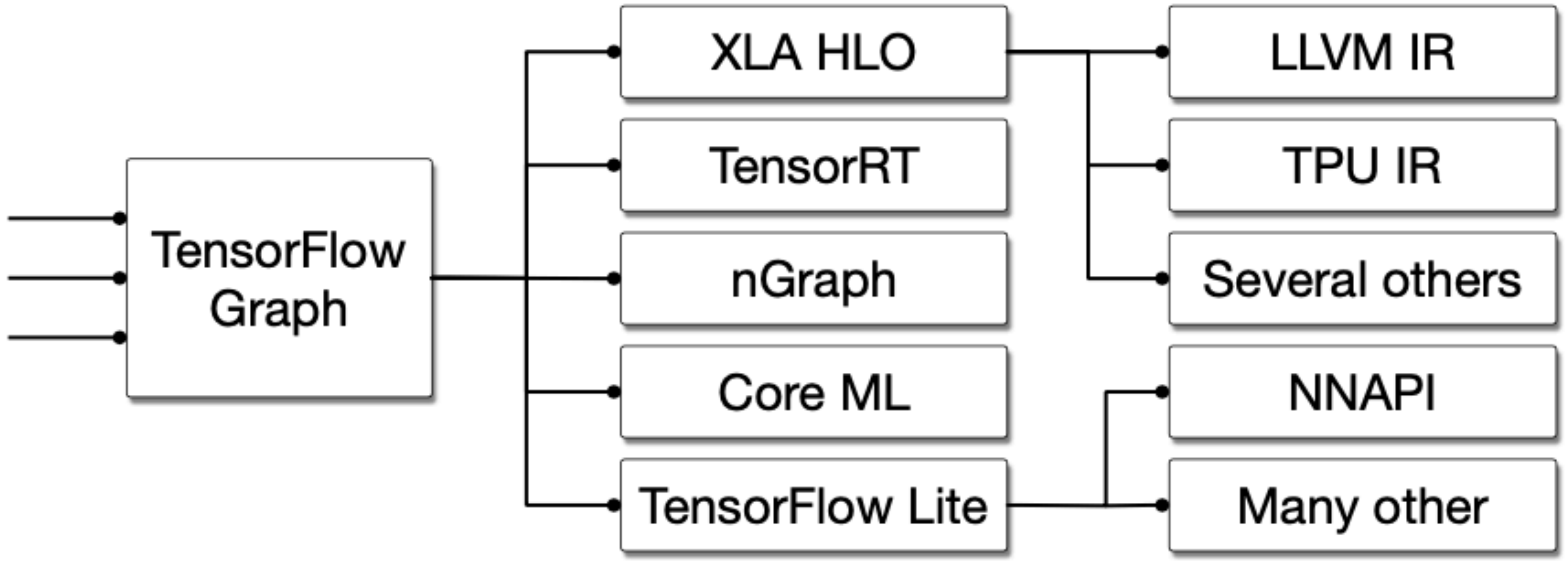

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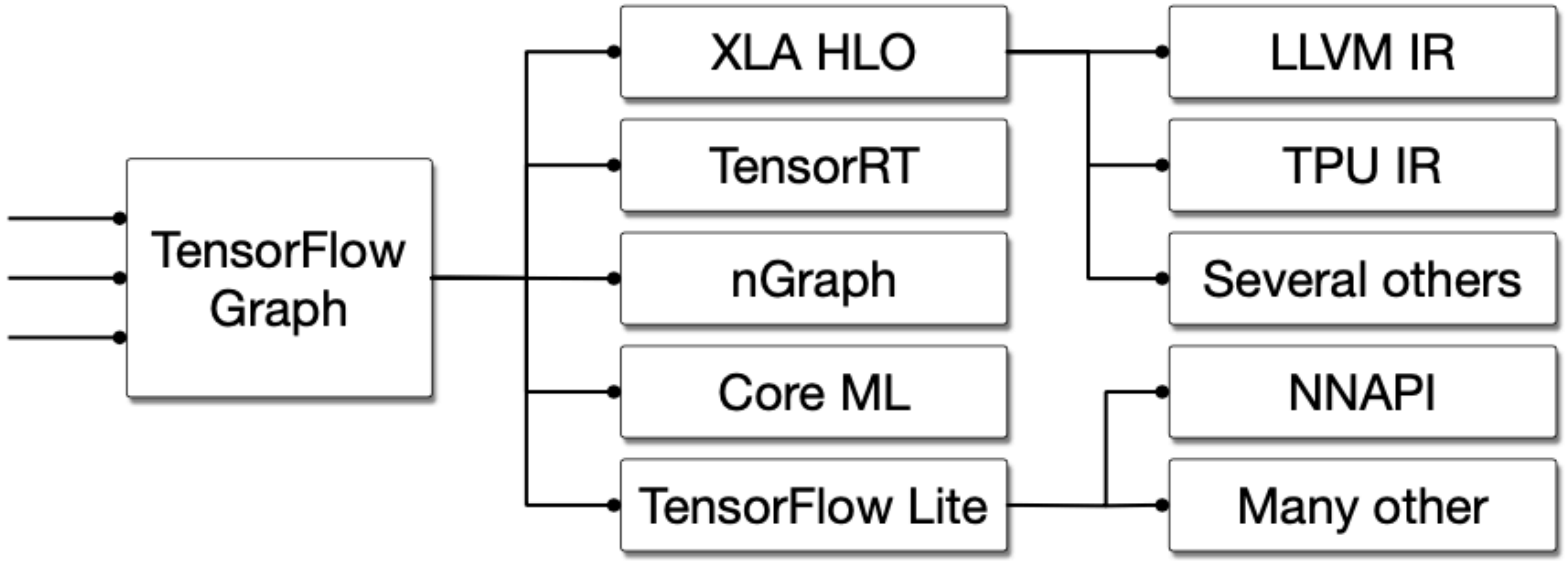

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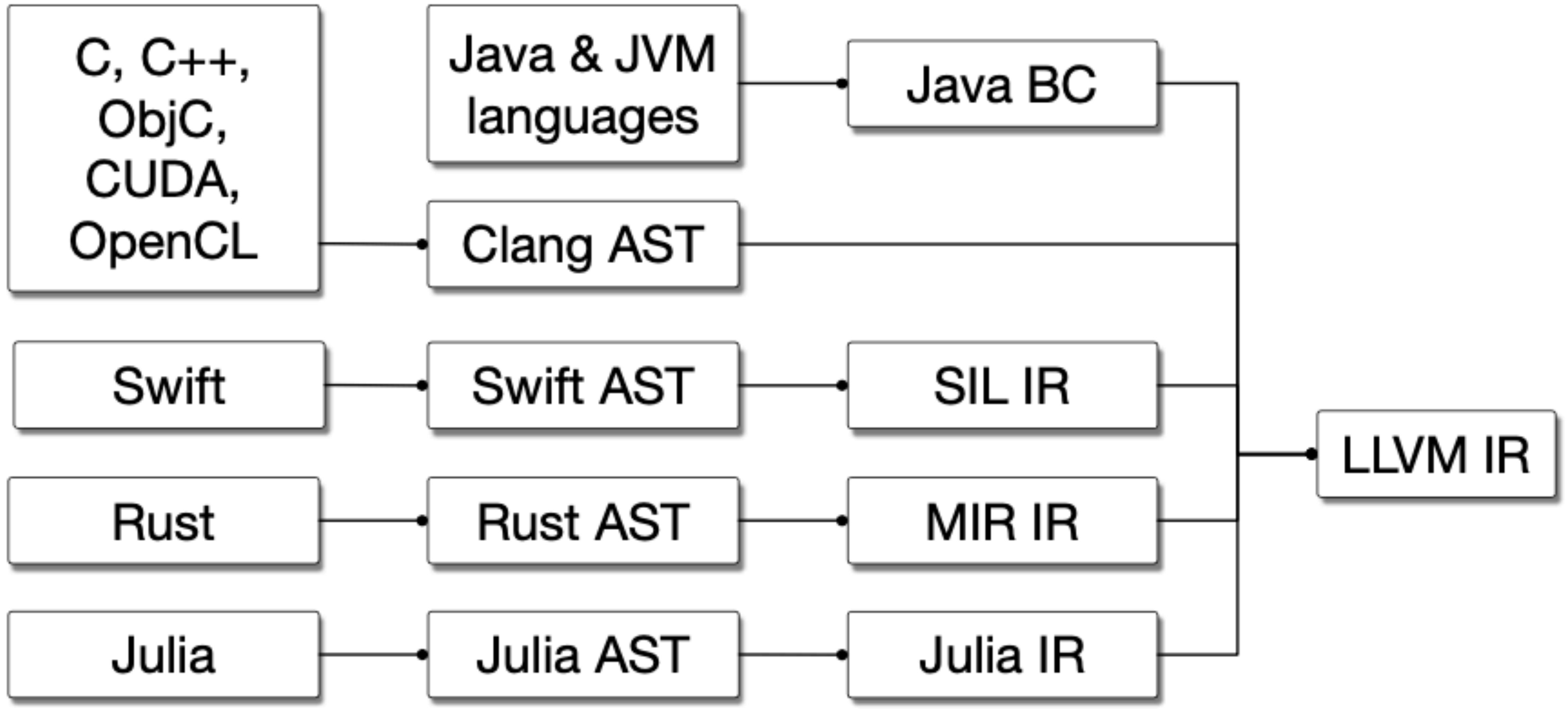

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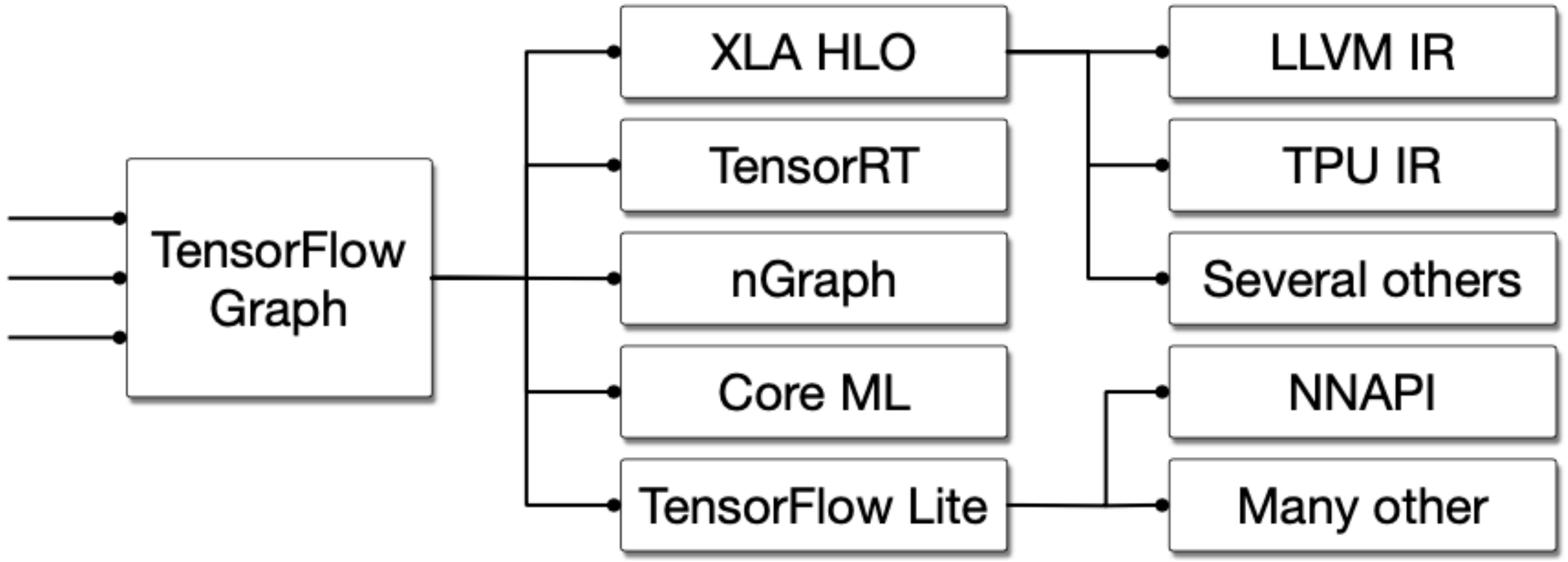

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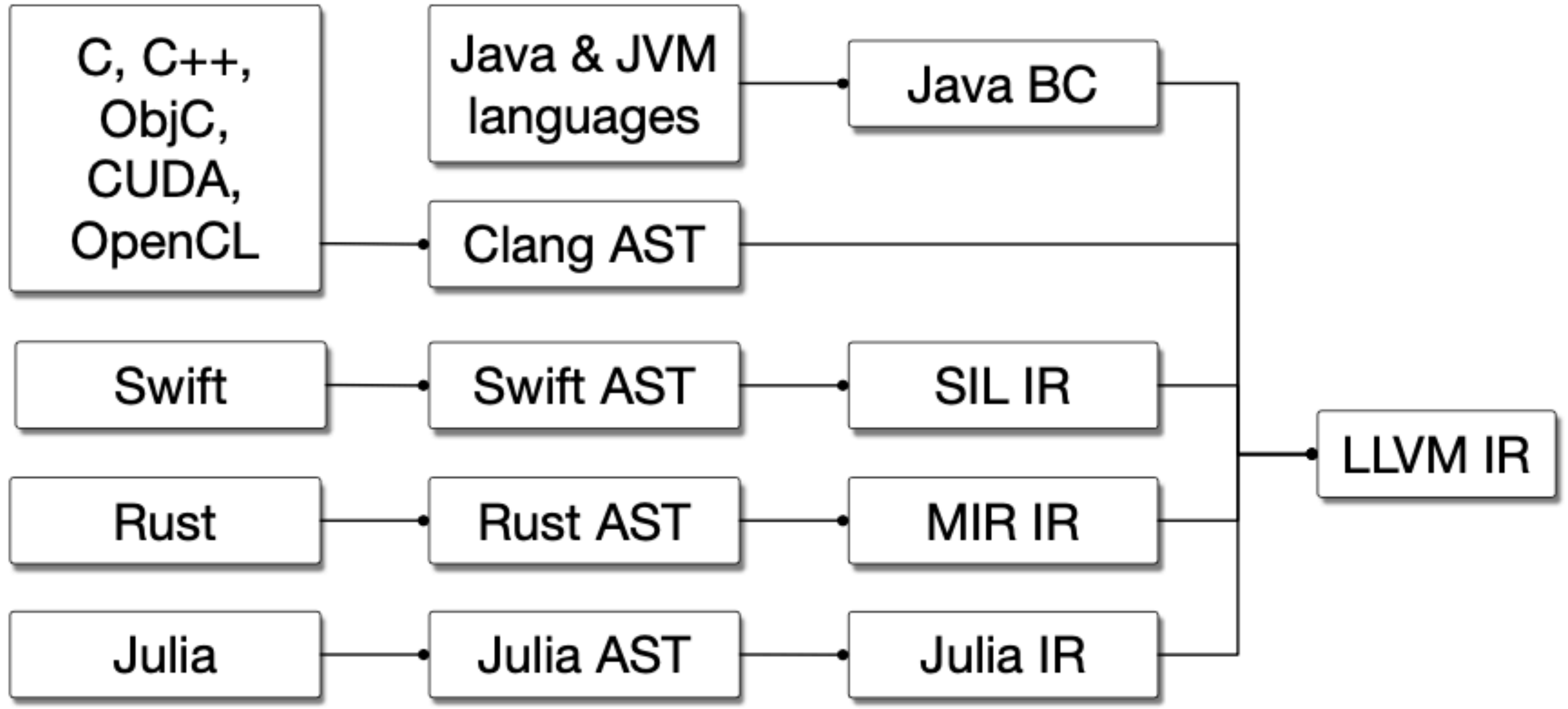

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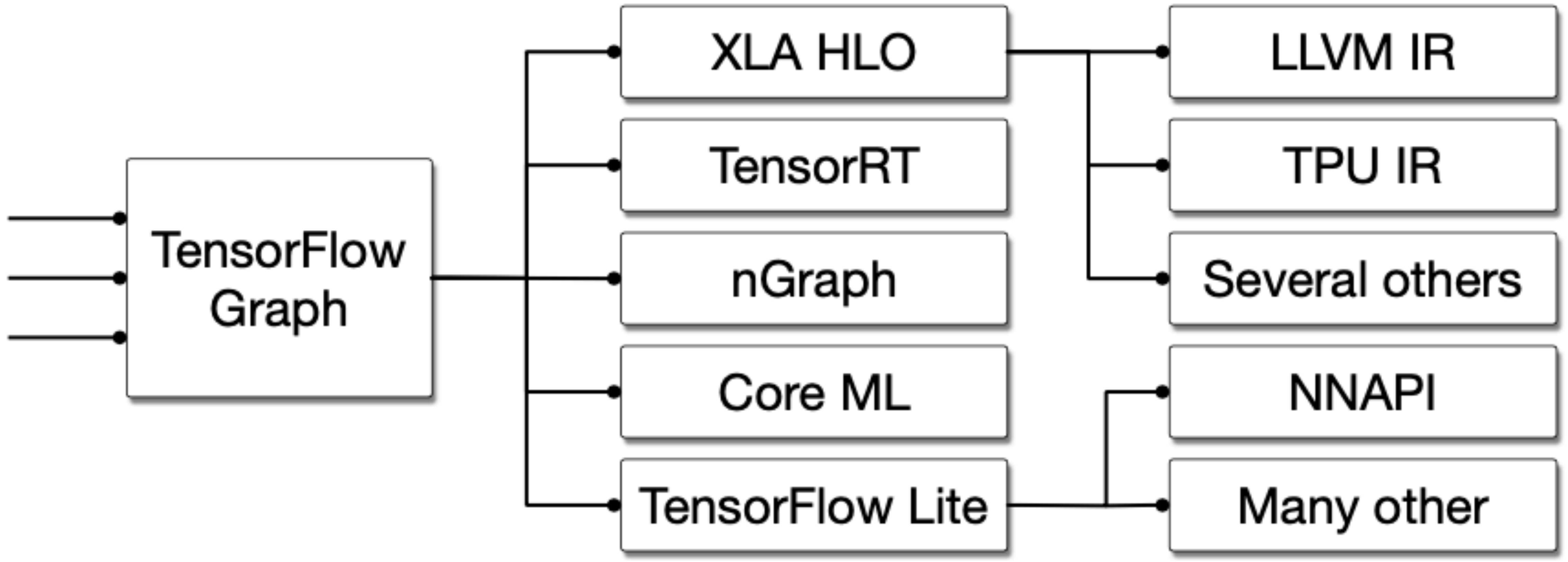

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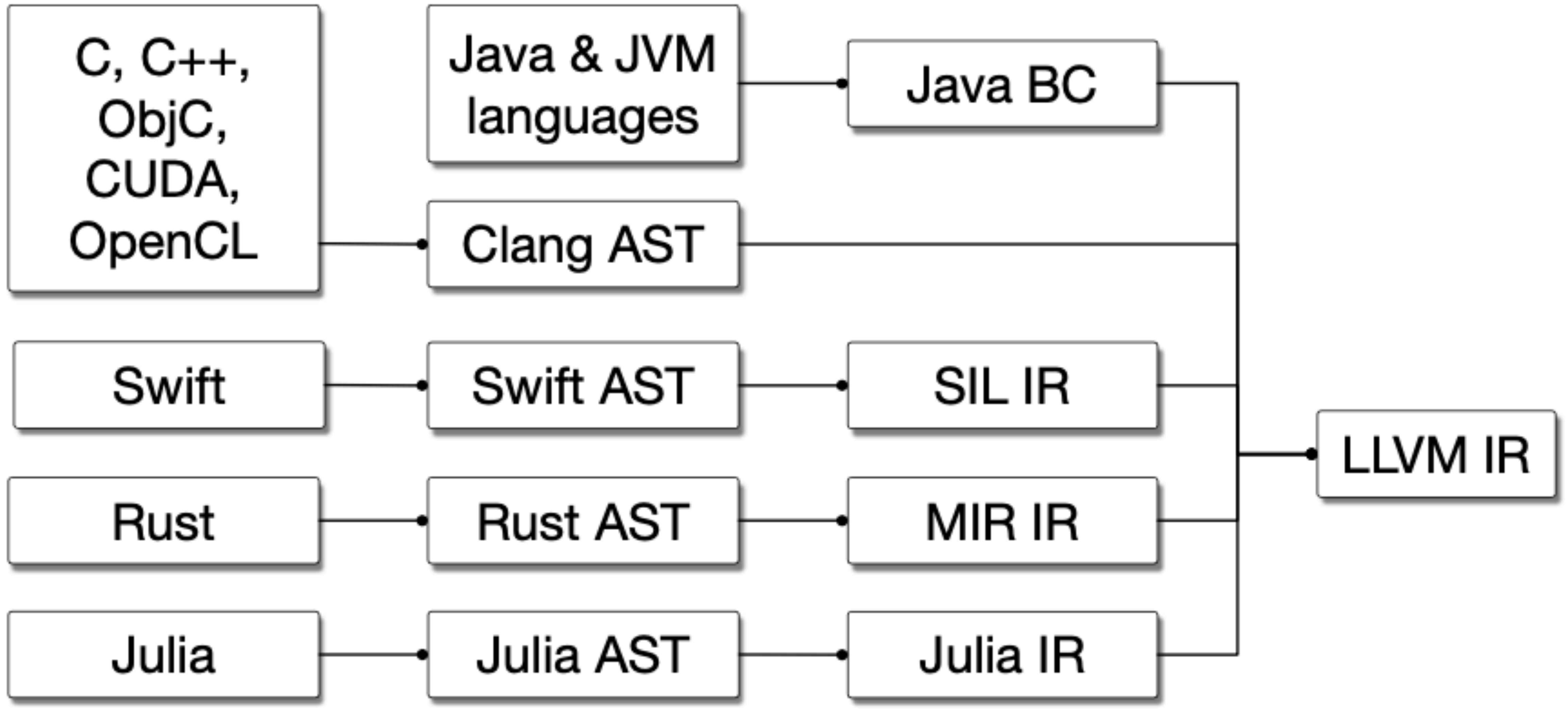

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➡ There is a need for a more general solution

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  "arc.yield"(%a)
}, {
  "arc.yield"(%b)
}) : (arc.bool) → (!arc.int)
```

MLIR - Meta-Syntax/Semantics

Meta-syntax (with some parts optional):

- `ASSIGNMENT ::= %VAR_NAME = OPERATION`
- `OPERATION ::= "DIALECT.OP_NAME"(ARGS) (REGIONS) {ATTRS} : (TYPES) → (TYPES)`
- `TYPE ::= !DIALECT.TYPE_NAME<TYPES>`

Meta-semantics: All values are **SSA**, **typed**, **scoped** (and so on)

Example:

Compute the
<u>max of two values</u>

```
c = a > b
max = if c {
  a
} else {
  b
}
```

```
%c = "arc.greater_than"(%a, %b) : (!arc.int, !arc.int) → (!arc.bool)
%max = "arc.if"(%c) ({
  "arc.yield"(%a) : (!arc.int) → (!arc.int)
}, {
  "arc.yield"(%b) : (!arc.int) → (!arc.int)
}) : (arc.bool) → (!arc.int)
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MLIR - Defining Operations

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The **structure** of each operation is defined using an high-level **DSL**, while **details** are implemented in **C++**

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Example:

```
def GreaterThanOp : Op<"greater_than", [...........................]> {









}
```

MLIR - Defining Operations

The **structure** of each operation is defined using an high-level **DSL**, while **details** are implemented in **C++**

Example:

```
def GreaterThanOp : Op<"greater_than", [............................]> {
  let summary     = "greater than operation";
  let description = [{ Returns true if $left is greater than $right }];




}
```

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The **structure** of each operation is defined using an high-level **DSL**, while **details** are implemented in **C++**

Example:

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def GreaterThanOp : Op<"greater_than", [............................]> {
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  let arguments   = (ins AnyType:$left, AnyType:$right);







}
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def GreaterThanOp : Op<"greater_than", [............................]> {
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}
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The **structure** of each operation is defined using an high-level **DSL**, while **details** are implemented in **C++**

Example:

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def GreaterThanOp : Op<"greater_than", [ArgsAreSameType, NoSideEffect]> {
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def GreaterThanOp : Op<"greater_than", [ArgsAreSameType, NoSideEffect]> {
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  let description = [{ Returns true if $left is greater than $right }];
  let arguments   = (ins AnyType:$left, AnyType:$right);
  let results     = (outs BoolType:$output);
  // Optional
  let regions     = ...
  let verifier    = ...
  let parser      = ...
  let printer     = ...
}
```
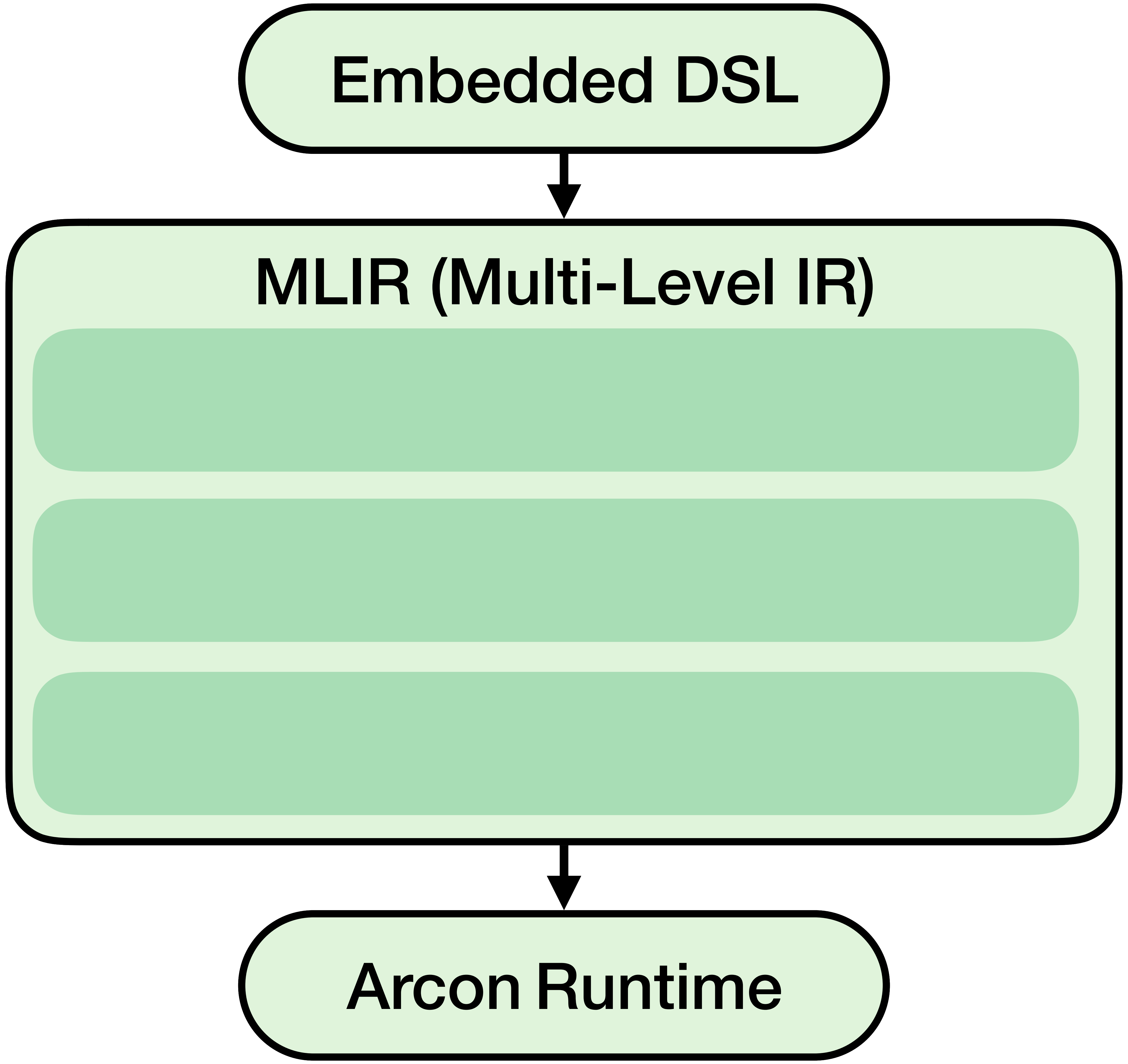

Current approach



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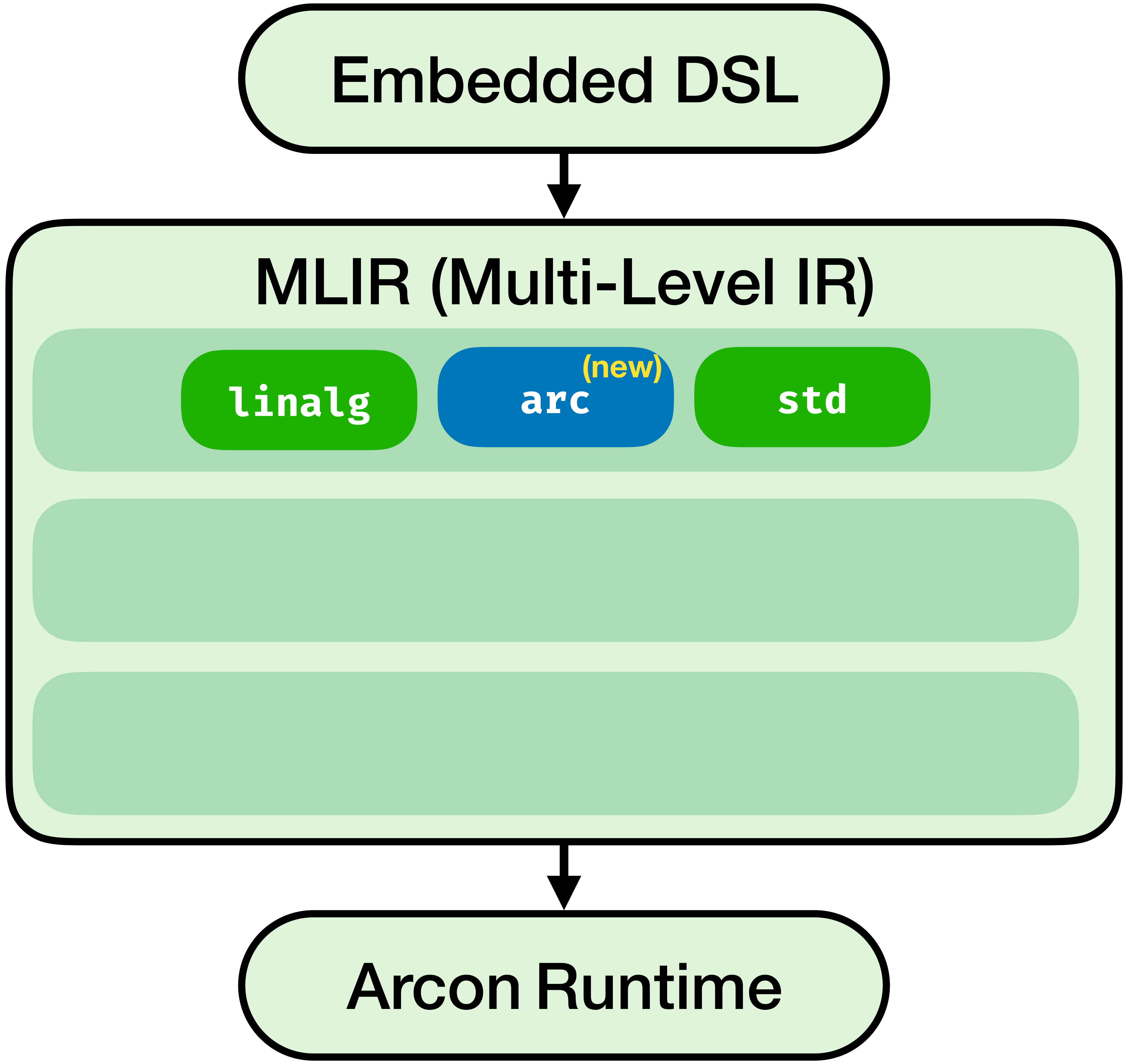

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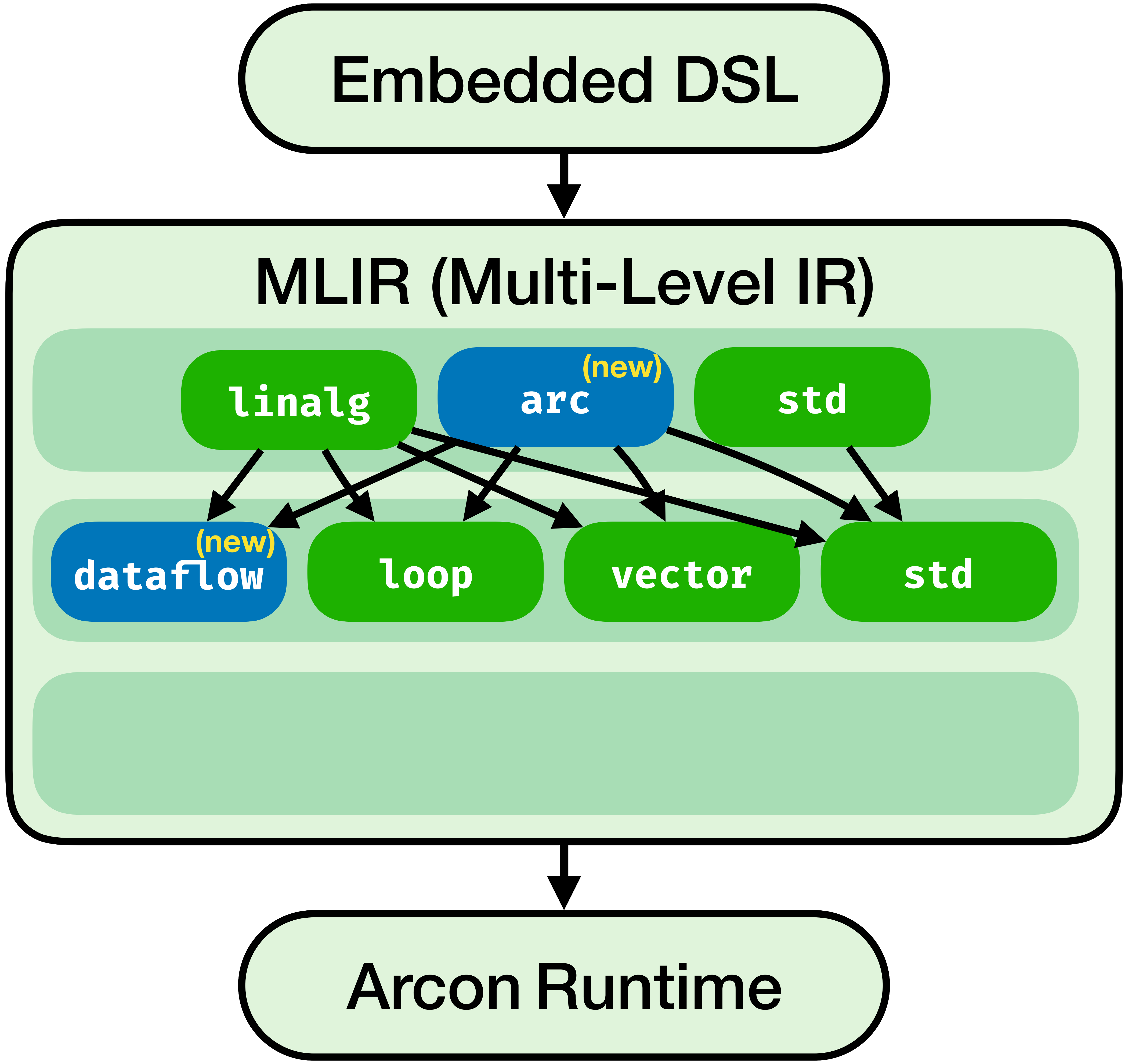

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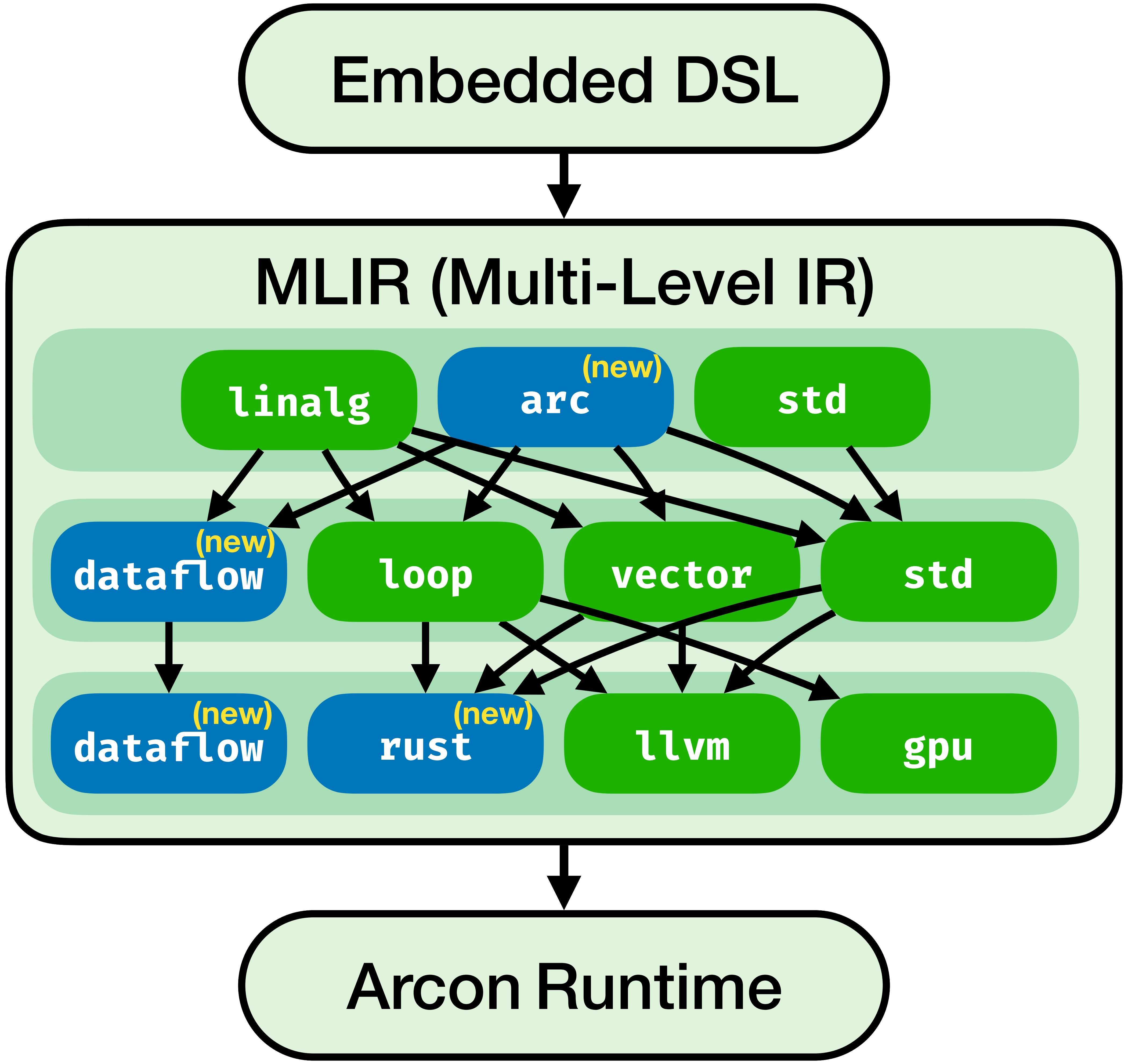
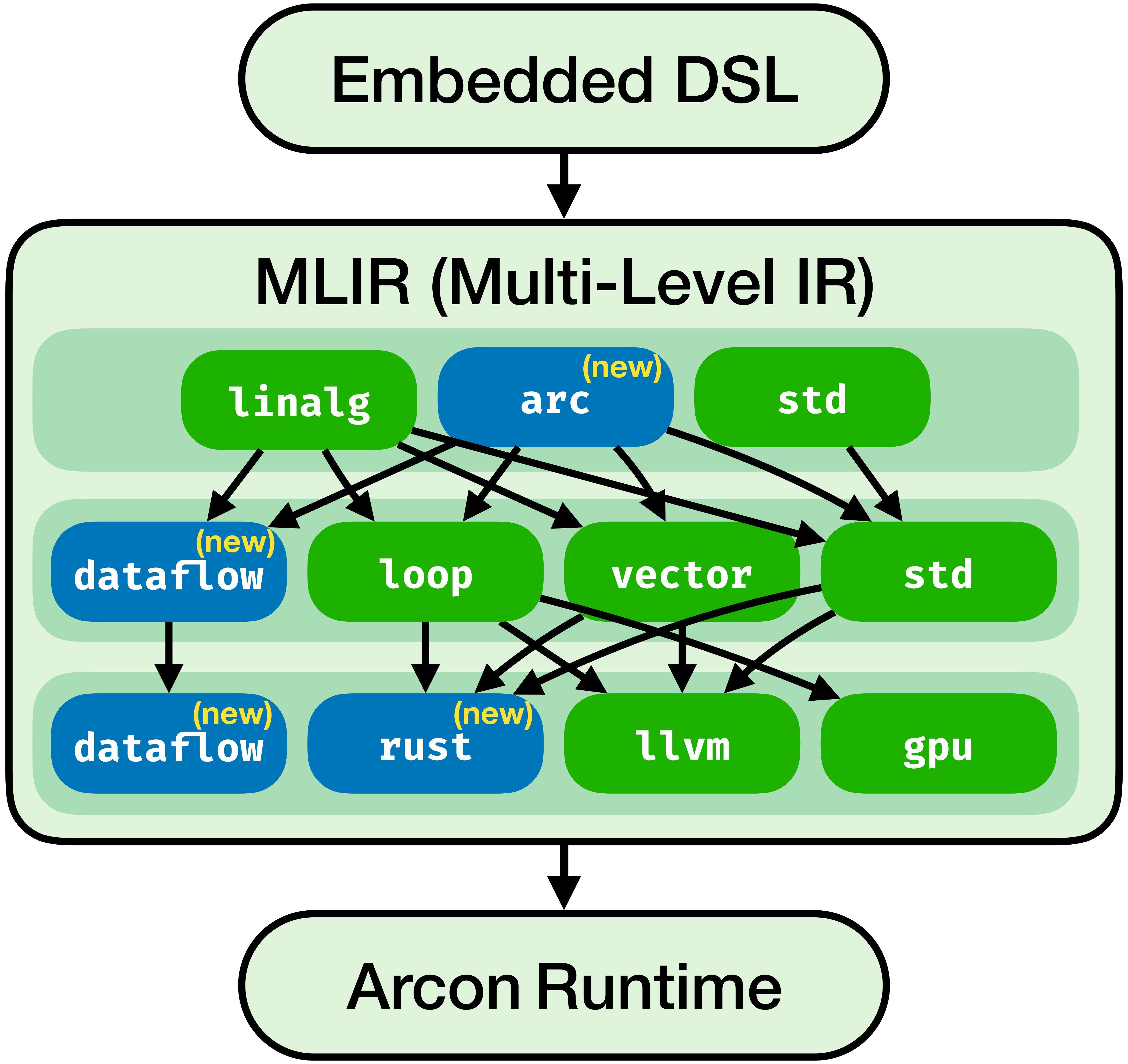


Summary

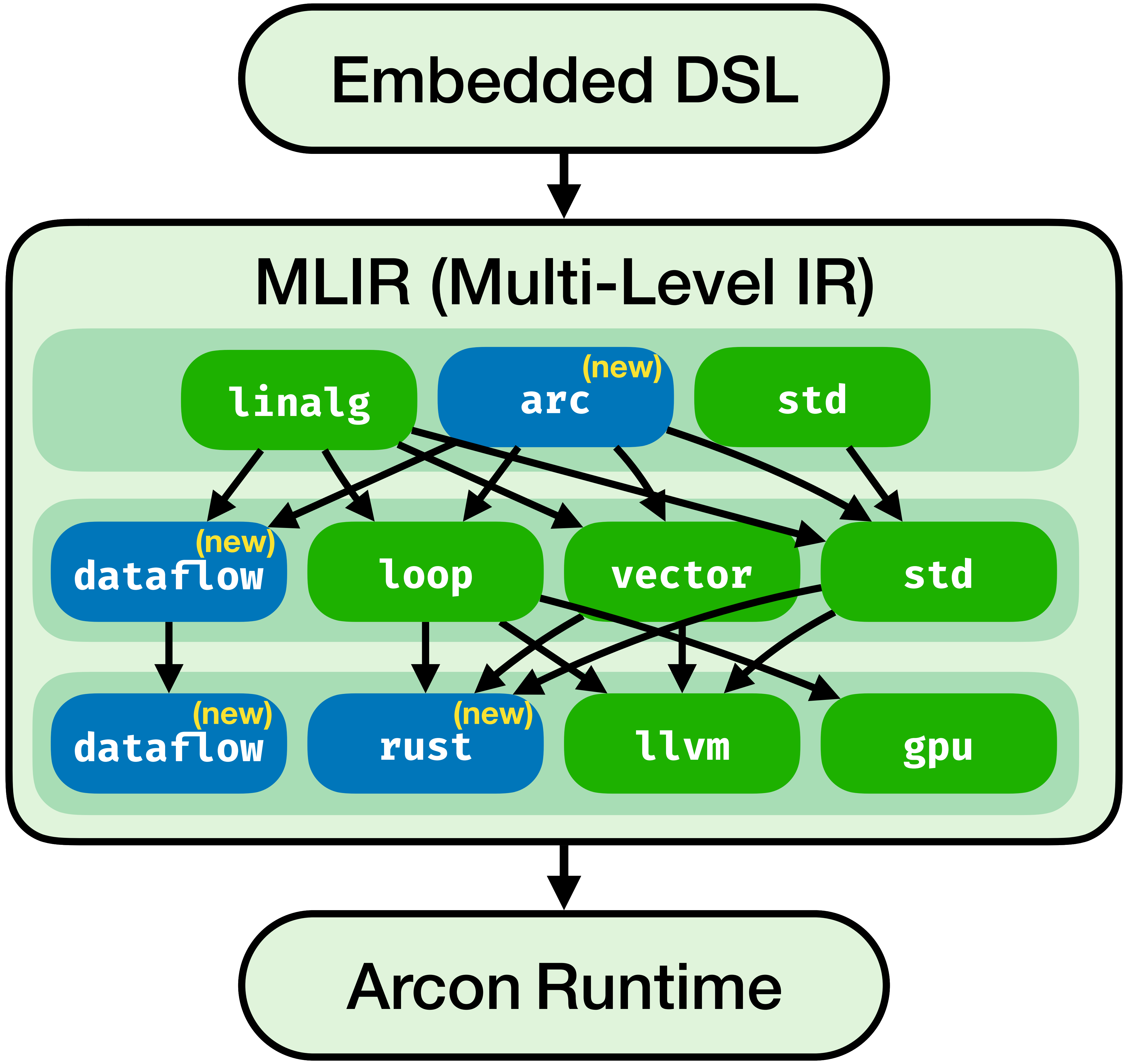
Current approach



Summary

Arc is a dialect in **MLIR** for data analytics that takes inspiration from **Lara**

Current approach



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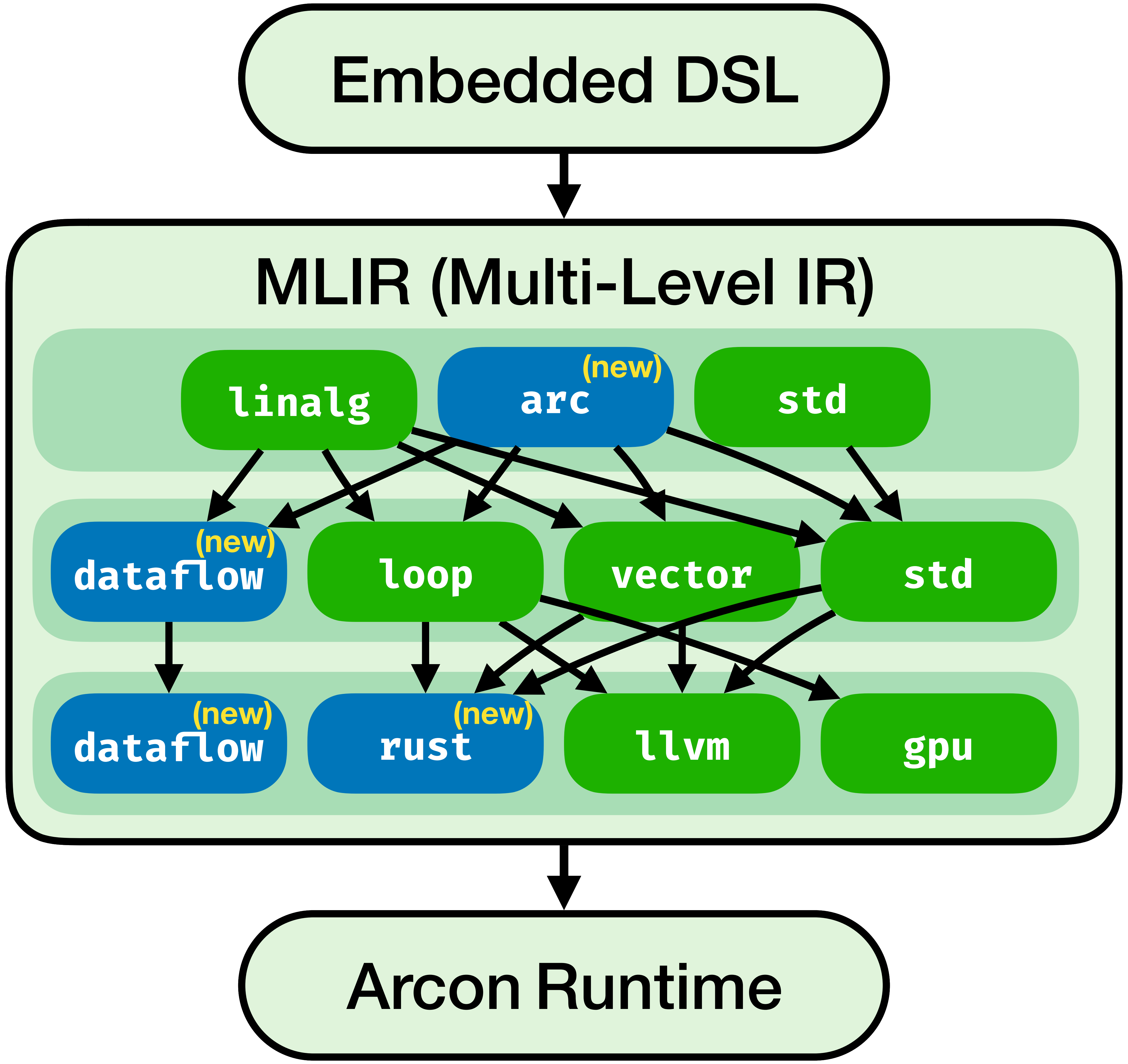
Arc is a dialect in **MLIR** for data analytics that takes inspiration from **Lara**

Arc aims to **extend Lara**'s model with support for **`Stream`** data types

Current approach



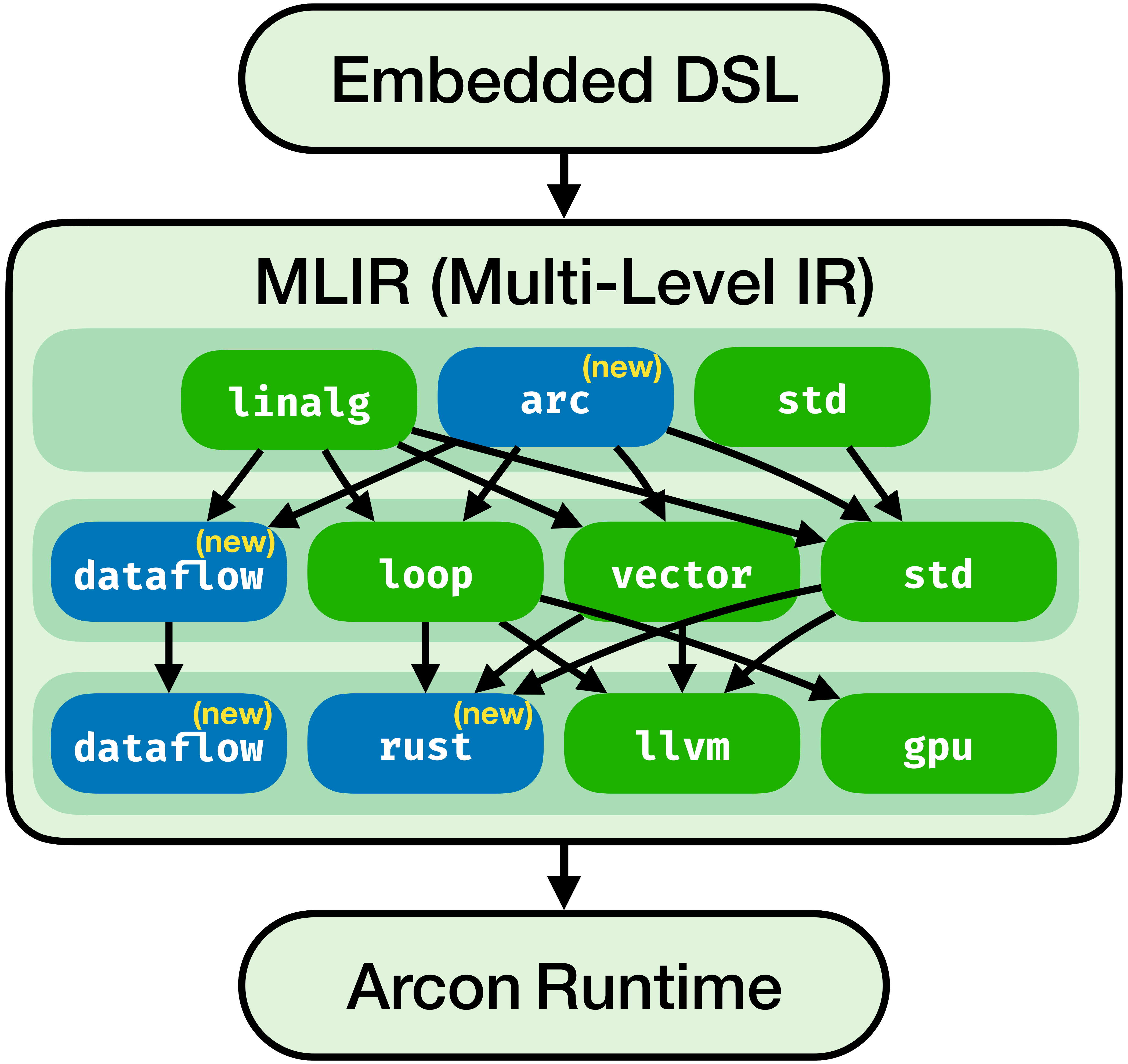
Summary

Arc is a dialect in **MLIR** for data analytics that takes inspiration from **Lara**

Arc aims to **extend Lara**'s model with support for **`Stream`** data types

Through MLIR, Arc can **reuse** existing compiler technology and widen its **scope**

Current approach



Summary

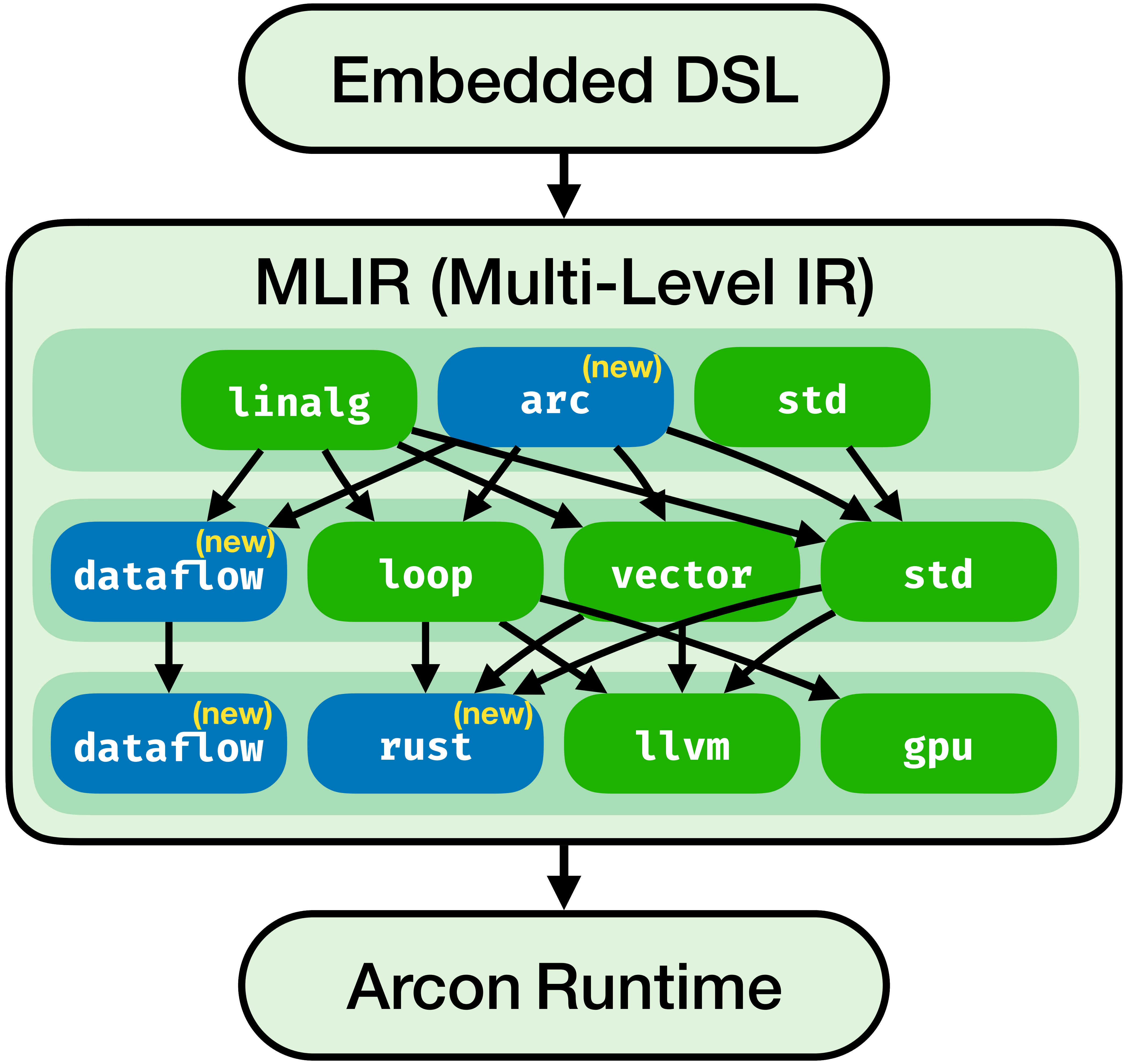
Arc is a dialect in **MLIR** for data analytics that takes inspiration from **Lara**

Arc aims to **extend Lara**'s model with support for **`Stream`** data types

Through MLIR, Arc can **reuse** existing compiler technology and widen its **scope**

Upcoming work: Embedded DSL Design

Current approach



Extra slides

Presenter: Klas Segeljakt <klasseg@kth.se>

Lara's DSL - Example

Lara's DSL - Example

Description

Based on **numerical** and **categorical** data, train a **Ridge Regression** model with **3-fold cross-validation**, and **Mean Squared Error** as the loss function, to the predict number of future clicks on advertisements

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```
// Column 0 contains the target variable, columns 1-10 contain
// numerical and columns 11-15 contain categorical features
val dataset  = readAndClean("/path/to/data")
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// Grid search over hyperparameter candidates
val regCandidates: Seq[Double] = // ...
for (lambda <- regCandidates) {















}
```

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for (lambda <- regCandidates) {
  // 3-fold cross-validation for the hyperparameter lambda
  val errors = ML.crossValidate(3, X, y) {
    (X_train, X_test, y_train, y_test) =>









  }
  // Print mean error for chosen hyperparameter
  println(errors.sum / k)
}
```

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Based on **numerical** and **categorical** data, train a **Ridge Regression** model with **3-fold cross-validation**, and **Mean Squared Error** as the loss function, to the predict number of future clicks on advertisements

$$\hat{\mathbf{w}}_{ridge} = \arg\min_{\mathbf{w}} \sum_{i=1}^{N} \left(\mathbf{y}_i - \mathbf{X}_i\mathbf{w}\right)^2 + \lambda \sum_{i=1}^{K} \mathbf{w}_i^2$$

Input data: [L,N,N,N,N,N,N,N,N,N,N,C,C,C,C,C]

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Lara's DSL - Example

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Based on **numerical** and **categorical** data, train a **Ridge Regression** model with **3-fold cross-validation**, and **Mean Squared Error** as the loss function, to the predict number of future clicks on advertisements

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$$\hat{\mathbf{w}}_{ridge} = (\mathbf{X}^{\mathrm{T}}\mathbf{X} + \lambda\mathbf{I})^{-1}(\mathbf{X}^{\mathrm{T}}\mathbf{y})$$

Input data: [L,N,N,N,N,N,N,N,N,N,N,C,C,C,C,C]

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Lara's DSL - Example

Description

Based on **numerical** and **categorical** data, train a **Ridge Regression** model with **3-fold cross-validation**, and **Mean Squared Error** as the loss function, to the predict number of future clicks on advertisements

$$\hat{\mathbf{w}}_{ridge} = \arg\min_{\mathbf{w}} \sum_{i=1}^{N} \left(\mathbf{y}_i - \mathbf{X}_i \mathbf{w}\right)^2 + \lambda \sum_{i=1}^{K} \mathbf{w}_i^2$$

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    val reg = Matrix.eye(X_train.nCols) * lambda
    val XtX = X_train.t ** X_train + reg
    val Xty = X_train.t ** y_train
    val w   = XtX \ Xty



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    val XtX = X_train.t ** X_train + reg
    val Xty = X_train.t ** y_train
    val w   = XtX \ Xty
    // Calculate mean squared error on test set


  }
  // Print mean error for chosen hyperparameter
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Based on **numerical** and **categorical** data, train a **Ridge Regression** model with **3-fold cross-validation**, and **Mean Squared Error** as the loss function, to the predict number of future clicks on advertisements

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$$\left.\begin{aligned} \hat{\mathbf{w}}_{ridge} &= (\mathbf{X}^{\mathrm{T}}\mathbf{X} + \lambda \mathbf{I})^{-1}(\mathbf{X}^{\mathrm{T}}\mathbf{y}) \\ \hat{\mathbf{w}}_{ridge} &= (\mathbf{X}^{\mathrm{T}}\mathbf{X} + \lambda \mathbf{I}) \setminus (\mathbf{X}^{\mathrm{T}}\mathbf{y}) \end{aligned}\right\\}$$

$$\textbf{MSE} = \frac{1}{N} \sum_{i=1}^{N} \left(\mathbf{y}_i - \mathbf{X}_i \mathbf{w}\right)^2$$

Input data: [L,N,N,N,N,N,N,N,N,N,N,C,C,C,C,C]

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// Column 0 contains the target variable, columns 1-10 contain
// numerical and columns 11-15 contain categorical features
val dataset  = readAndClean("/path/to/data")
val encoded  = dummyEncode(dataset, 11 to 15)
val vectors  = concatNumericalFeatures(encoded, 1 to 10)
val features = concatVectors(vectors)
// y = 0: extract 1st column as target vector y
val (M, y)   = Matrix(features, y = 0)
val X        = Matrix.normalize(M, 1 to 10)
// Grid search over hyperparameter candidates
val regCandidates: Seq[Double] = // ...
for (lambda <- regCandidates) {
  // 3-fold cross-validation for the hyperparameter lambda
  val errors = ML.crossValidate(3, X, y) {
    (X_train, X_test, y_train, y_test) =>
    // Ridge regression
    val reg = Matrix.eye(X_train.nCols) * lambda
    val XtX = X_train.t ** X_train + reg
    val Xty = X_train.t ** y_train
    val w   = XtX \ Xty
    // Calculate mean squared error on test set


  }
  // Print mean error for chosen hyperparameter
  println(errors.sum / k)
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Lara's DSL - Example

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    val Xty = X_train.t ** y_train
    val w   = XtX \ Xty
    // Calculate mean squared error on test set
    val residuals = y_test - (X_test ** w)
    residuals.map(r => r * r).agg(_ + _) / y_test.size
  }
  // Print mean error for chosen hyperparameter
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```

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