Weld: A Common Runtime for Data Analytics

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Motivation

Modern data apps combine many disjoint processing libraries & functions

- » Relational, statistics, machine learning, …
- » E.g. PyData stack

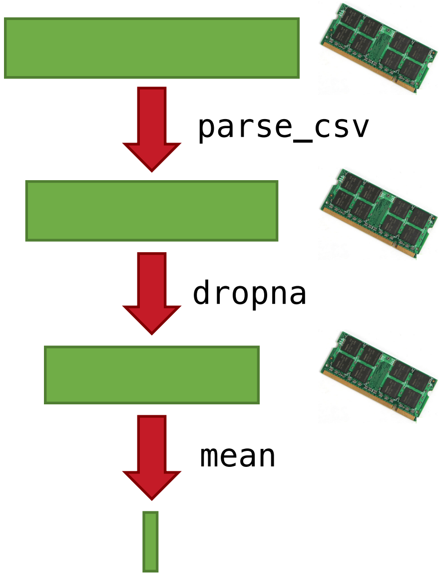
+ Great results leveraging work of 1000s of authors

– No optimization across these functions

How Bad is This Problem?

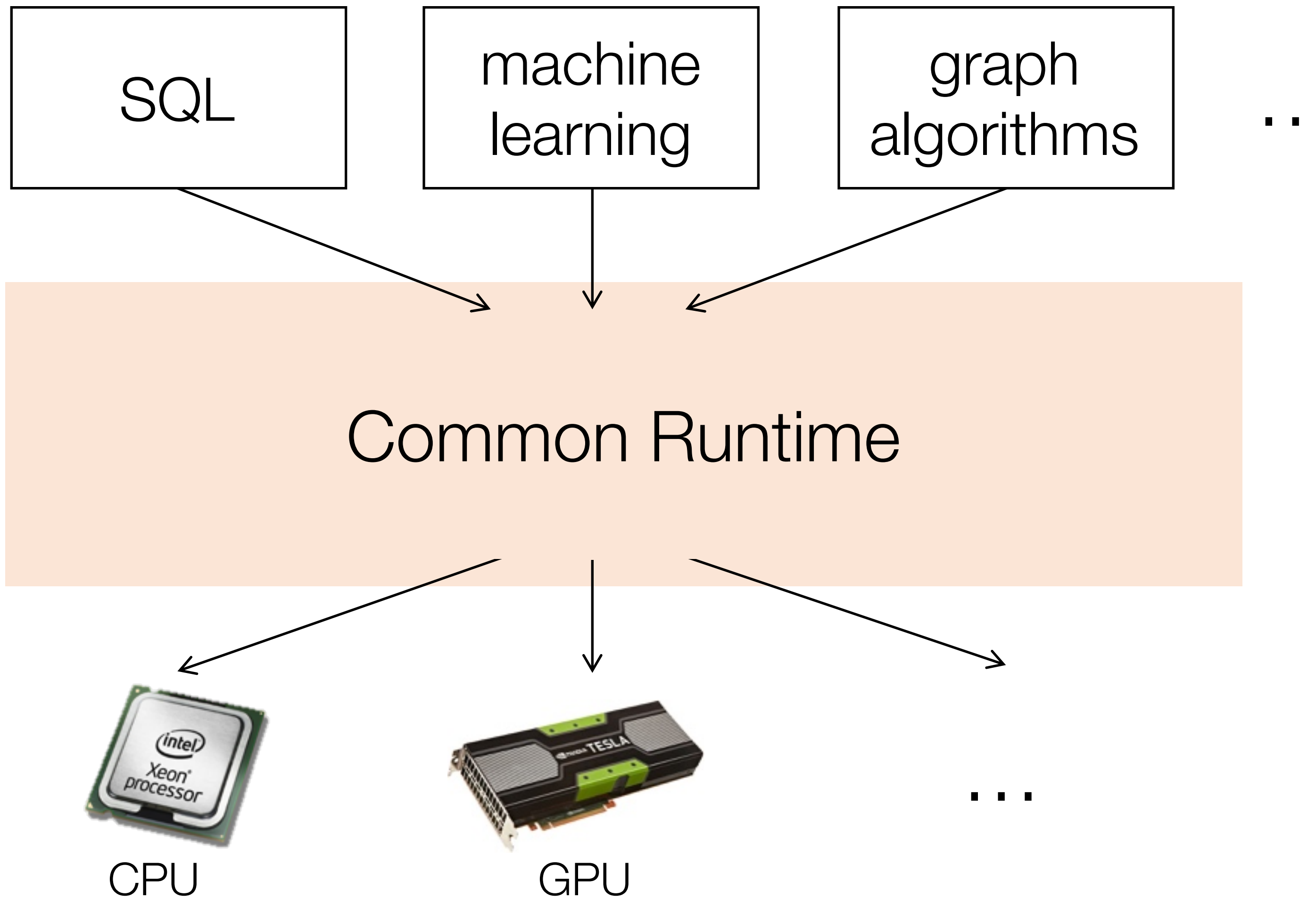
Growing gap between memory/processing makes traditional way of combining functions worse

```
data = pandas.parse_csv(string)

filtered = pandas.dropna(data)

avg = numpy.mean(filtered)
```



5-30x slowdowns in NumPy, Pandas, TensorFlow, etc

How We Solve This



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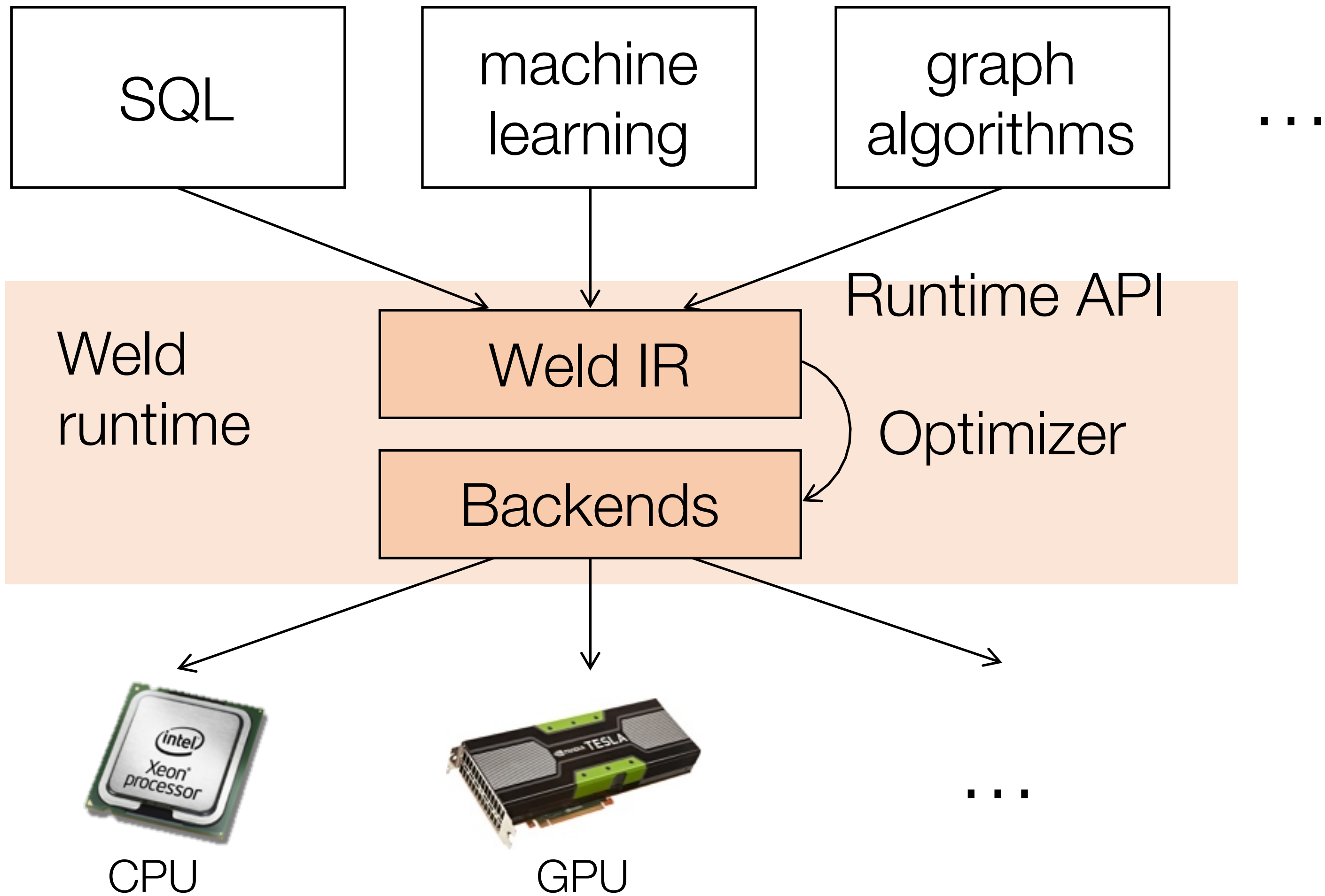
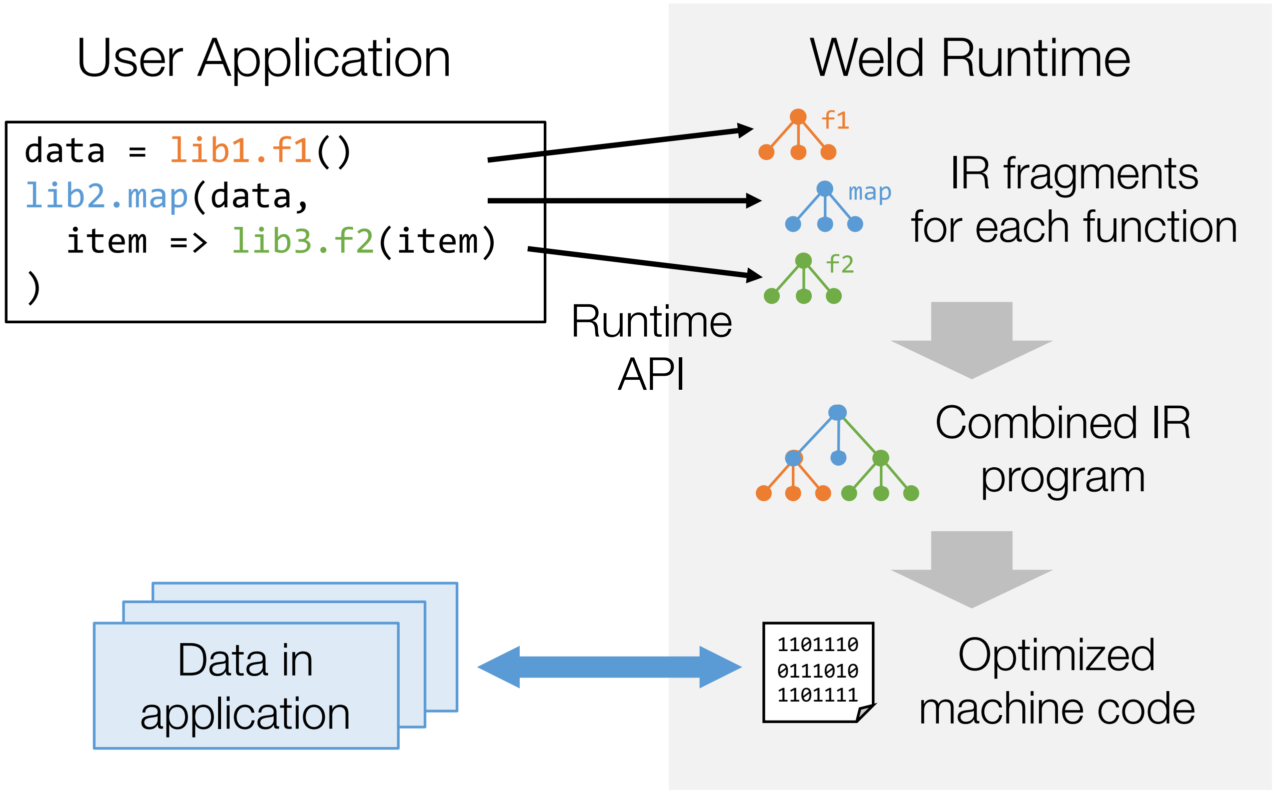


Runtime API

Uses lazy evaluation to collect work across libraries



Weld IR

Designed to meet three goals:

1. **Library composition:** support complete workloads such as nested parallel calls

2. **Ability to express optimizations:** e.g. loop fusion, vectorization, loop tiling

3. **Explicit parallelism and targeting parallel hardware**

Weld IR

Small, powerful design inspired by “monad comprehensions”

Parallel loops: iterate over a dataset

Builders: declarative objects for producing results

- » E.g. append items to a list, compute a sum
- » Can be implemented differently on different hardware

Captures relational algebra, functional APIs like Spark, linear algebra, and composition thereof

Examples

Implement functional operators using builders

```
def map(data, f):
    builder = new vecbuilder[int]
    for x in data:
        merge(builder, f(x))
    result(builder)


def reduce(data, zero, func):
    builder = new merger[zero, func]
    for x in data:
        merge(builder, x)
    result(builder)
```

Example Optimization: Fusion

```
squares = map(data, x => x * x)
sum = reduce(data, 0, +)
```

```
bld1 = new vecbuilder[int]
bld2 = new merger[0, +]
for x in data:
    merge(bld1, x * x)
    merge(bld2, x)
```

Loops can be merged into one pass over data

Heterogeneous Hardware

A platform for heterogeneous computing.

One example: Creating a storage engine using FPGAs.

- Loading data from a persistent format into a memory format is often compute bound.
- Weld can accelerate these workloads

Implementation

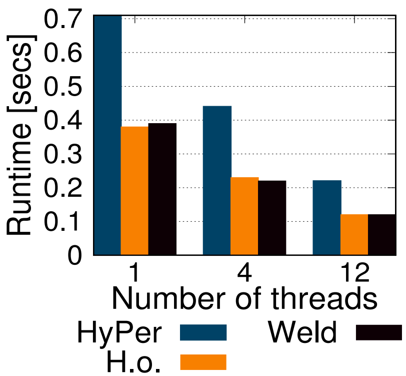
Prototype with APIs in Scala and Python

» LLVM and Voodoo for code gen

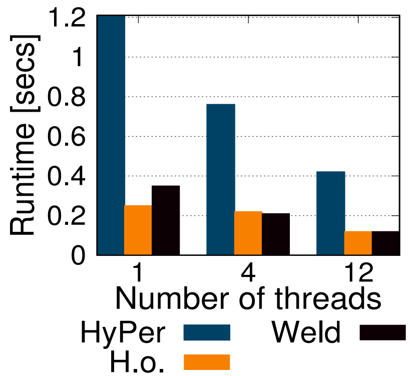
Integrations: TensorFlow, NumPy, Pandas, Spark

Results: Individual Workloads

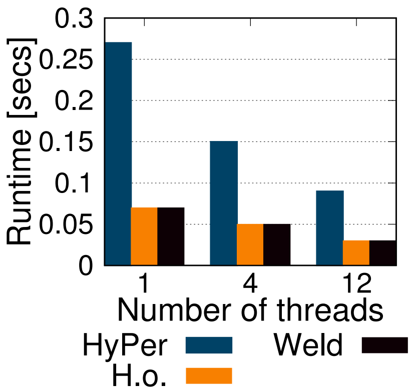
SQL (TPC-H)



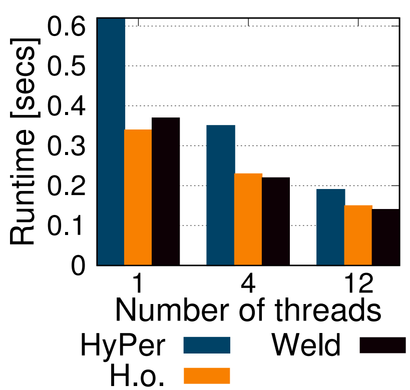
Q1



Q3

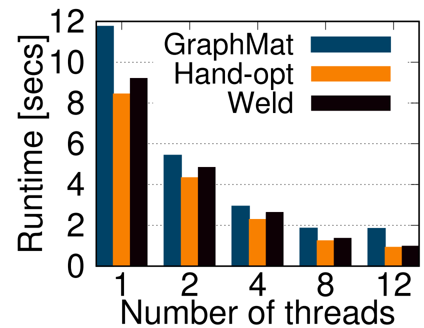


Q6

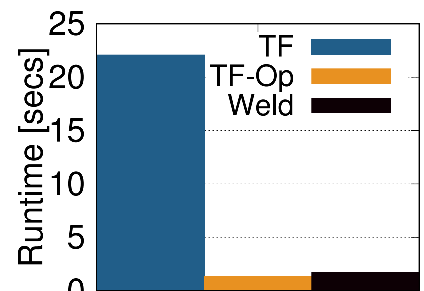


Q12

PageRank

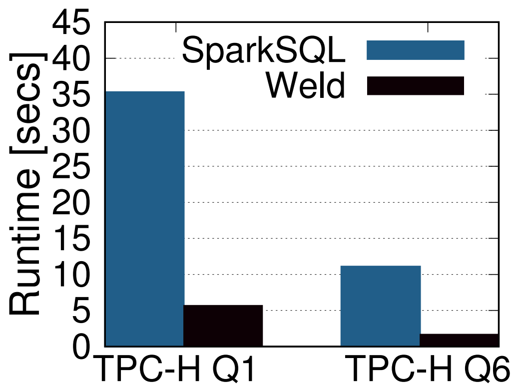


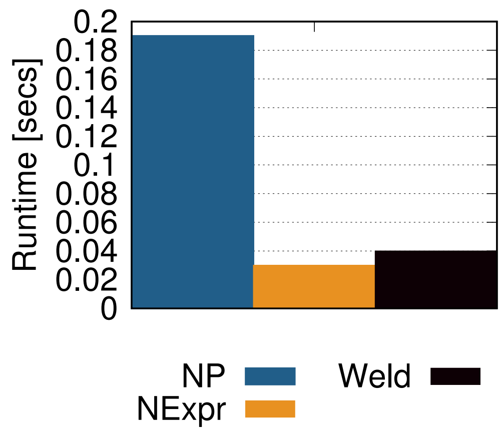
Word2Vec

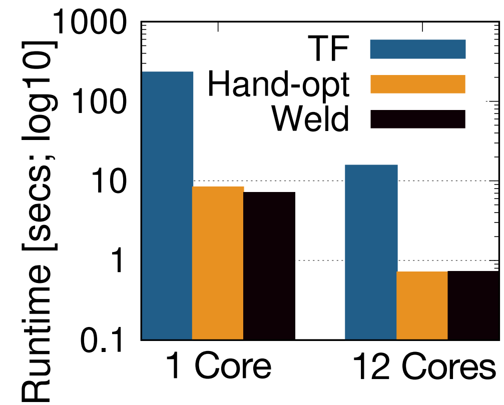


TF-Op = C++ operator

Results: Existing Frameworks







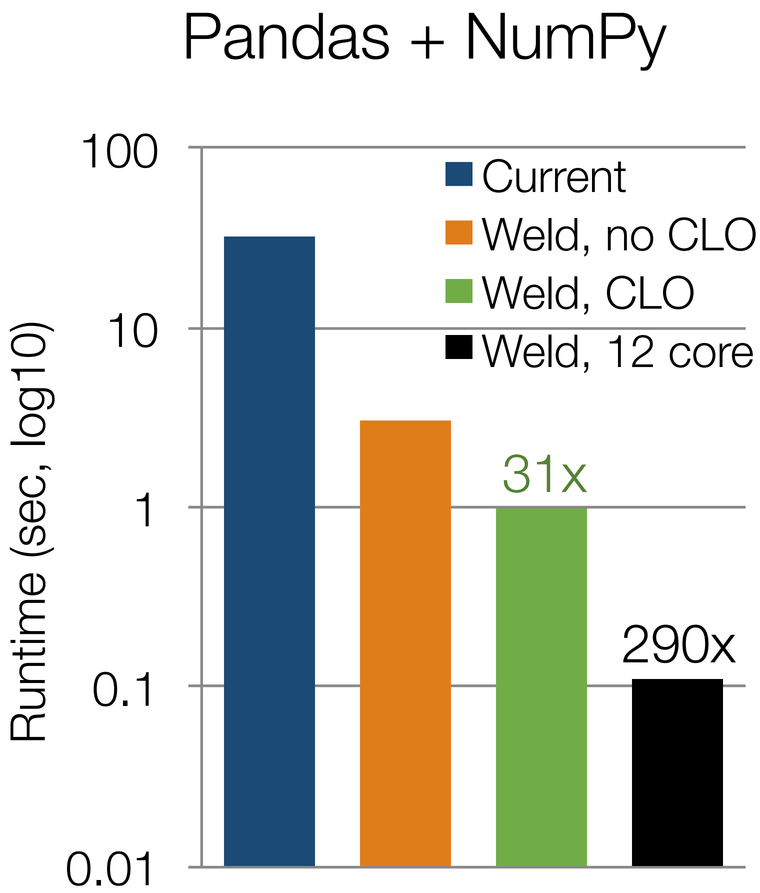
TPC-H

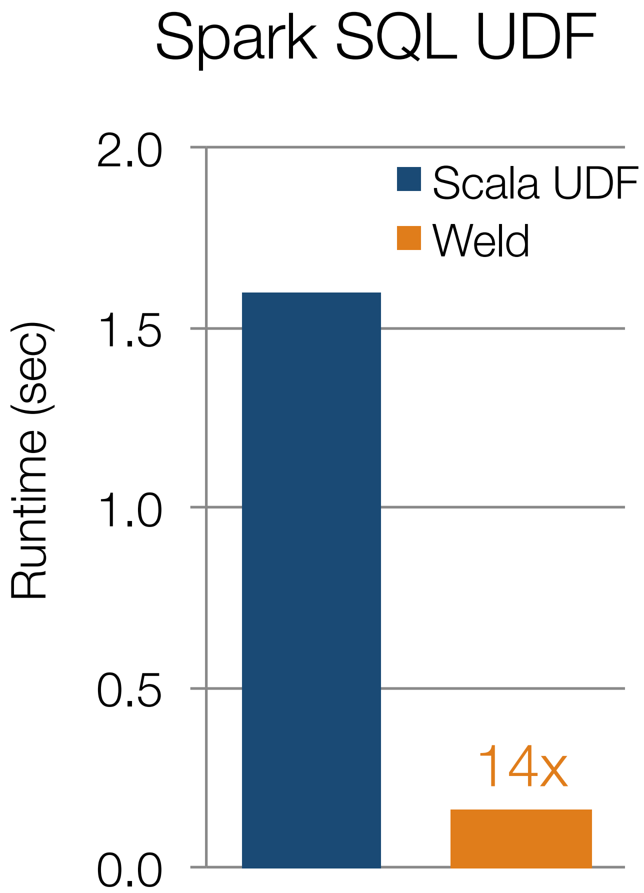
Vector Sum

Logistic Regression

Integration effort: 500 lines glue, 30 lines/operator

Results: Cross-Library Optimization





Conclusion

The way we compose software will have to change to efficiently use modern hardware

Lots of open questions and design decisions!

» Leveraging specialized hardware, domain info, …

Open source: soon!

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Why Don't Compilers Solve This?

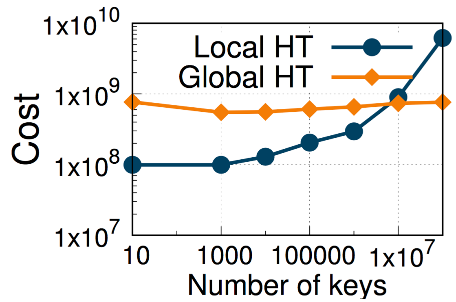
Languages and intermediate representations (IRs) make it hard to optimize across libraries

- Main abstraction is shared memory
 (must worry about aliasing, order, etc)

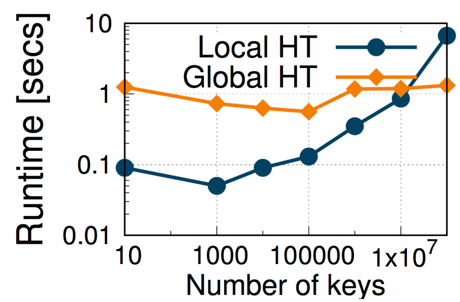
Most compilers don't model parallel operations

- Makes high performance code generation for heterogeneous parallel hardware even more difficult

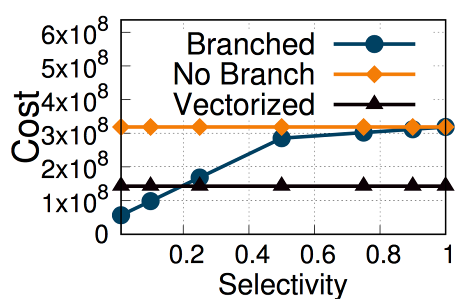
Results: Modeling Costs



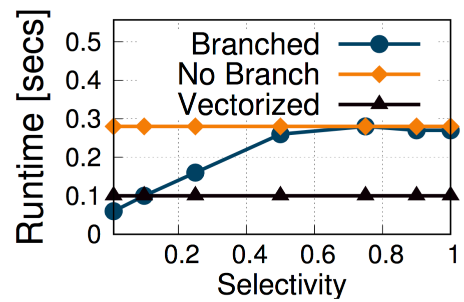
(a) TPCH Q1 Cost Estimates.



(b) TPCH Q1 Runtimes.



(e) TPCH Q6 Cost Estimates.



(f) TPCH Q6 Runtimes.

Takeaway: Cost curves *resemble* actual runtimes

Cost Model

Inspired by cost models for in-memory databases

+ modeling nested parallelism and choices among implementations of data structures

Models cache contention, costs of atomic instructions, etc.

Builders

Hardware independent and explicitly parallel

Three operators:

`merge(builder, value):` Merge a value into the builder and return a new builder

`result(builder):` destroy the builder and return a value

`for(data, builders, func):` iterate over data, potentially merging values into one or more builders in parallel

Optimizer

Cost Based Optimizer similar to an RDBMS

Builder Implementations: How to implement a particular builder (e.g., global vs. local hash tables)

Transforms: Should expressions be fused, vectorized, inlined, etc.

Quantifies choices among optimizations using data from the program

Related Work

HyPer, LegoBase, Tupleware: target relational algebra and serial UDFs; no nested parallelism

LLVM, OpenCL: low-level shared-memory model

NESL, parallel FPs: not closed under optimizations

DSLs: Weld focuses on integration with existing libraries and cross-library optimization

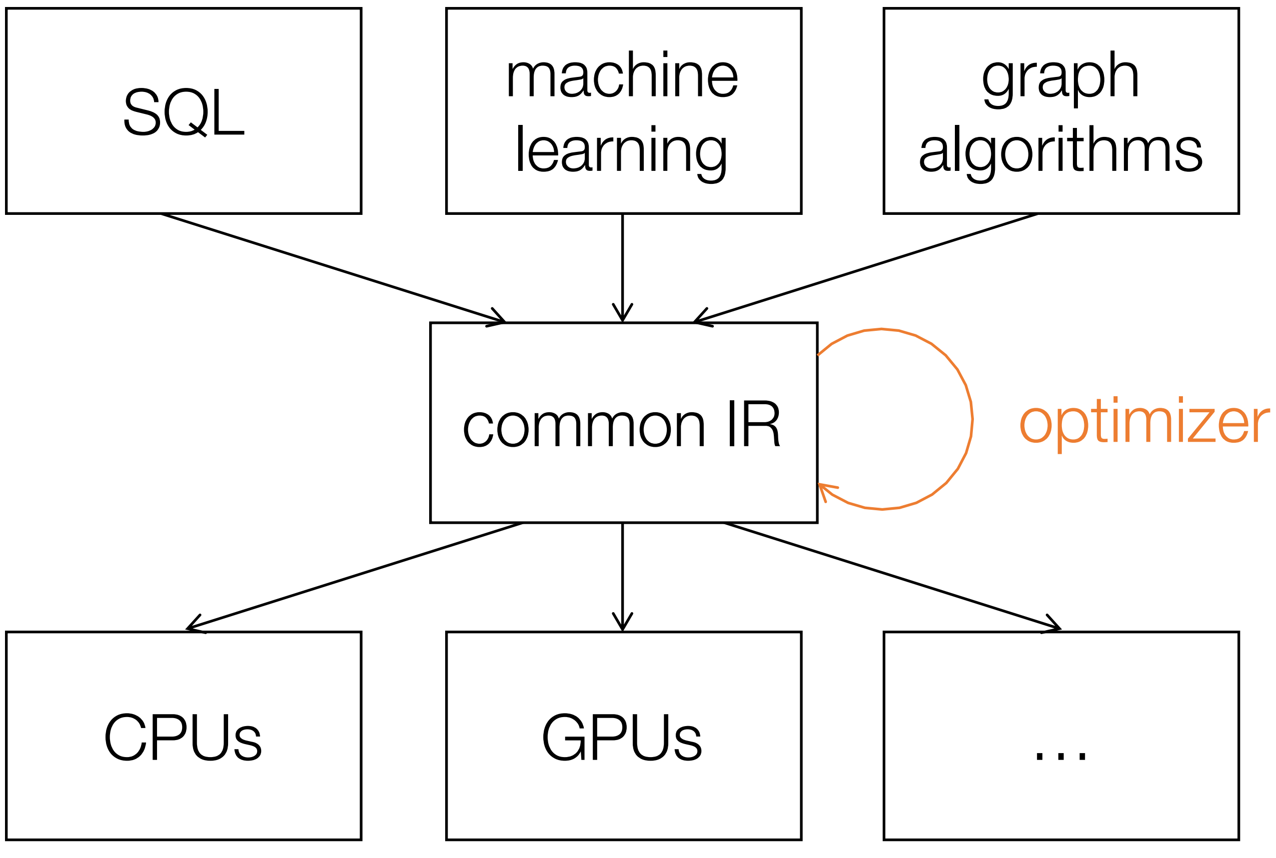
Observation

Many analytics algorithms can be written with a few “embarrassingly parallel” operators

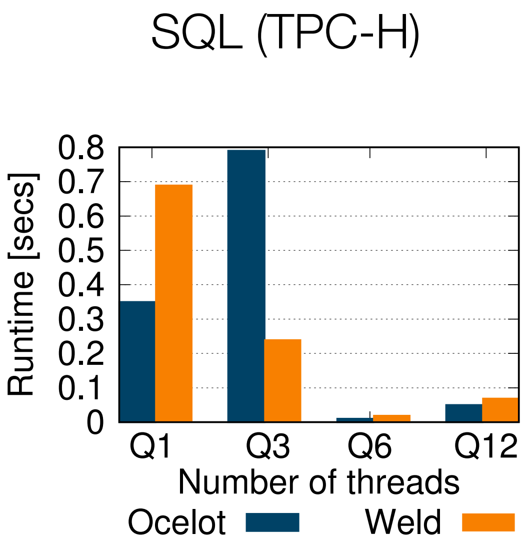
- » See how many run on MapReduce / Spark

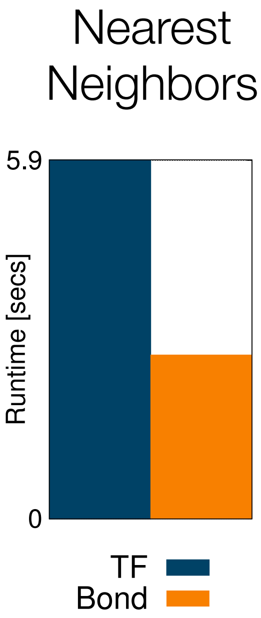
Focus on these instead of general programs

The Goal


SQL
machine learning
graph algorithms
common IR
optimizer
CPUs
GPUs
...

Results on GPUs





Example Transformations

```
def query(products: vec[{dept:int, price:int}]):
  sum = 0
  for p in products:
    if p.dept == 20: sum += p.price
```

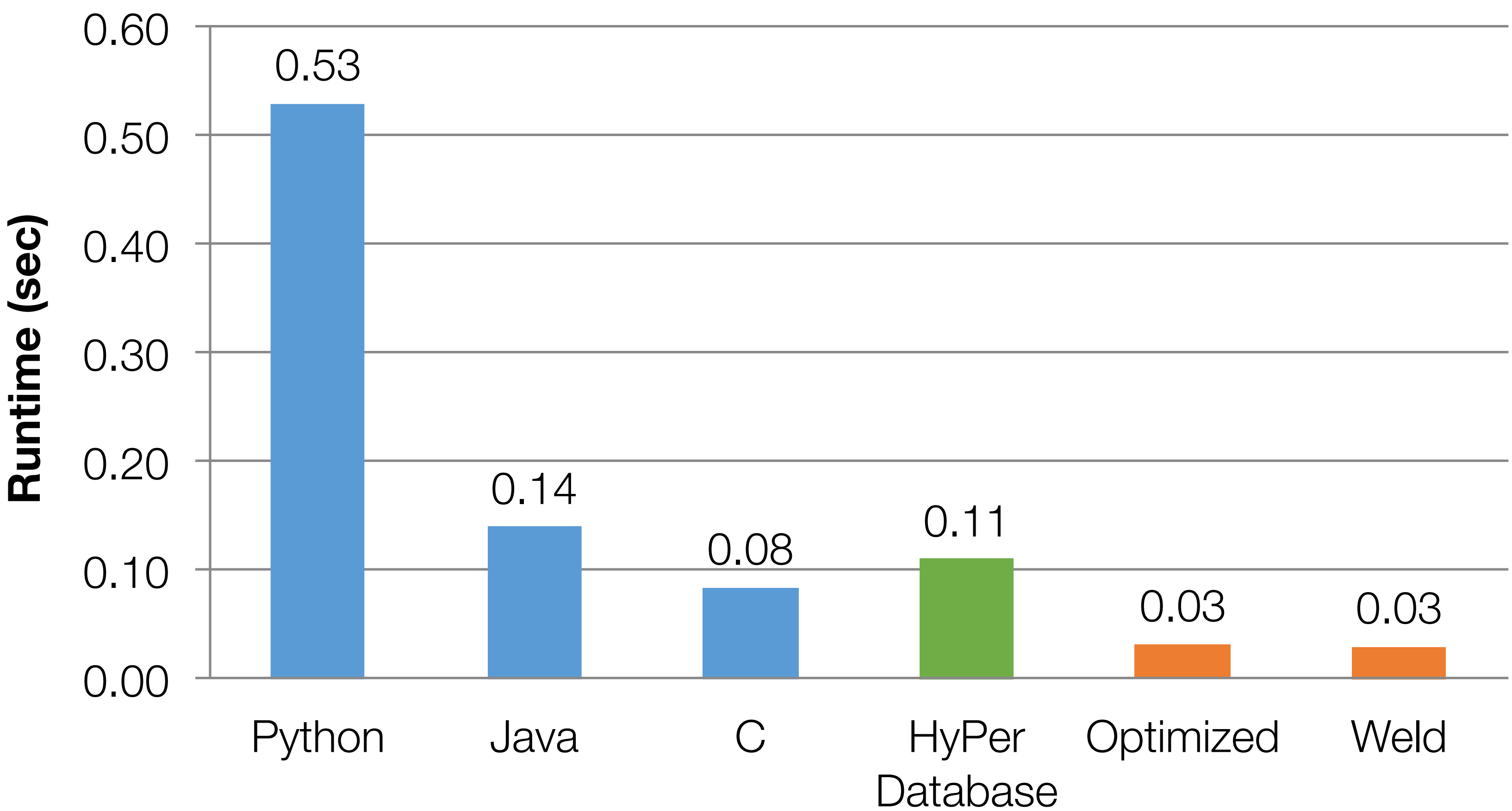
row-to-column

```
def query(dept: vec[int], price: vector[int]):
  sum = 0
  for i in 0..len(users):
    if dept[i] == 20: sum += price[i]
```

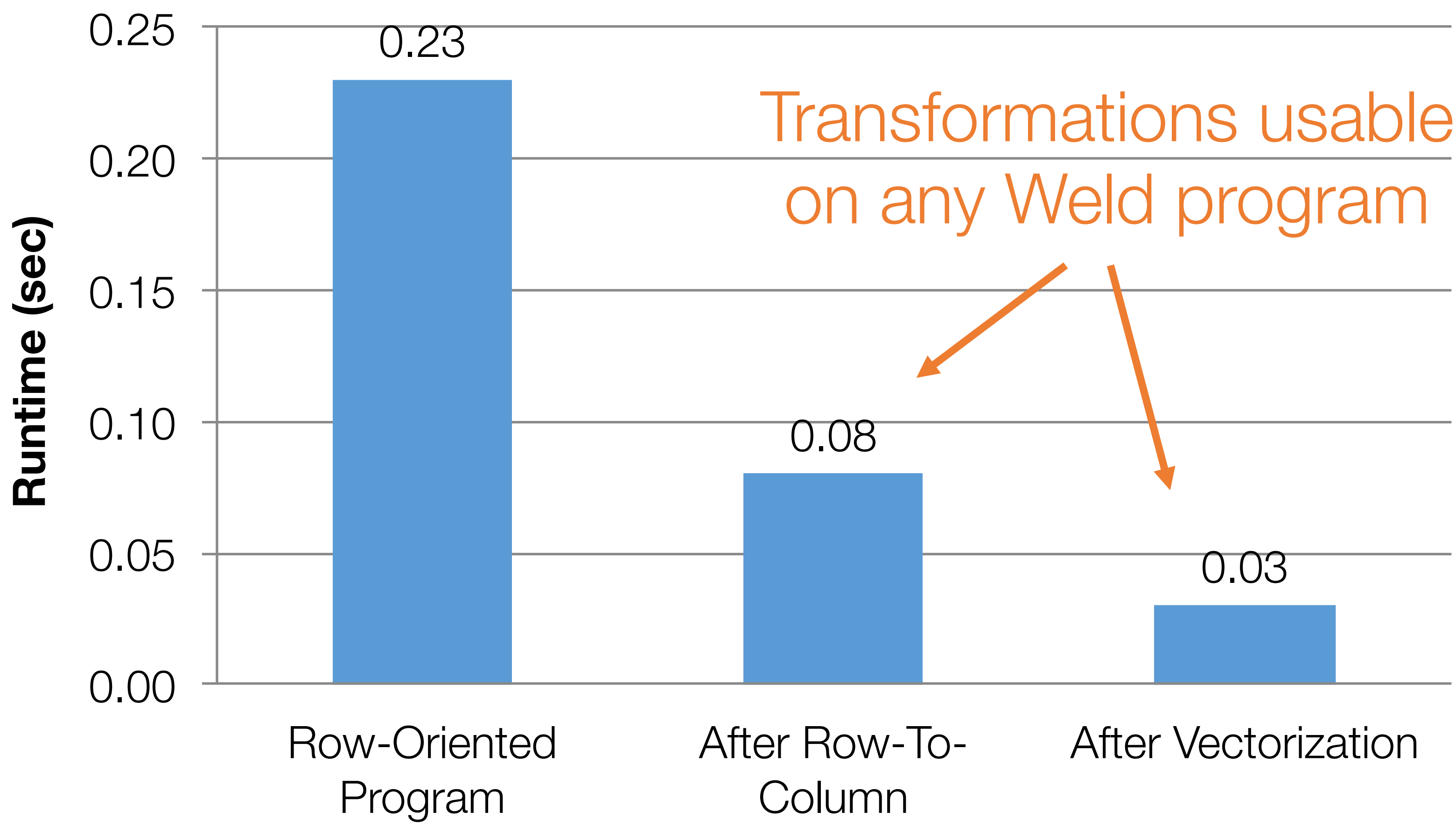
vectorization

```
  for i in 0..len(products) by 4:
    sum += price[i..i+4] * (dept[i..i+4] == [20,20,20,20])
```

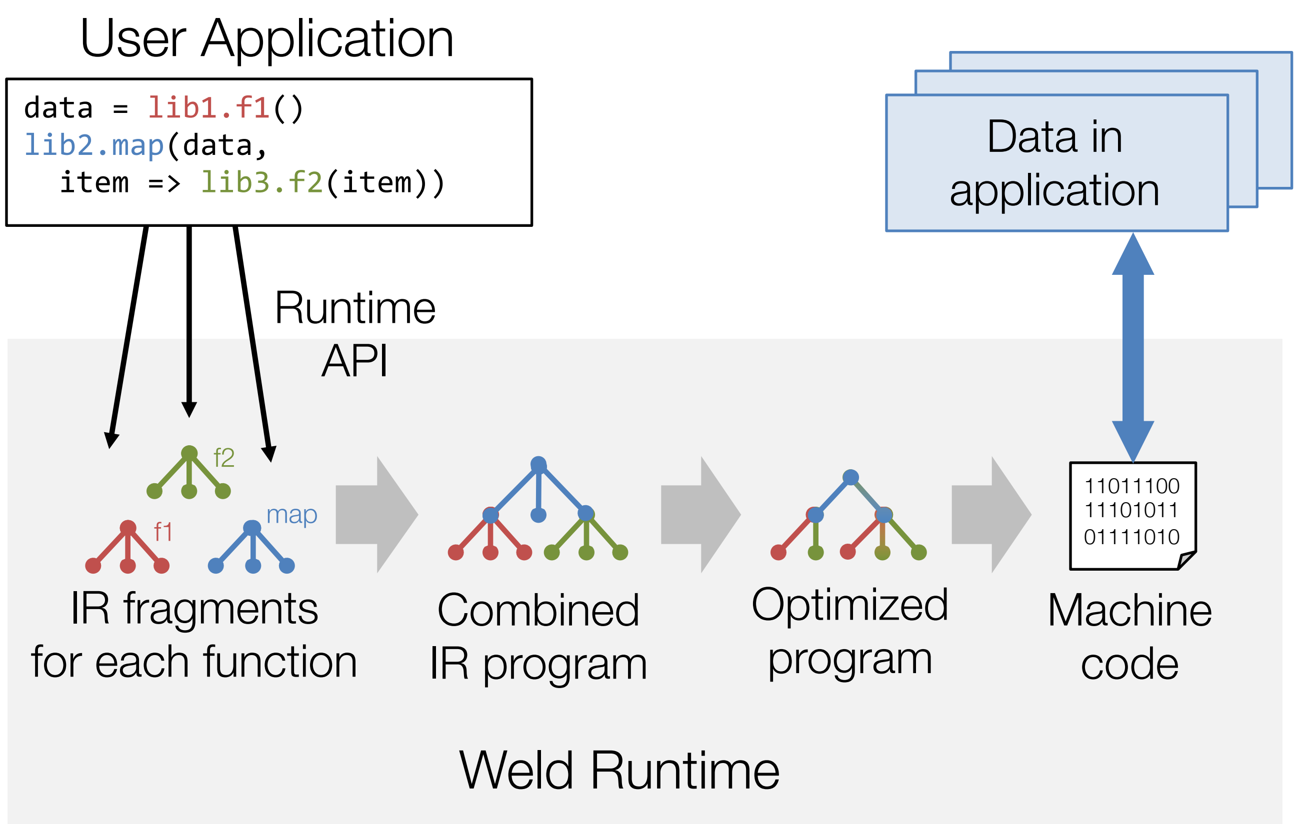
Weld Results: TPC-H Q6



Effect of Optimizations



How Weld Fits Into Applications



Example: Spark + NumPy

```
data = spark.sql("
  select user.features
  from users
  where age > 20")
```

Select some users using Spark SQL

```
scores = data.map(
  lambda vec: scoreMatrix * vec)
```

Score them using NumPy

```
average = scores.mean()
```

Compute average using Spark

Example: Spark + NumPy

```
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  from users
  where age > 20")

scores = data.map(
  lambda vec: scoreMatrix * vec)

average = scores.mean()
```
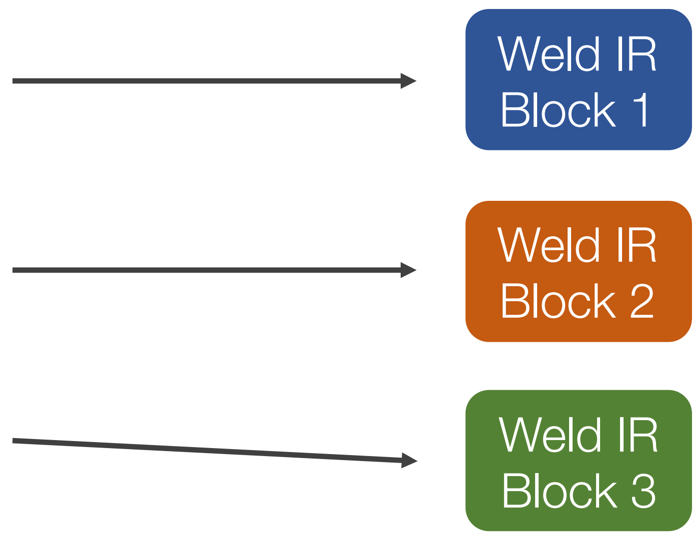
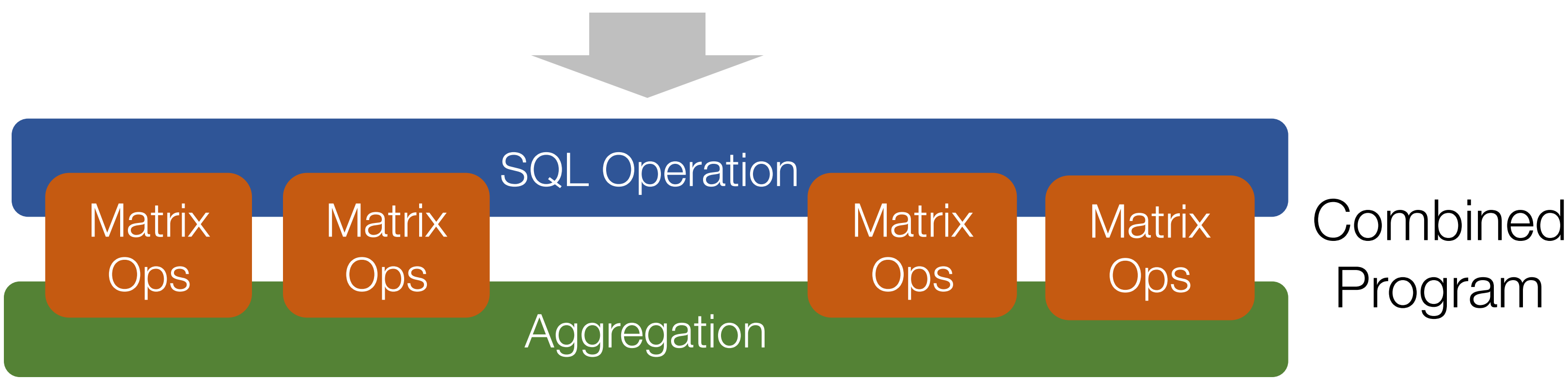
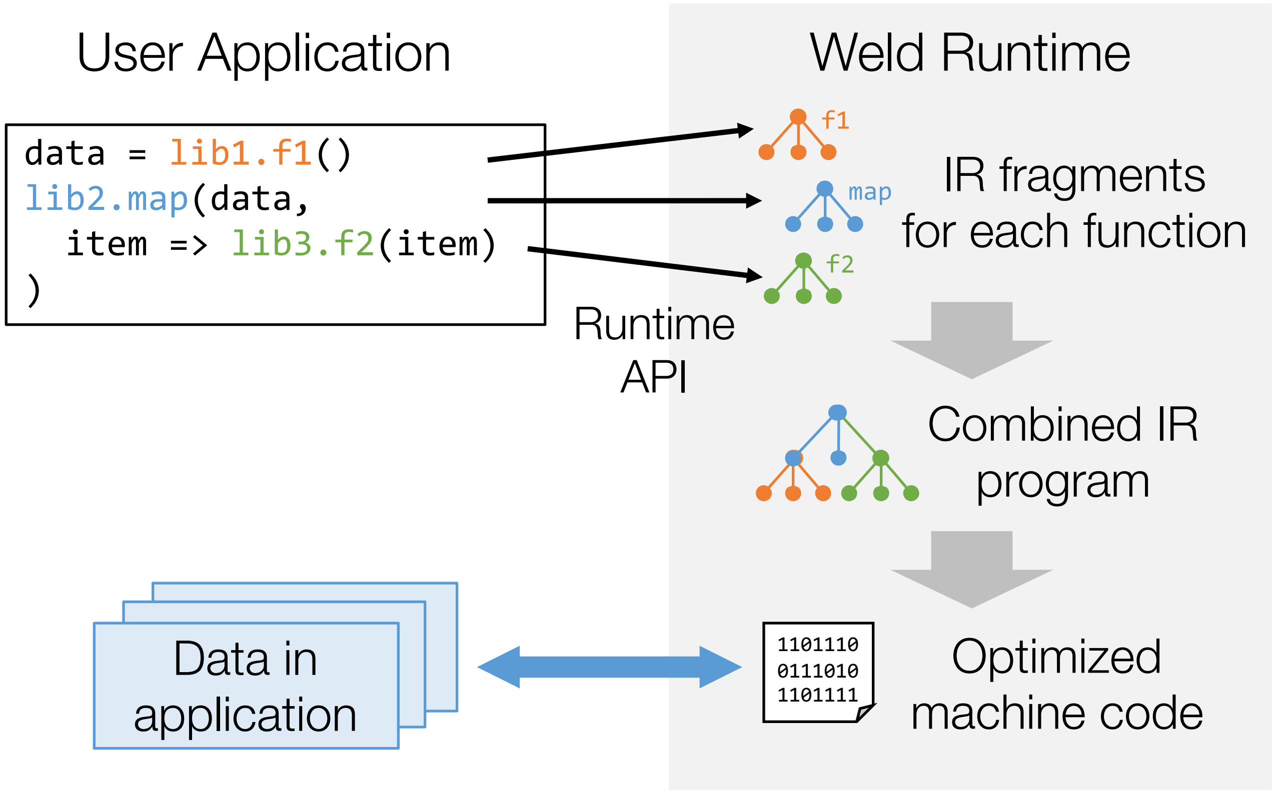





Runtime API

Uses lazy evaluation to collect work across libraries



Supported Optimizations

Loop Fusion

Row-to-Column

Common Subexpressions

Inlining

Insert free() Calls

Loop Tiling

Constant Folding

Branch Predication

Vectorization

…