Position Paper: Logic Programming for Parallel Irregular Applications

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Need for Parallel Graph Algorithms

- Graph algorithms important to computer science
  - Breadth-first search, PageRank, shortest paths, etc.
- New applications demand large graphs
  - Social network analysis, bioinformatics
- Problems beyond capacity of single processors
  - Both memory and CPU performance limitations
  - Need parallelism

Implementing Parallel Graph Algorithms

- Algorithms difficult to implement
  - Managing parallelism hard in general
  - Many programming models
  - Different approaches for different systems, data
- Limited portability
  - Shared memory vs. distributed memory
  - Cray XMT, GPUs, other systems
- Generic programming mitigates this partially
  - C++ limited for expressing vastly different computation models in the same code

Data Structures

- Different from those in most databases
- Vertex, edge properties can often be arrays
  - Might be distributed
- Graphs in compressed sparse row, adjacency list, STINGER, specialized GPU formats, many variants
- Want to support symbolically represented graphs
  - BDD-based state machines for model checking
  - Implicit graphs such as grids for computer vision
  - de Bruijn graphs for bioinformatics

Proposal: High-level Specification

- Write algorithms in a declarative language
- Compiler retargets them to different platforms
- Code generated for various
  - Platforms
  - Graph data structures
  - Data sizes
- Semi-automatically optimize code for each platform
- Graph algorithms easier to tune
  - Configure parameters to generator

Datalog

- Declarative language for querying databases
- Subset of Prolog
  - No function symbols
  - Fewer primitives
  - Limited negation (usually)
- Allows recursion
  - Unlike SQL or relational algebra
  - Does not need barriers between recursive steps
- Programs always terminate

Datalog Example

```
ancestor(X, Y) :- parent(X, Y).
```

"For any X and Y, if X is the parent of Y then X is an ancestor of Y."

```
ancestor(X, Z) :-
    ancestor(X, Y), ancestor(Y, Z).
```

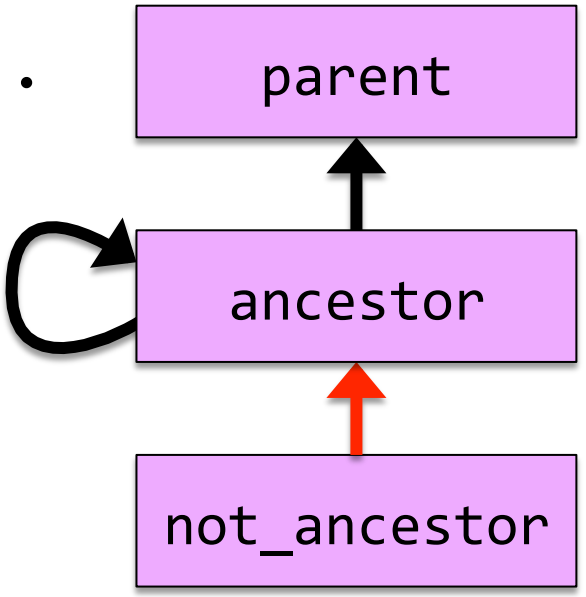
"For any X, Y, and Z, if X is an ancestor of Y and Y is an ancestor of Z, X is an ancestor of Z."

- Would not terminate in normal Prolog

Stratification

- Approach used for negation in Datalog
  - No cyclic dependencies containing negations
- Divide program into strongly connected components
- Negations only allowed between components

```
ancestor(X, Y) :- parent(X, Y).
ancestor(X, Z) :-
    ancestor(X, Y),
    ancestor(Y, Z).
not_ancestor(X, Y) :-
    ¬ ancestor(X, Y).
```

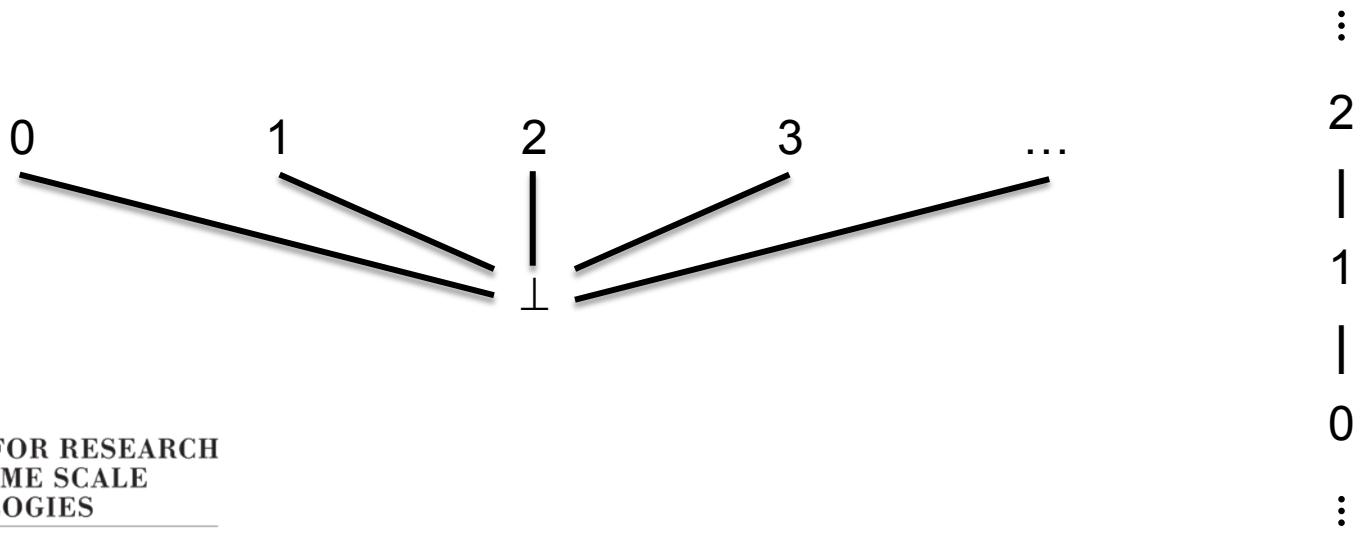


Need for Multi-Valued Logic

- Graph algorithms return non-Boolean results
  - Shortest paths returns optimal distances
  - Semiring often used as structure for this
- Normal Datalog predicates are either true or false
  - Using one argument to a predicate as the result does not allow updating
- Multi-valued logic generalizes predicate values
  - `dist(X, Y)` is valued as a number between $-\infty$ and ∞
- Monotonicity requirements similar to stratification
  - Algorithms such as betweenness centrality need multiple passes with barriers in between

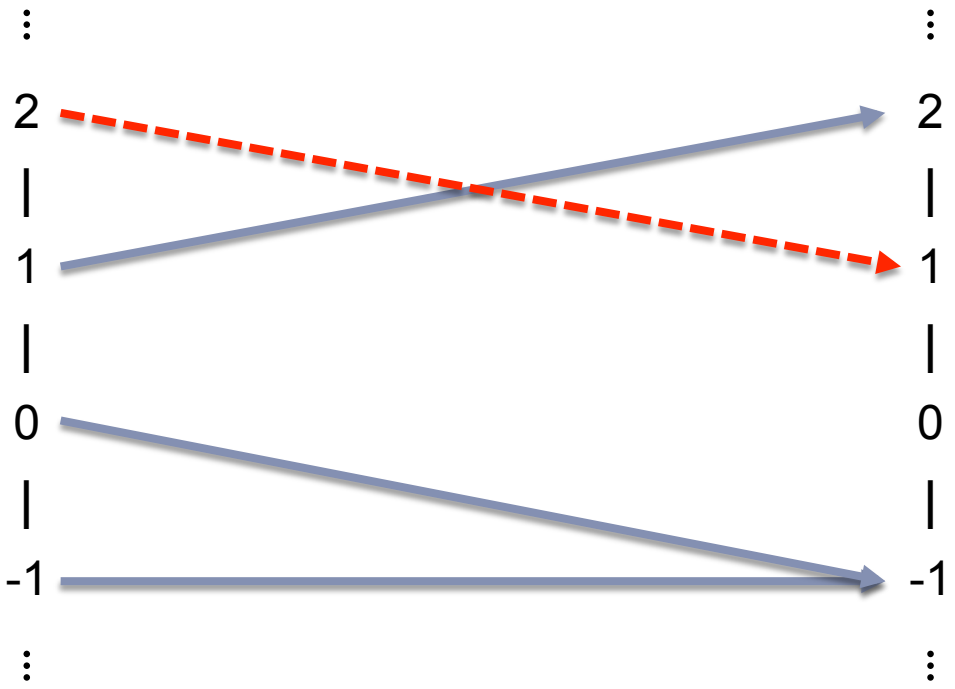
Semilattices

- Set with associative, commutative, idempotent binary operation ⊓ (“meet”)
- Operation defines partial order ⊑ on elements
  - $x \sqsubseteq y$ if and only if $x \sqcap y = x$
- Likely to relax commutativity in practice
  - Allow nondeterministic behavior in case of distance ties



Monotonicity

- Moving input of a function up or down semilattice moves function result the same direction
- Formally, $x \sqsubseteq y$ implies that $f(x) \sqsubseteq f(y)$



Lattice-Valued Datalog Example

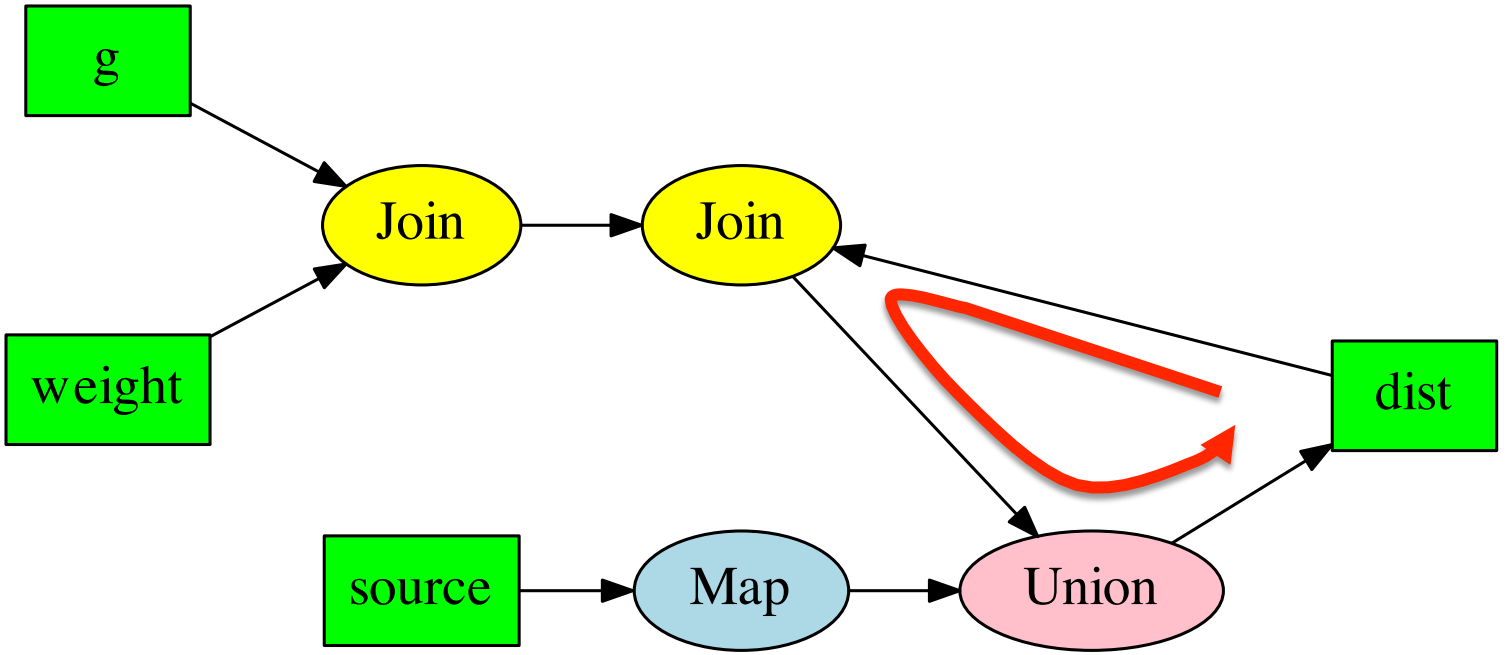
- Compute path length from source to each vertex(pseudocode), assuming no negative-length cycles:

  Define table `dist` using `min` as reduction operator.

```
dist(S) = source(S), 0.
dist(W) = g(V, W, E), (dist(V) + weight(E)).
```

- Aggregation done automatically
- Works because of monotonicity and distributivity, plus finite number of simple paths

Data Flow



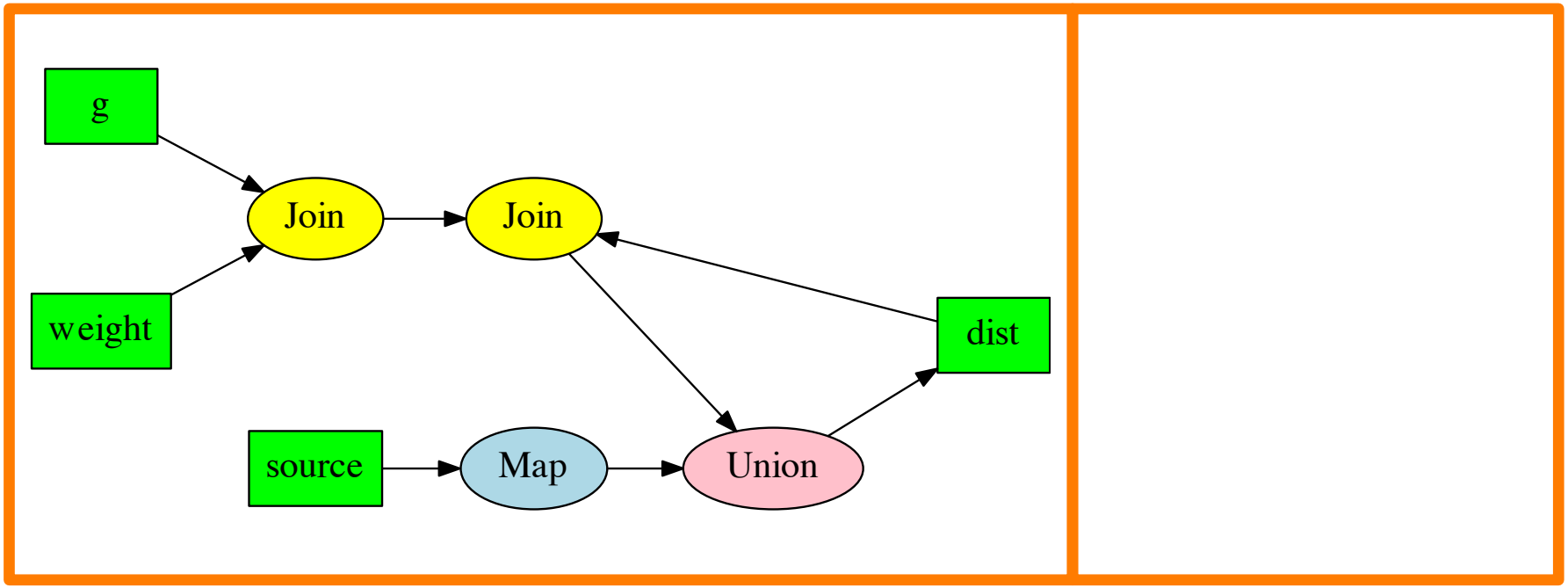
Lattice-Valued Datalog Stratification

- Stratification has been generalized to lattice-valued Datalog
- Non-monotonic operators treated as negations
- Same rules as before apply

- For applications, might want to stratify based on values, not just syntax:

```
foo(X, N+1) :- foo(Y, N), bar(X, Y).
```

Data Flow Adding Reciprocal



Explicit Aggregation

- Sums, averages, etc. not semilattice operations
  - Not idempotent
- Necessary for practical system
- Only allow these between strata
  - Compute input data, then do aggregate operator
  - Could do some operators incrementally
    - Associative, commutative, with inverses

Performance Hints

- Query optimizer may not get optimal performance
- Want ways to tune query plan, data structures, etc.
- One option is a “simple” implementation
  - Always uses a fixed query plan based on the program
  - User rearranges program to change behavior
  - Can be cumbersome to write some things in this model

```
dist(W) = dist(V) + (g(V, W, E), weight(E)).
```

- Can use same data structures as in hand-written code as long as query patterns are limited
- Will also need to import external data
  - Including from sources such as SQL databases

Comparison to Other Models

- Generalization of linear algebra over semirings
  - Multiple dimensions
  - Non-distributive operations (with imprecise results)
- Generalization of SQL, SPARQL, relational algebra
  - Allows recursion to be expressed directly
- Simplification of visitor-based models
  - Limits set of operations in visitors
  - Increases available parallelism
- Less limited than many graph DSLs
  - Recursion without requiring level-based iterations

Expressiveness

- Expresses simpler algorithms directly
  - “Simpler” is relative — more difficult algorithms are hard to write in any framework
- User queries are likely to be simple
  - Ad-hoc queries unlikely to use multilevel methods
  - Can still provide tuned kernels for these

Join and Fixpoint Algorithms

- Joins map directly to Datalog

```
abc_path(X, Y) :- a(X, Z), b(Z, W), c(W, Y).
```

- Compute paths using recursion

```
abstar_path(X, X).
abstar_path(X, Y) :- a(X, Z), b(Z, W), abstar_path(W, Y).

alternating_path(X, Y) :- abstar_path(X, Y).
alternating_path(X, Y) :- b(X, Z), abstar_path(Z, W).
```

- Might want performance hint about ordering to use
  - Somewhat similar to tag collections in Intel Concurrent Collections

Iterative Algorithms

- Some algorithms normally written level-synchronous
  - Breadth-first search
  - PageRank
- Most of these have formulations with fewer barriers
  - Often not as work-efficient as with barrier

```
pr_iter(0, V, …).
pr_iter(N+1, V, …) :- pr_iter(N, …, …).
pagerank(V, PR) :- stop_iter(N), pr_iter(N, V, PR).
```

Multi-Level Algorithms

- Most difficult class to express in this model
- Would need same features as iterative algorithms
- Maybe easier to use relational algebra directly?
  - Or linear-algebra-like operations with recursion?

Programmability

- Graph data sets likely to have few types of relationships used in a single query
  - Using many inputs at once leads to verbose code
- Can define helper relations to abstract out intermediate computations
- Datalog being first-order might be a limitation
- User experience would be needed
  - SQL is commonly used, and constructs used are similar
  - Logic programming likely to be unfamiliar to most users
- Researchers have developed specialized front-ends

Prior Work on Datalog

- Automatic parallelization
- Automatic incrementalization
- Implementation using SQL
- Implementation on binary decision diagrams (BDDs)
- Datalog for distributed systems
  - Bloom^L
  - StarLog
- Front-ends generating Datalog
  - Program Query Language
  - GraphQL

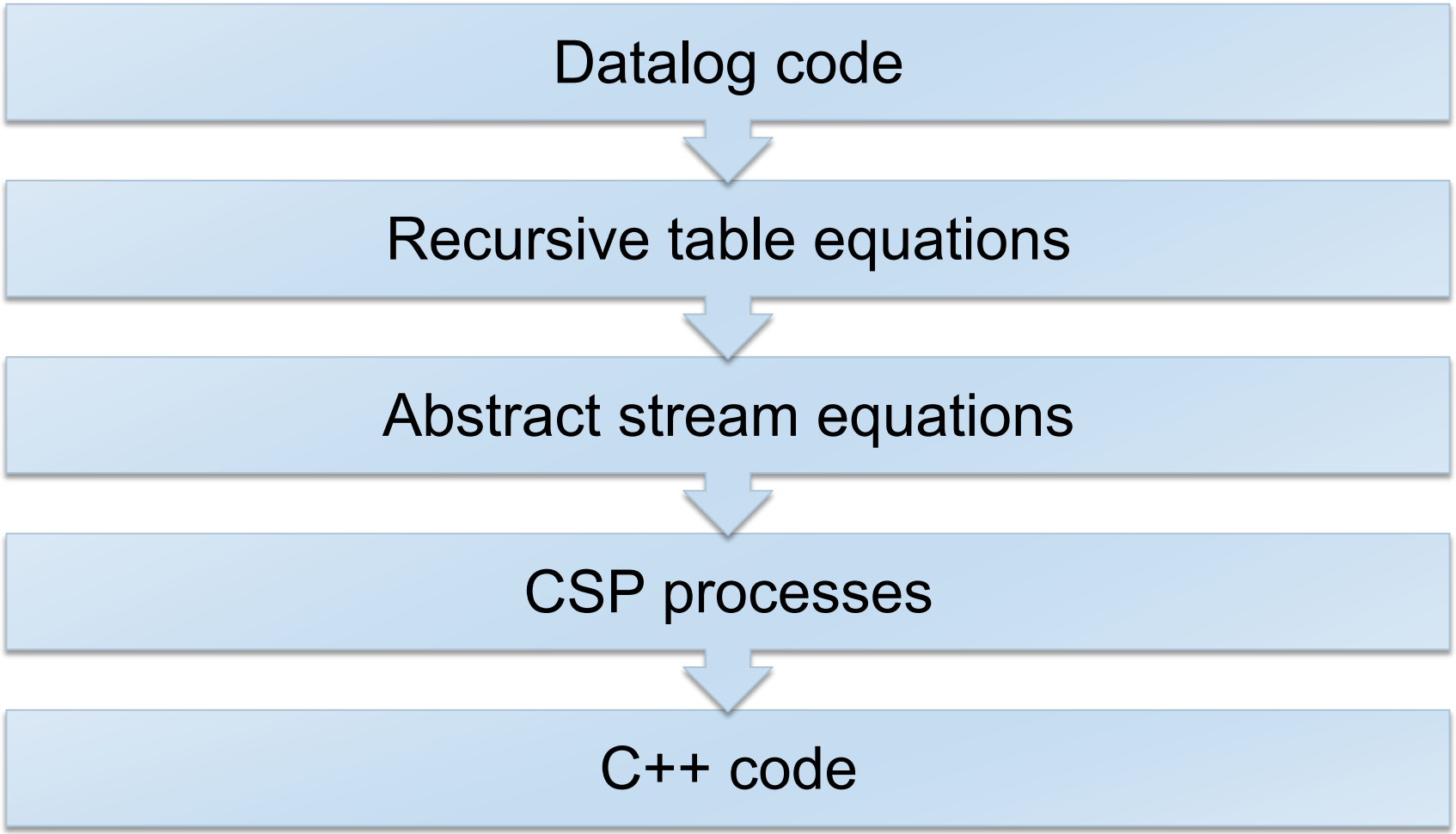
Conclusion

- Lattice-valued Datalog advocated as a good high-level specification for irregular algorithms
  - Aids productivity
  - Simplifies tuning
- Generate code for various platforms, data structures from a single specification
  - Plus possibly some platform-specific hints
- Hybrid approaches possible
  - Datalog plus hand-written execution strategy/query plan
  - Parts of implementation given manually
    - Might include problem- and/or platform-specific data structures

Prototype Compiler

- Translates lattice-valued Datalog to C++
- Currently targets
  - Sequential code
  - SQLite
  - Larrabee intrinsics
- Designed to target other platforms in the future
- Likely to become JIT

Compiler Structure



Datalog Code (S-expressions)

```
(InputTable 'source (TableType `(,(VertexT)) (TypeAndReducer (VoidT) (FlatR))) (SingleEntryTable))
(ResultTable 'dist (TableType `(,(VertexT)) (TypeAndReducer (FloatT) (MinR))) (ArrayTable))
(InputTable 'g (TableType `(,(VertexT) ,(VertexT) ,(EdgeT)) (TypeAndReducer (VoidT) (FlatR))) (GraphTable))
(InputTable 'weight (TableType `(,(EdgeT)) (TypeAndReducer (FloatT) (MinR))) (ArrayTable))
```

```
((TableRef 'dist '(W))
 . ← .
 (Combine
  add-combiner
  (TableRef 'dist '(V))
  (Combine
   second-combiner
   (TableRef 'g '(V W E))
   (TableRef 'weight '(E)))))
((TableRef 'dist '(S))
 . ← .
 (Map
  (const-map-func (FloatT) (MinR) (ConstE "0.0"))
  (TableRef 'source '(S))))))
```

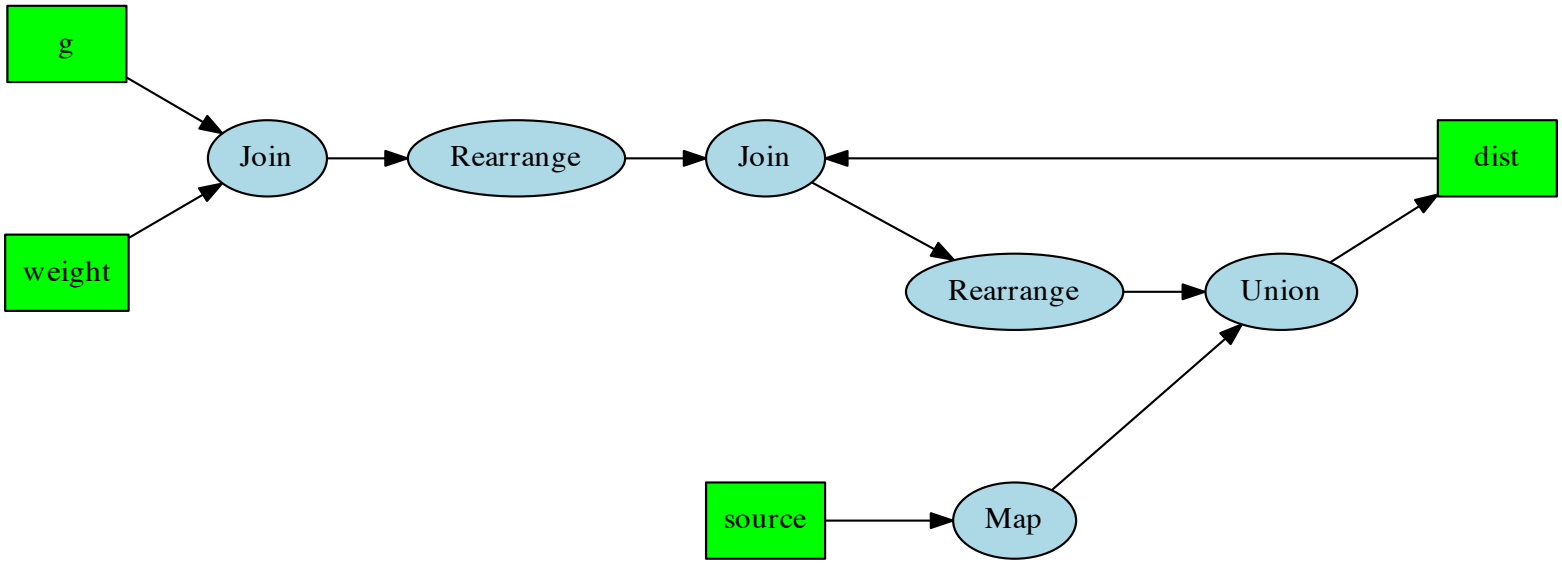
Conversion to Table Equations

- Combine all rules for a single relation
- Normalize conjunctions into joins
- Insert wildcard elements and projections (aggregation of multiple results)

Table Equations

```
(g .      #(struct:Empty
            #(struct:TableType
              (#(struct:IntT) #(struct:IntT) #(struct:LongT))
              #(struct:TypeAndReducer #(struct:VoidT) #(struct:FlatR)))))
(source . #(struct:Empty
            #(struct:TableType
              (#(struct:IntT))
              #(struct:TypeAndReducer #(struct:VoidT) #(struct:FlatR)))))
(dist .   #(struct:Union
            #(struct:TEMap
              #(struct:MapFunc #<procedure:const> #<procedure:const>)
              #(struct:ReadTable source (0)))
            #(struct:Rearrange
              (E W V)
              (W)
              #(struct:TECombine
                #(struct:CombineFunc
                  #<procedure:...log/datalog4.rkt:75:3>
                  #<procedure:...log/datalog4.rkt:79:3>)
                #(struct:ReadTable dist (#f #f 0))
                #(struct:Rearrange
                  (V W E)
                  (E W V)
                  #(struct:TECombine
                    #(struct:CombineFunc
                      #<procedure:...log/datalog4.rkt:93:3>
                      #<procedure:...log/datalog4.rkt:94:3>)
                    #(struct:ReadTable g (0 1 2))
                    #(struct:ReadTable weight (#f #f 0)))))))))
(weight . #(struct:Empty
            #(struct:TableType
              (#(struct:LongT))
              #(struct:TypeAndReducer #(struct:FloatT) #(struct:MinR))))))
```

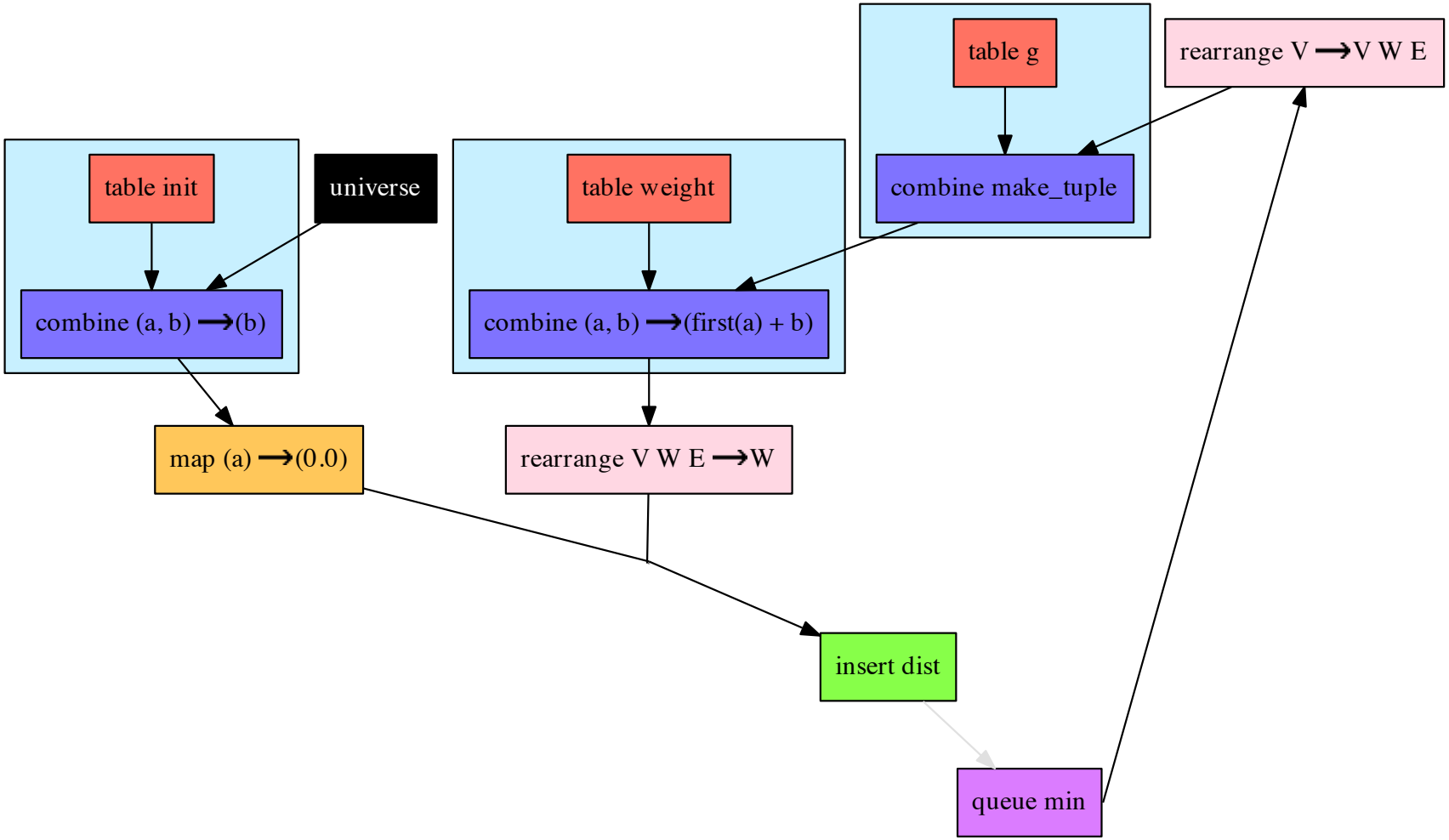
Recursive Table Equations



Stream Equation Generation

- Define processing of newly added/updated elements
  - Seminaïve evaluation
- Normalize joins to input stream and single relation
  - Add dummy streams as needed
- Insert explicit queues
  - Order of tuple processing matters for performance
  - Dijkstra's algorithm uses increasing order of distances

Stream Equations



Implementing Stream Operators

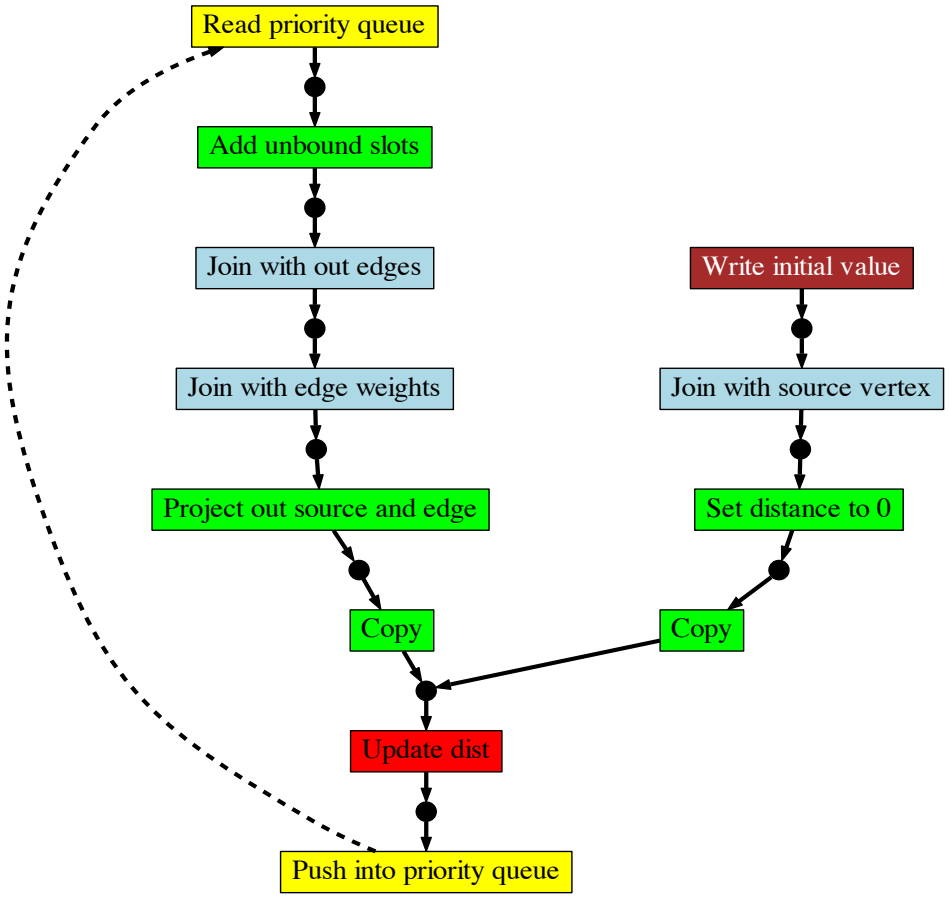
- Query optimization
- Solve for modes of tuples being passed around
  - Which elements are not filled in
- Determine best formats for streams
  - Scalar variables, SIMD, SQL tables, etc.
- Based on user-defined formats for relations

- Optimizer is currently simple
- Most platform-specific configuration will be here

Coroutine Generation

- Convert each stream operator into coroutines
- Communication by CSP channels
  - Bounded resources, simple to implement
- Data sent in channels depends on implementation
- “Real” (non-coroutine) parallelism done by data parallelism
  - Local coroutine-handling code does not need to know about it

Coroutine Structure



Code Generation

- Coroutines interleaved statically into a single thread
- Channels implemented using variables
  - Synchronization done by code generator

- Generates control flow graph
- Convert CFG into C++ code