

Differential Dataflow

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Isard, Michael

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08th November 2016

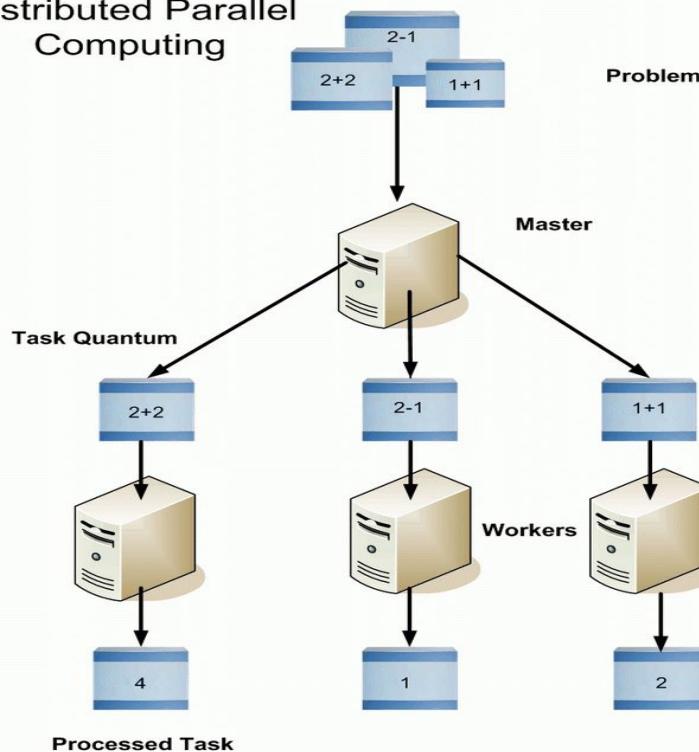
Outline

- Motivation for Differential Dataflow
- Key Concepts
- Differential Dataflow in practice
- Discussion

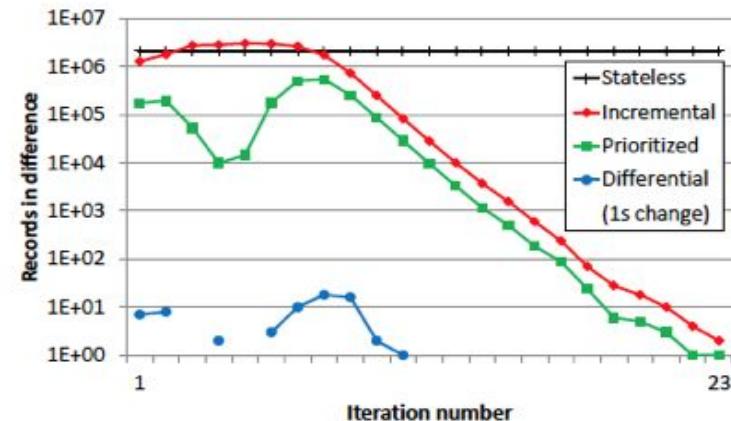
Motivation

Traditional data parallel processing

Distributed Parallel Computing



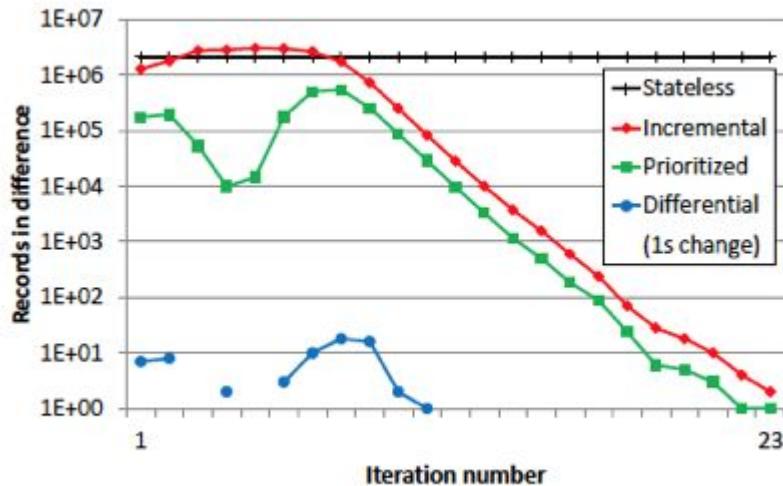
- Take input data in batches.
- Process and output.
- Highly evolved - Hadoop, Spark.
- Mostly stateless.



Interactive - Twitter Mention Graph

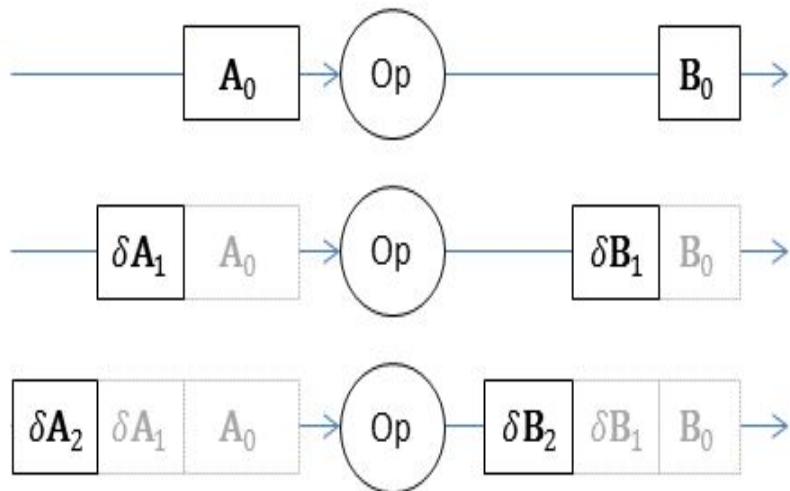
- Used to find trending #hashtags.
- Billions of vertices and edges.
- Millions of updates per second (storm).
- Needs low latency of streaming and throughput of spark.
- Similar issue with interactive analytics

Loop Processing



- Some algorithms require iterations
 - Pagerank
 - Connected components
- Usually requires transferring entire state between iterations
- Spark, Hadoop etc execution times \sim stateless

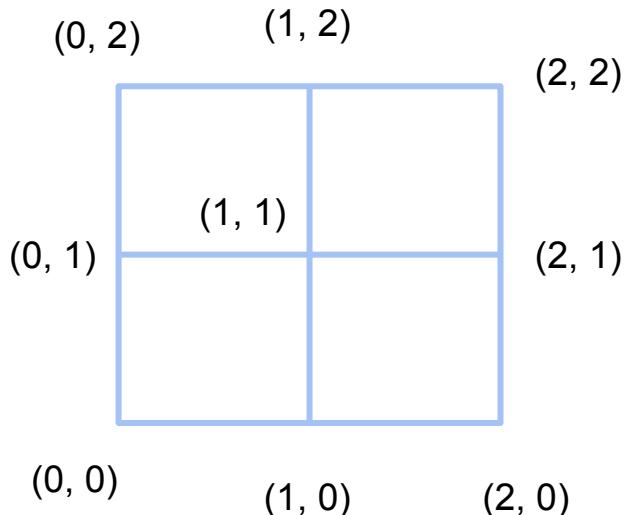
Incremental Dataflow



- Stateful.
- Get the differences of collections.
- Only calculate changes.
- Example
 - Wordcount in Hadoop Online.
- Can deal with changes due to,
 - Loops
 - New Data
- But NOT both!!

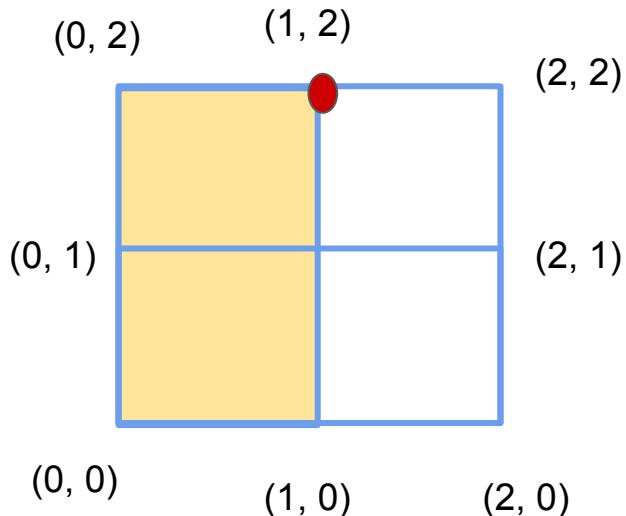
Concepts

Total vs Partial Ordering



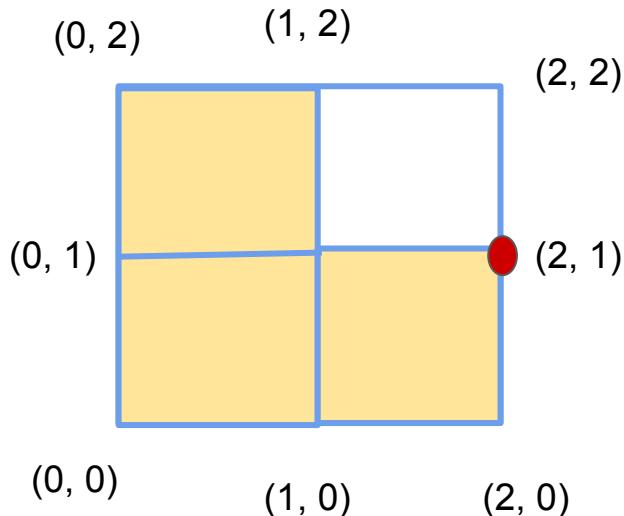
- Traditional dataflow systems expect total ordering
 - Multiple variables are a problem
- A partial ordering uses a time vector for ordering
 - Deals well with multiple variables
- Partial because ordering by variable x gives only a partial ordering

Total vs Partial Ordering



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Total vs Partial Ordering

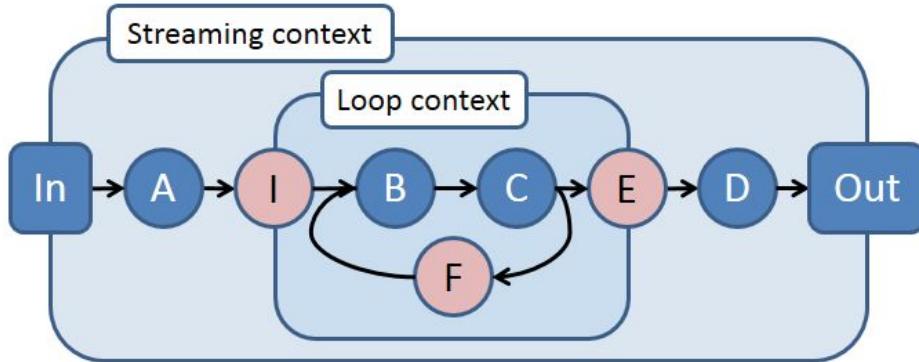


- Traditional dataflow systems expect total ordering
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Differential Dataflow

- Computational Model
 - Defines how to process partially ordered data.
 - Defines state between iterations
- Goals
 - Do less calculation per change
 - Converge quicker per iteration

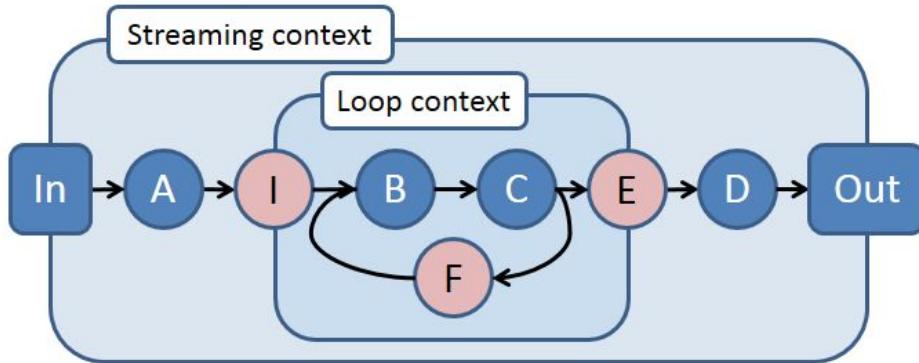
Timely Dataflow



- Performs Iterative Calculations
- Computational model with directed graph
- Vertices exchange messages
- Logical Timestamps for messages

: $\overbrace{(e \in \mathbb{N}, \langle c_1, \dots, c_k \rangle \in \mathbb{N}^k)}$ $\overbrace{\text{epoch}} \quad \overbrace{\text{loop counters}}$

Timely Dataflow

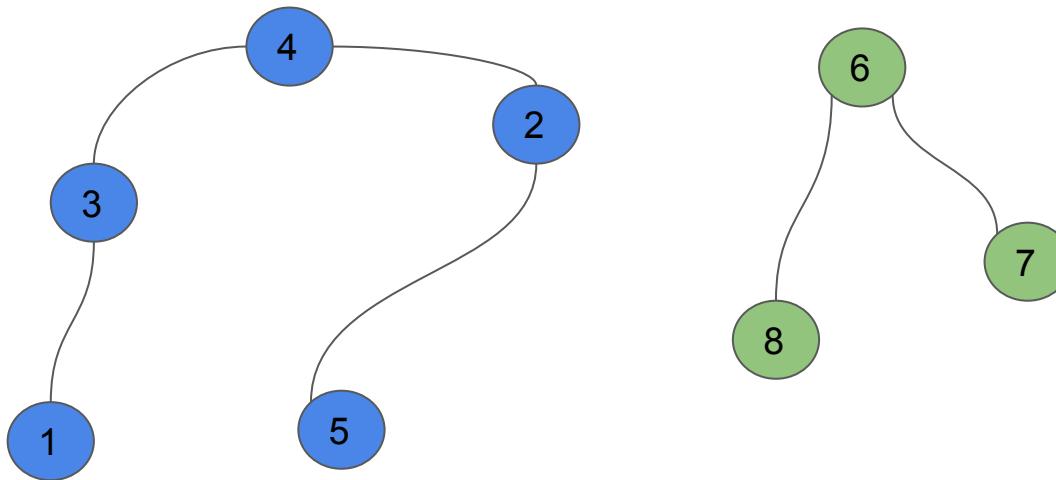


- Loops denoted by,
 - Ingress - adds a counter
 - Feedback - increments a counter
 - Egress - removes a counter
- Pointstamps - events at location and time

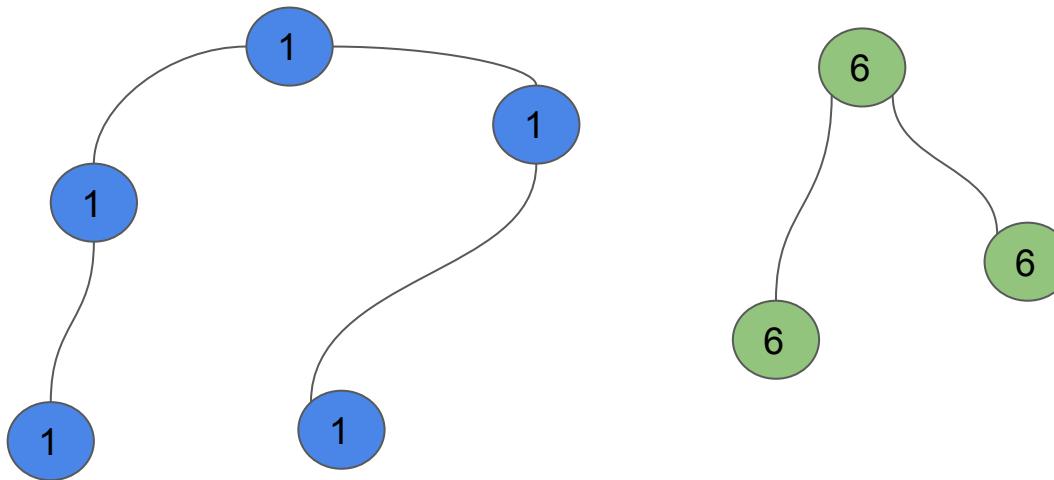
$$(t \in \text{Timestamp}, \overbrace{l \in \text{Edge} \cup \text{Vertex}}^{\text{location}})$$

Differential Dataflow in practise

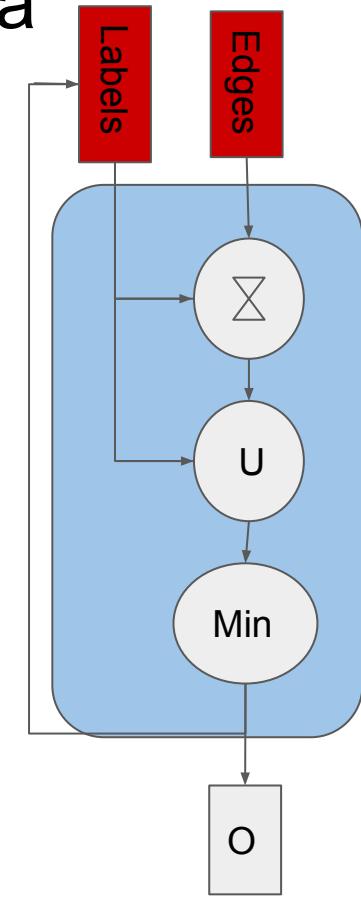
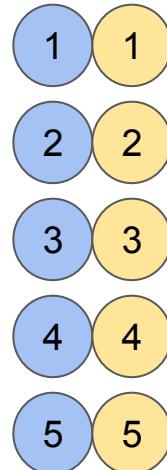
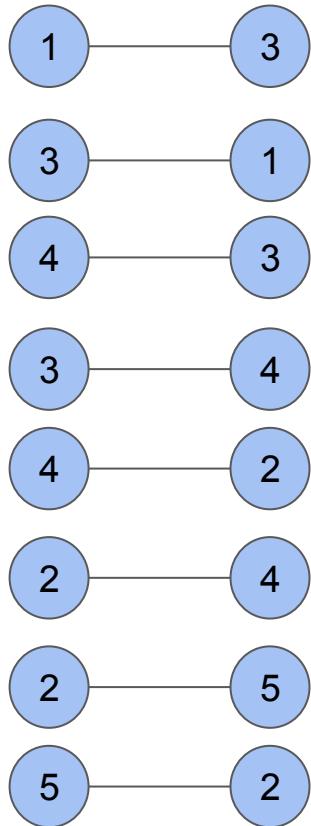
The Connected Graph Problem



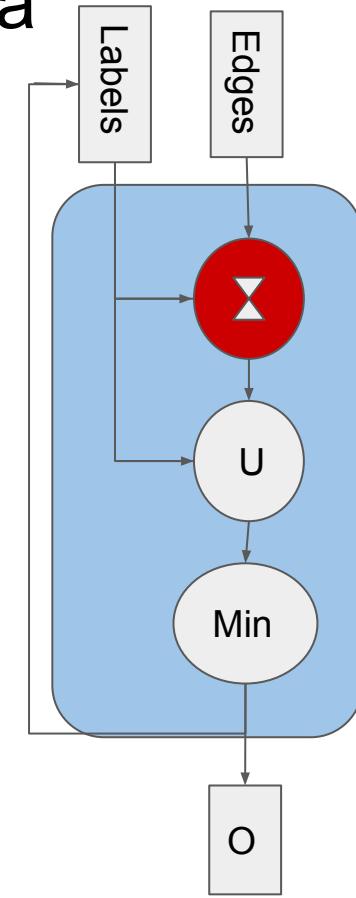
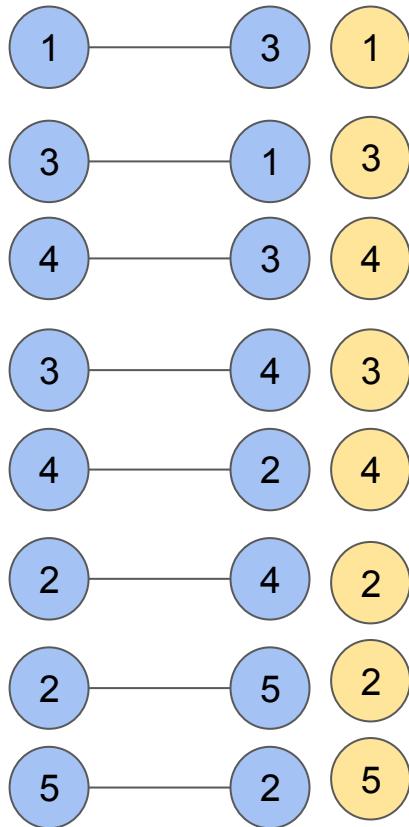
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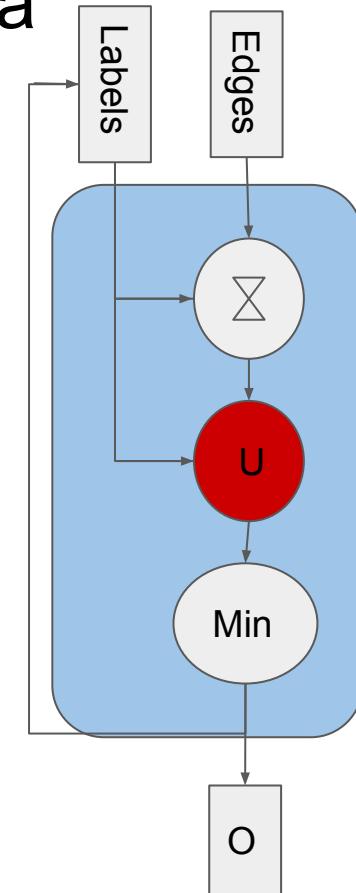
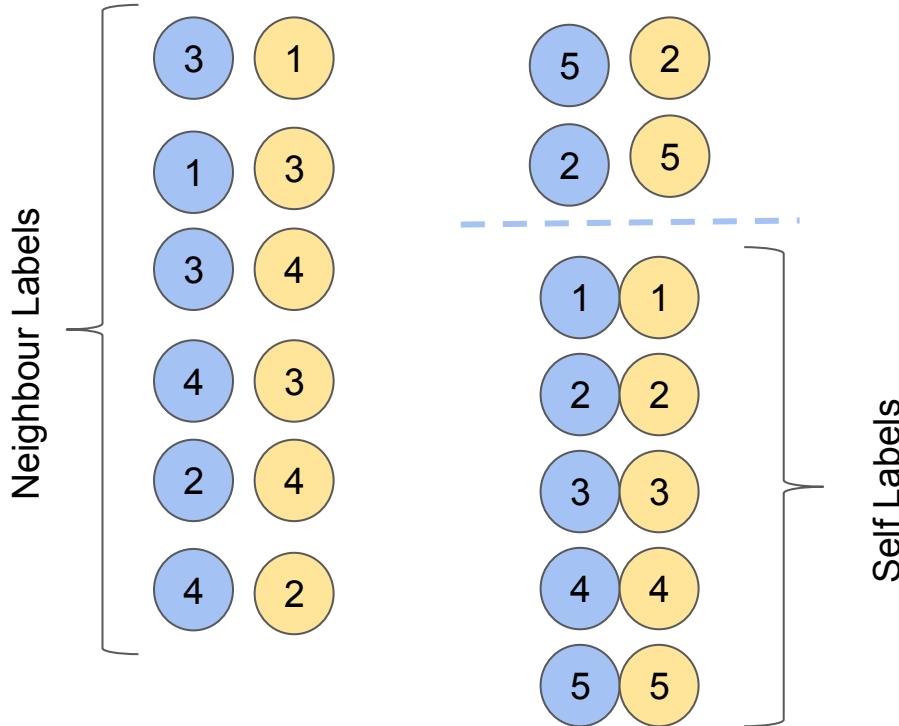
Connected Graph with Relational Algebra



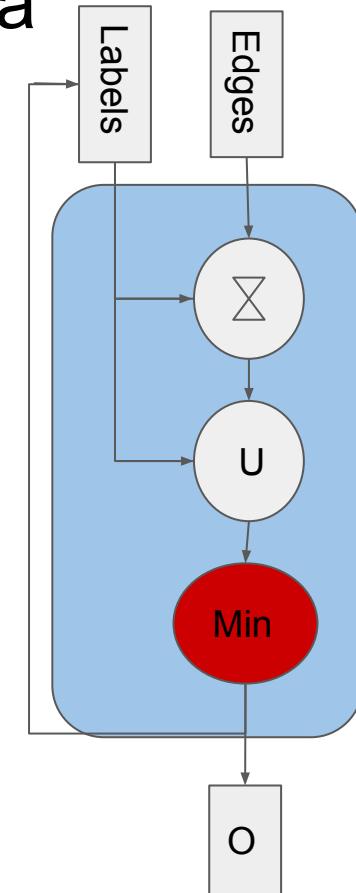
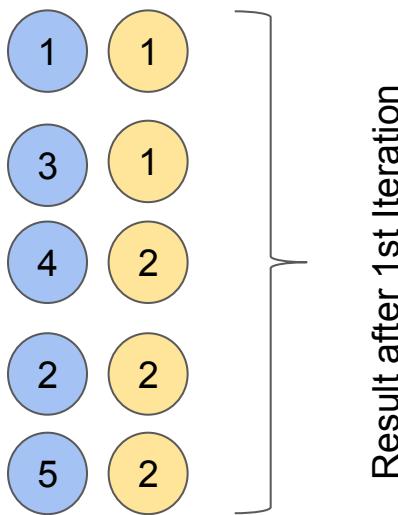
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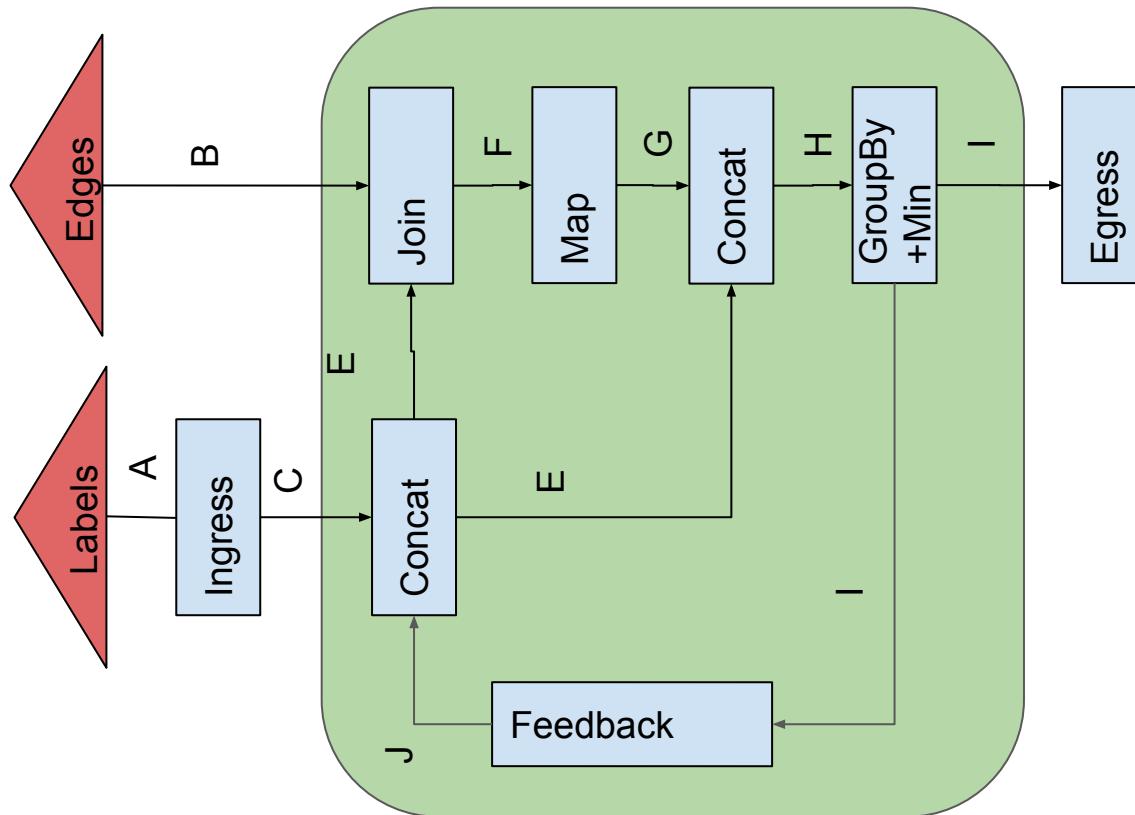
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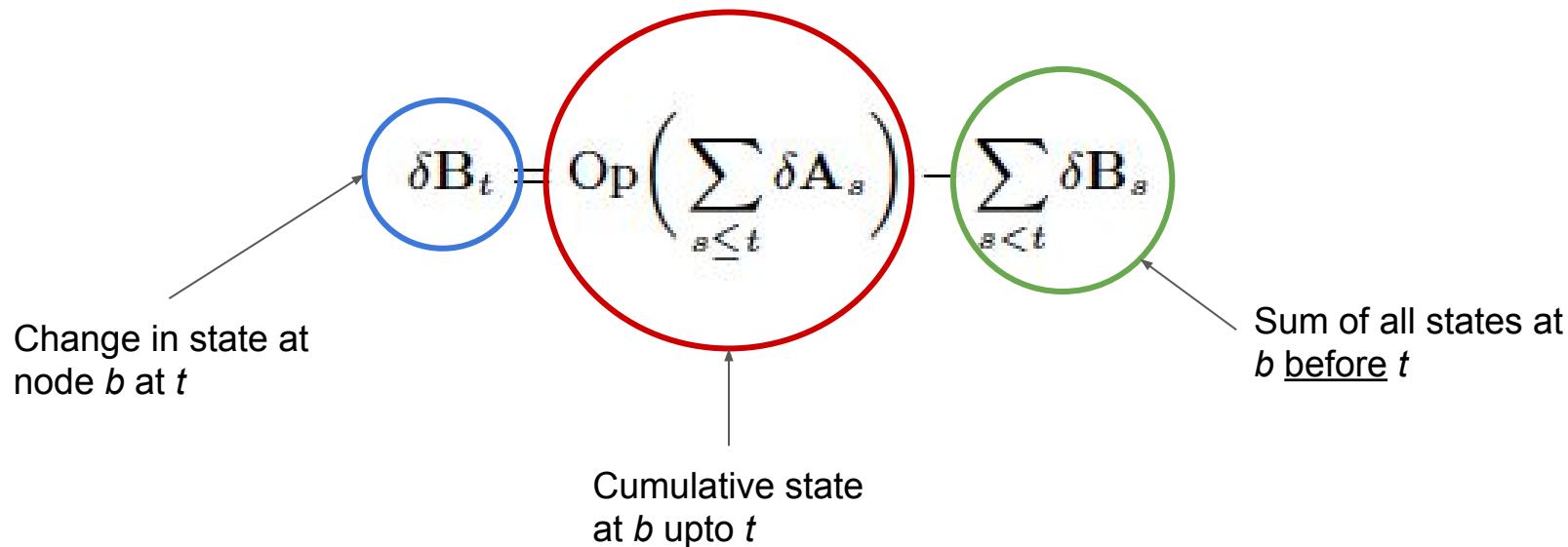


Connected Graph in Timely

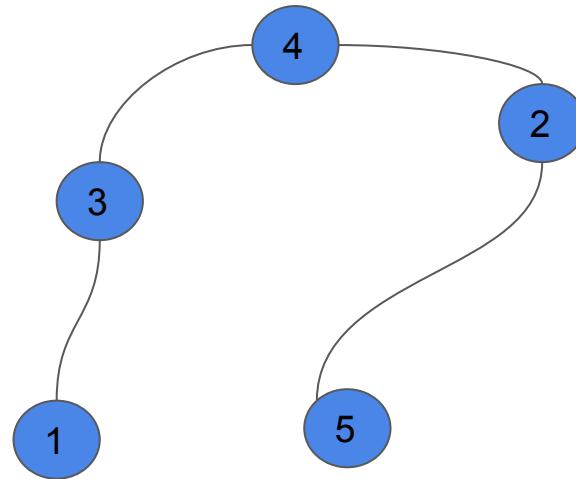


- Edges are available constantly
- Add counter at Ingress
- Remove Counter at egress
- Increment counter at feedback
- Map converts joined tuples into node/label tuples
- Concat performs the union

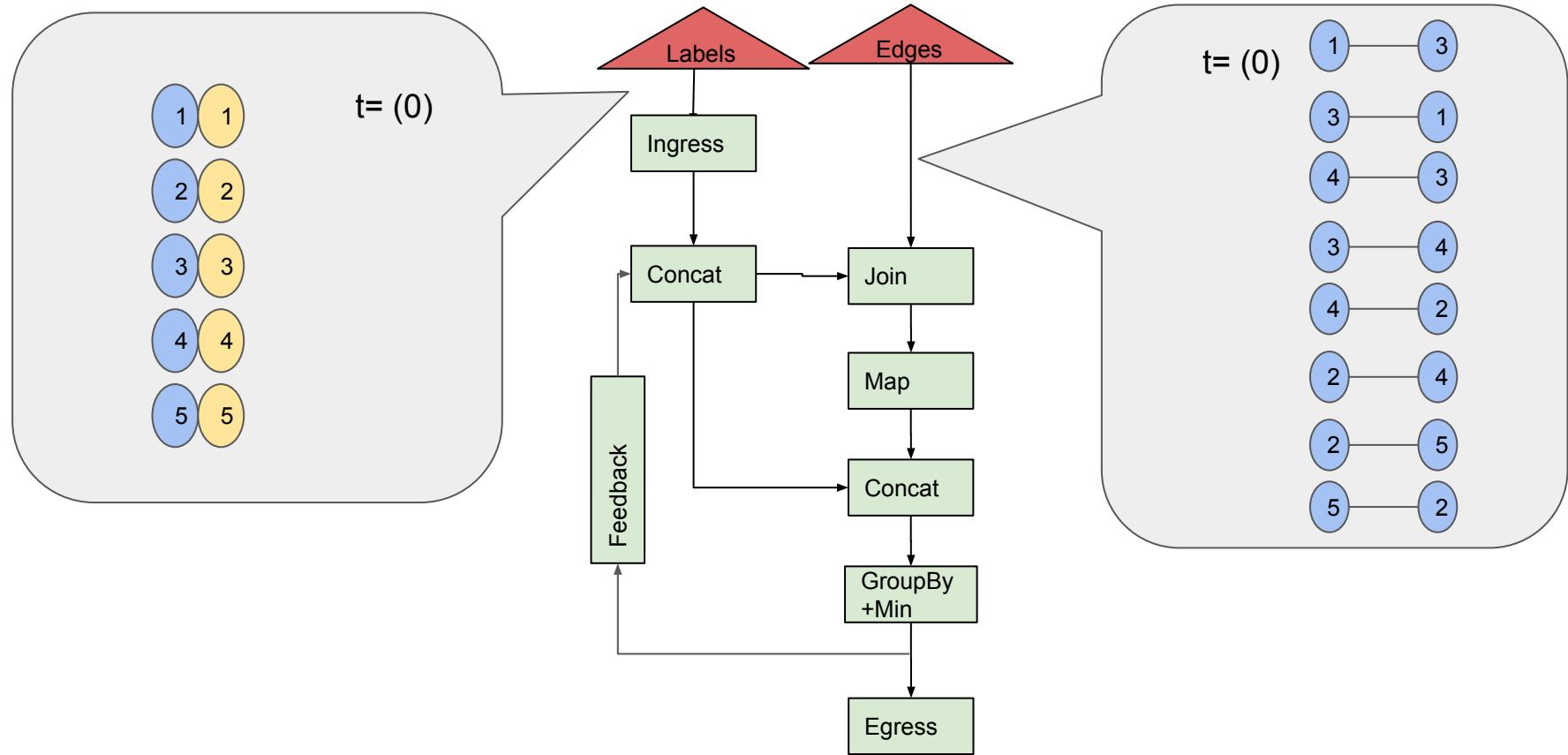
Maintaining State in Differential Dataflow



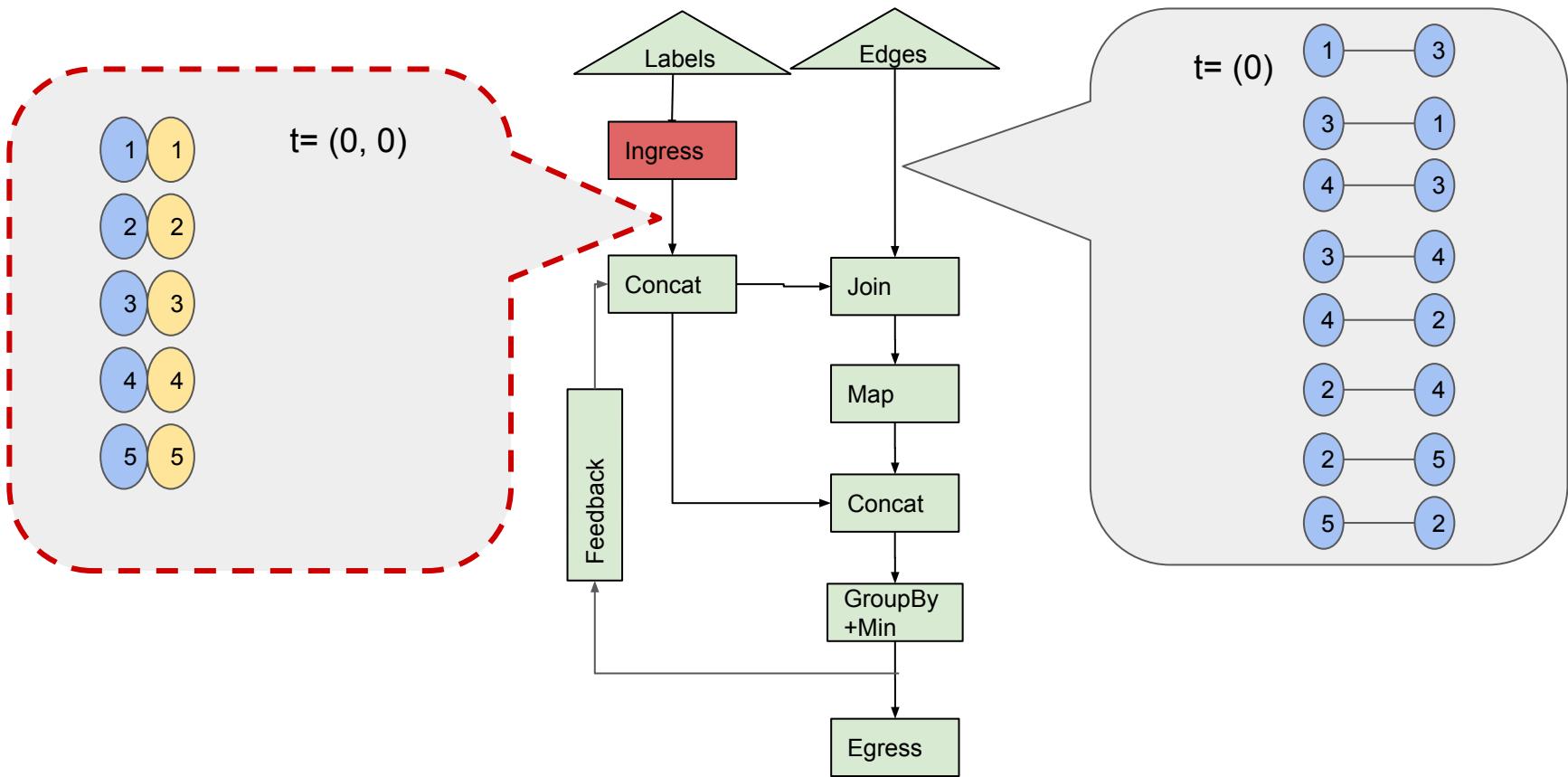
Connected Graph



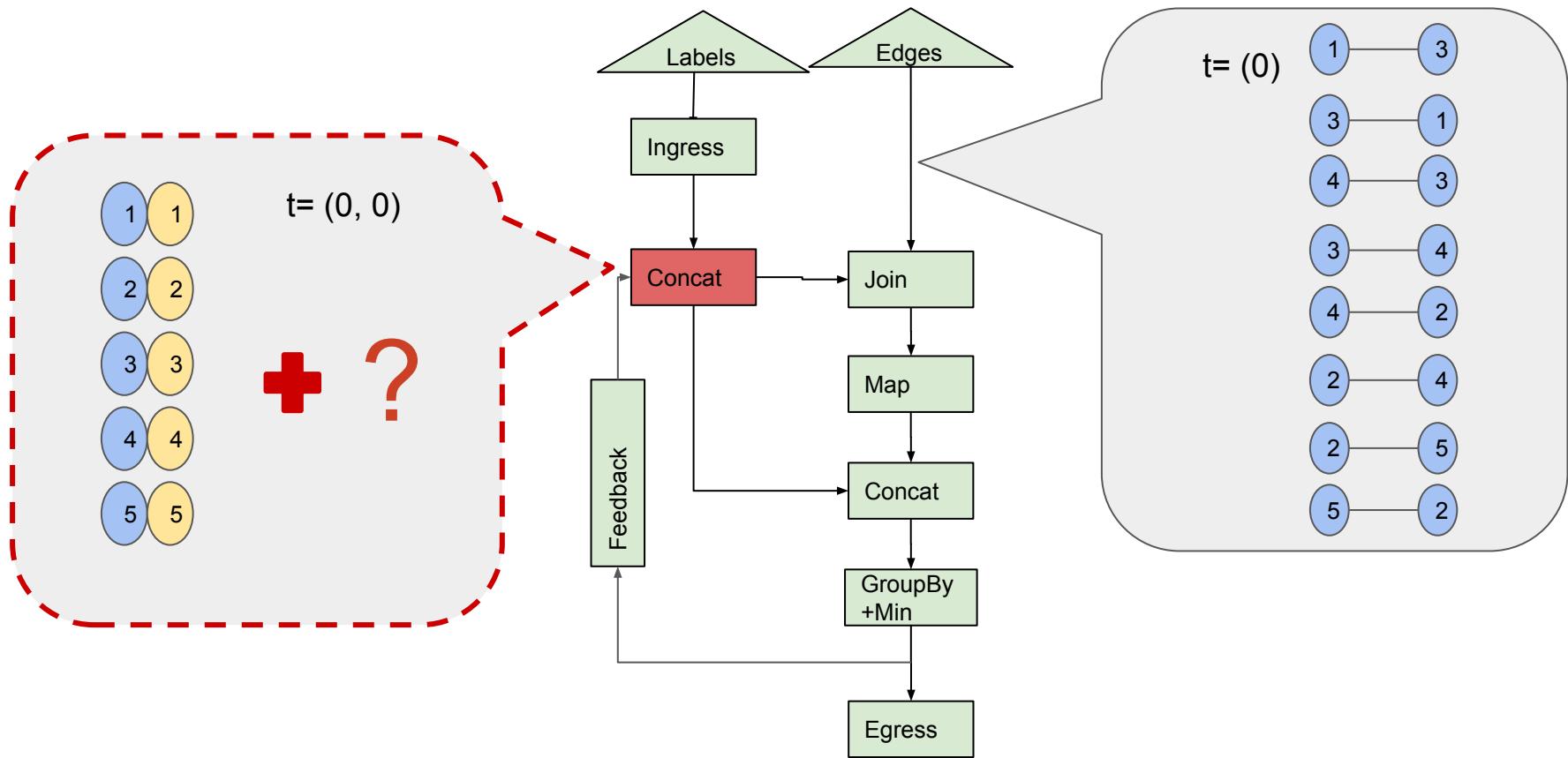
Connected Graph in Differential



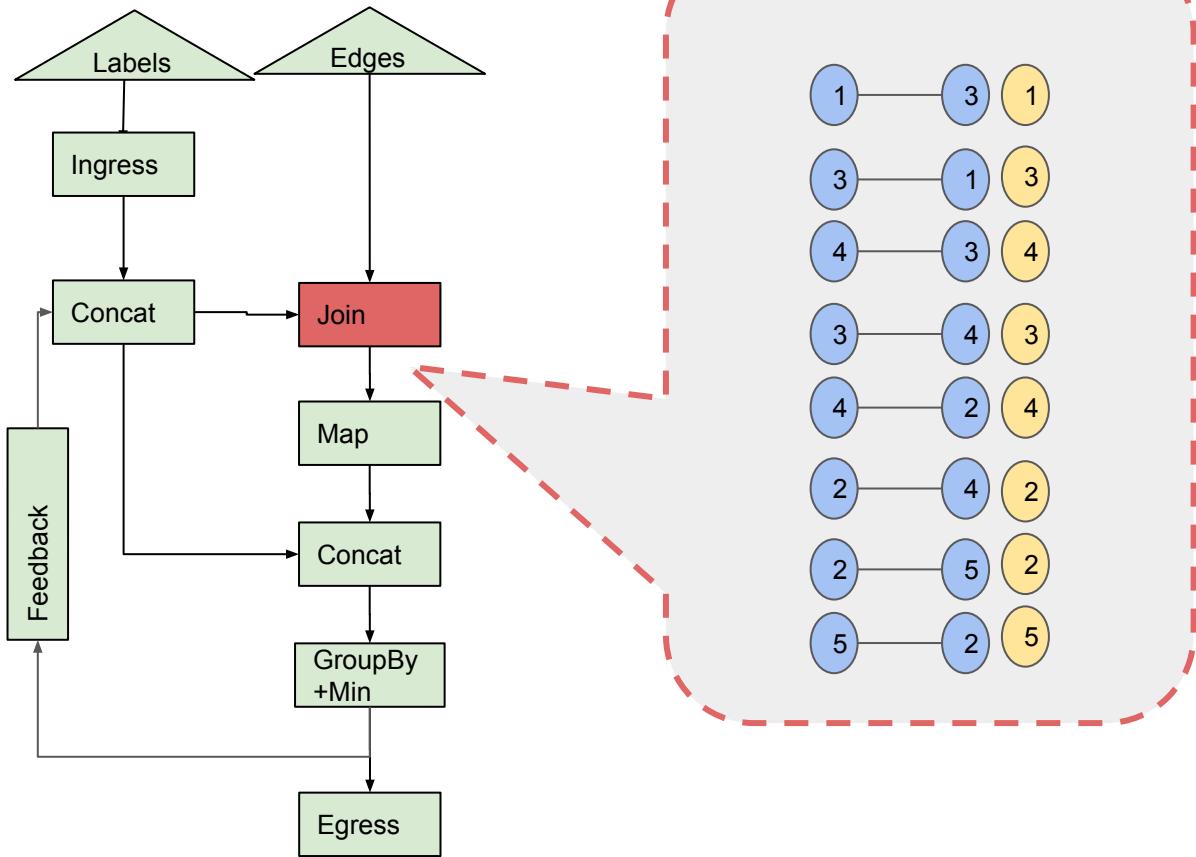
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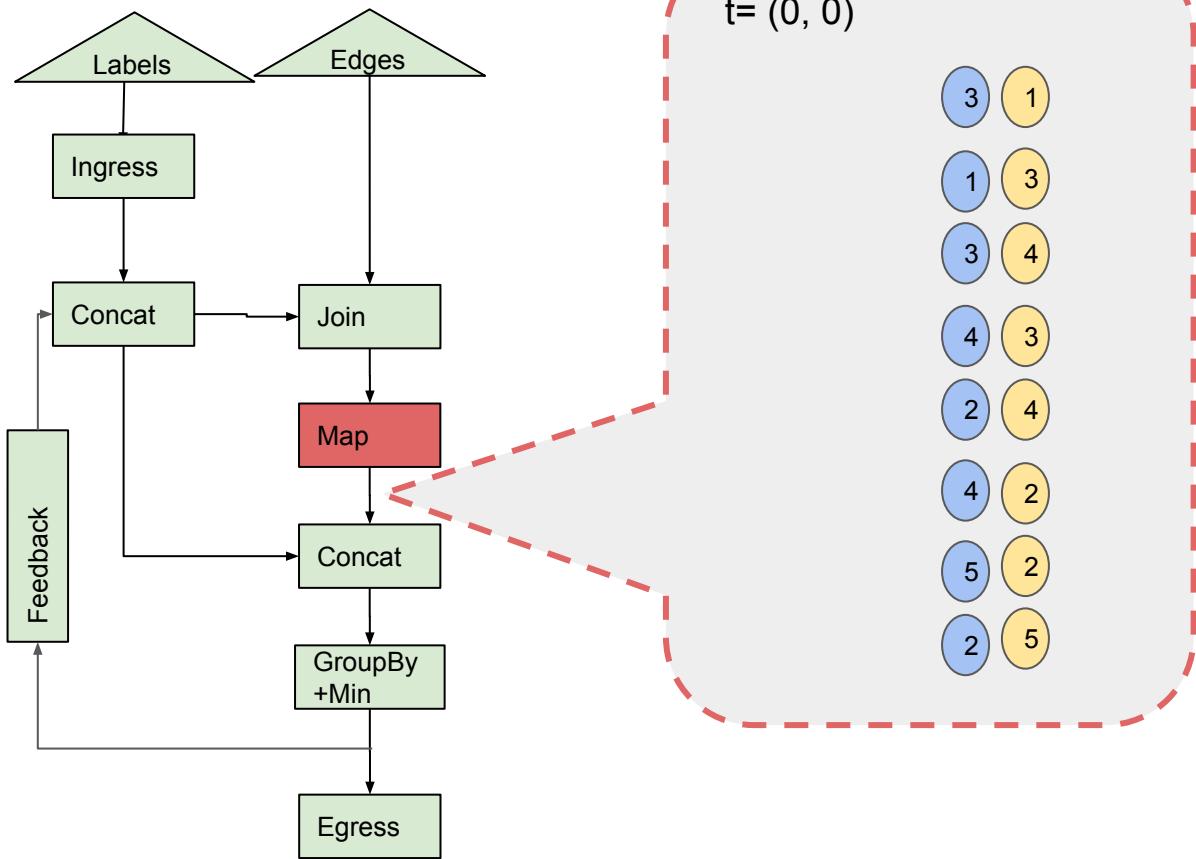
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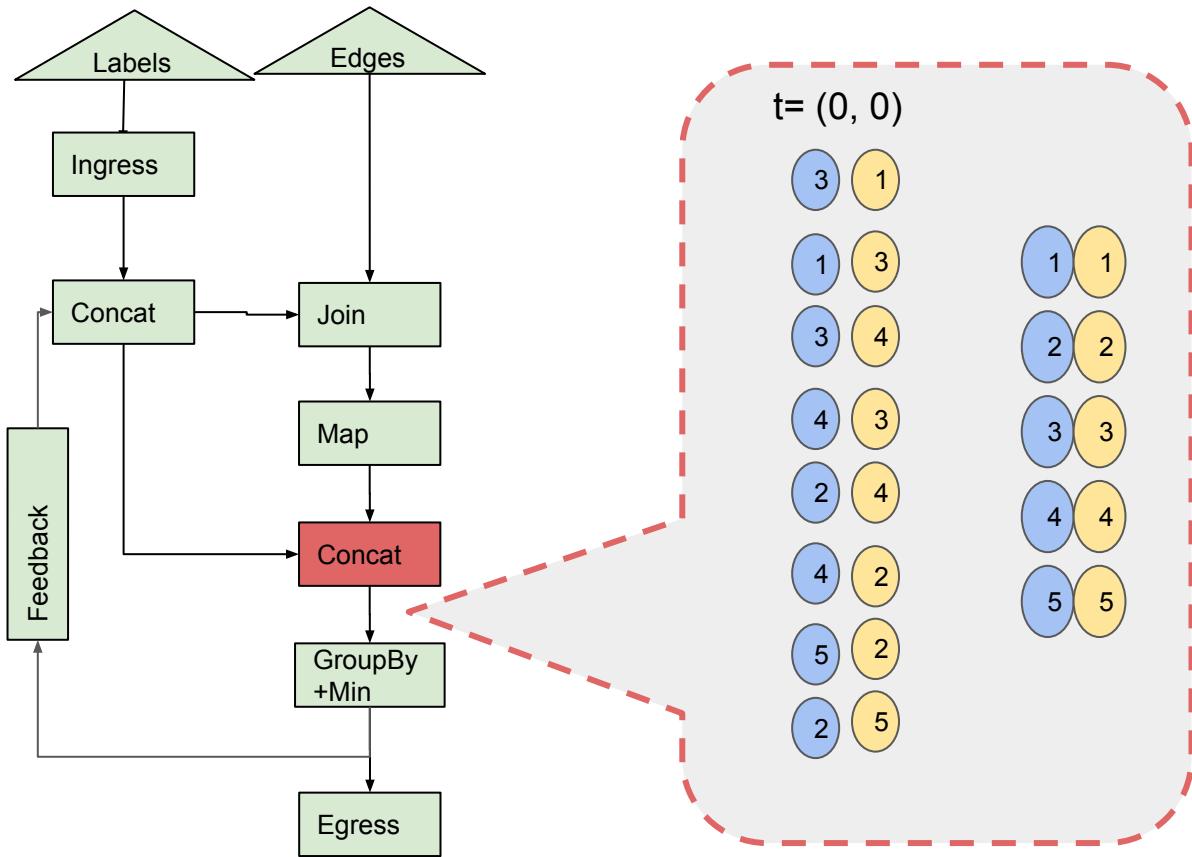
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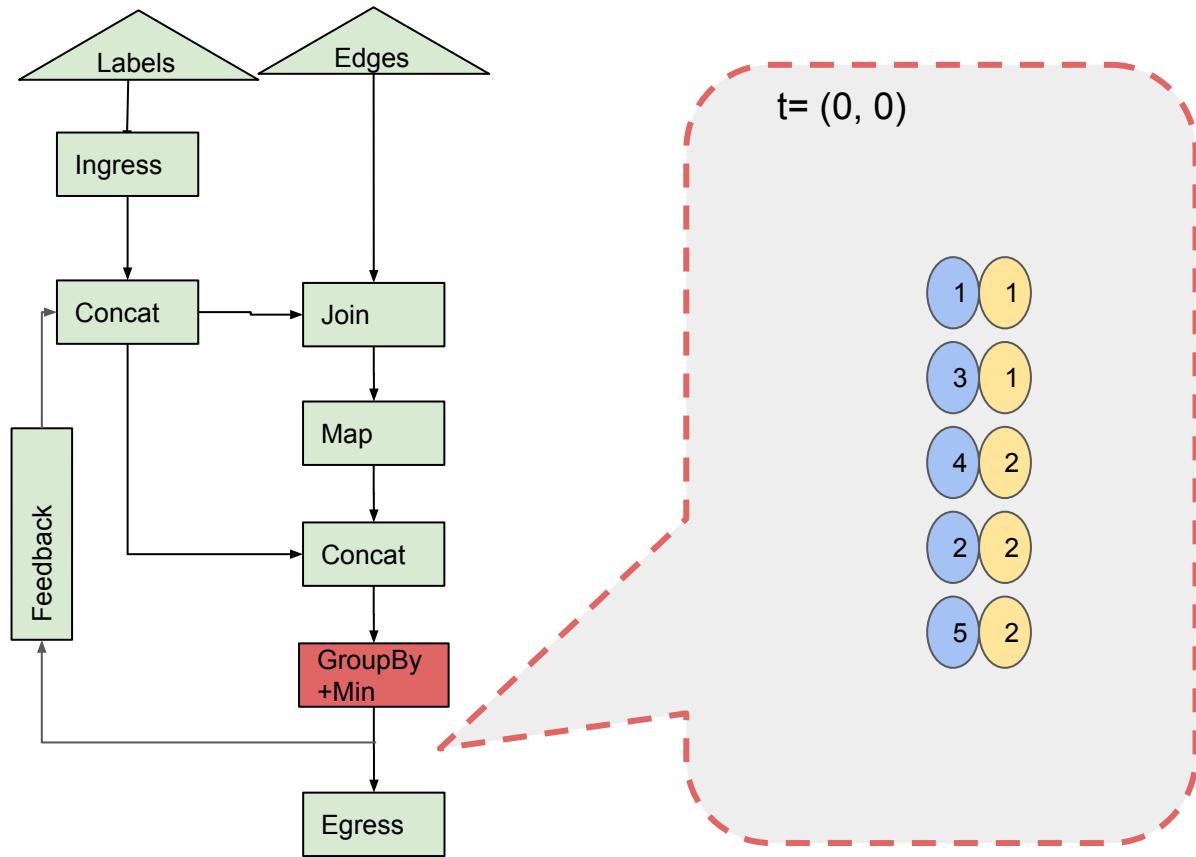
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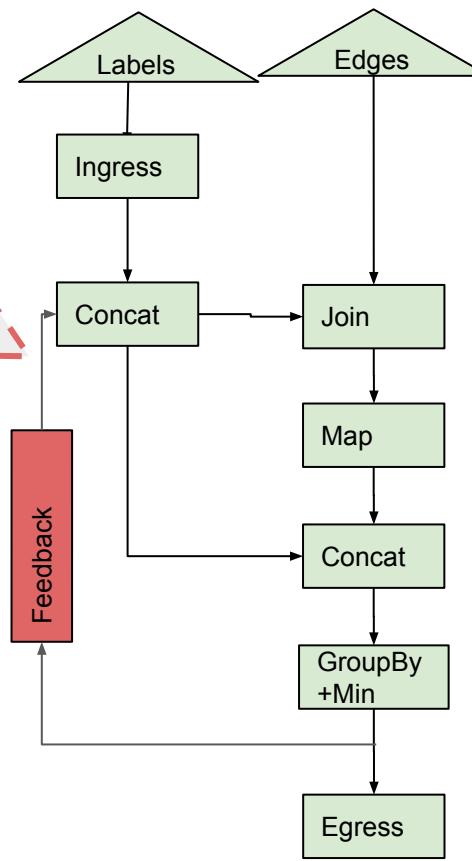
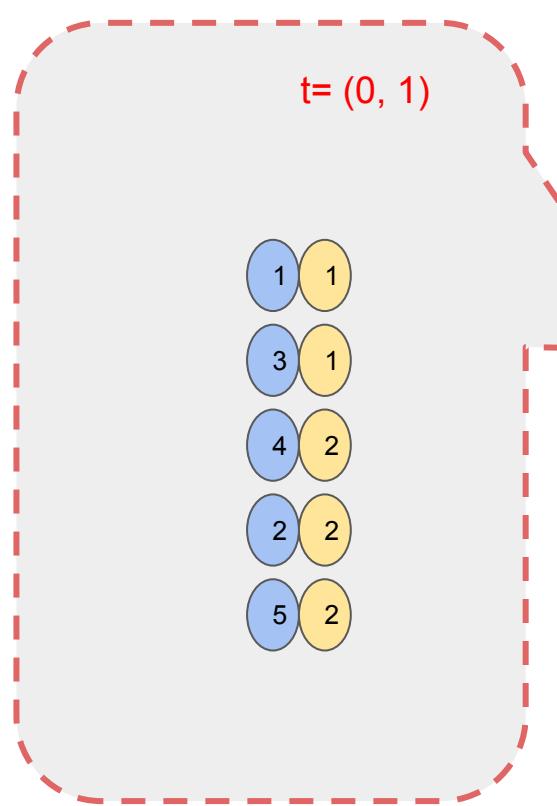
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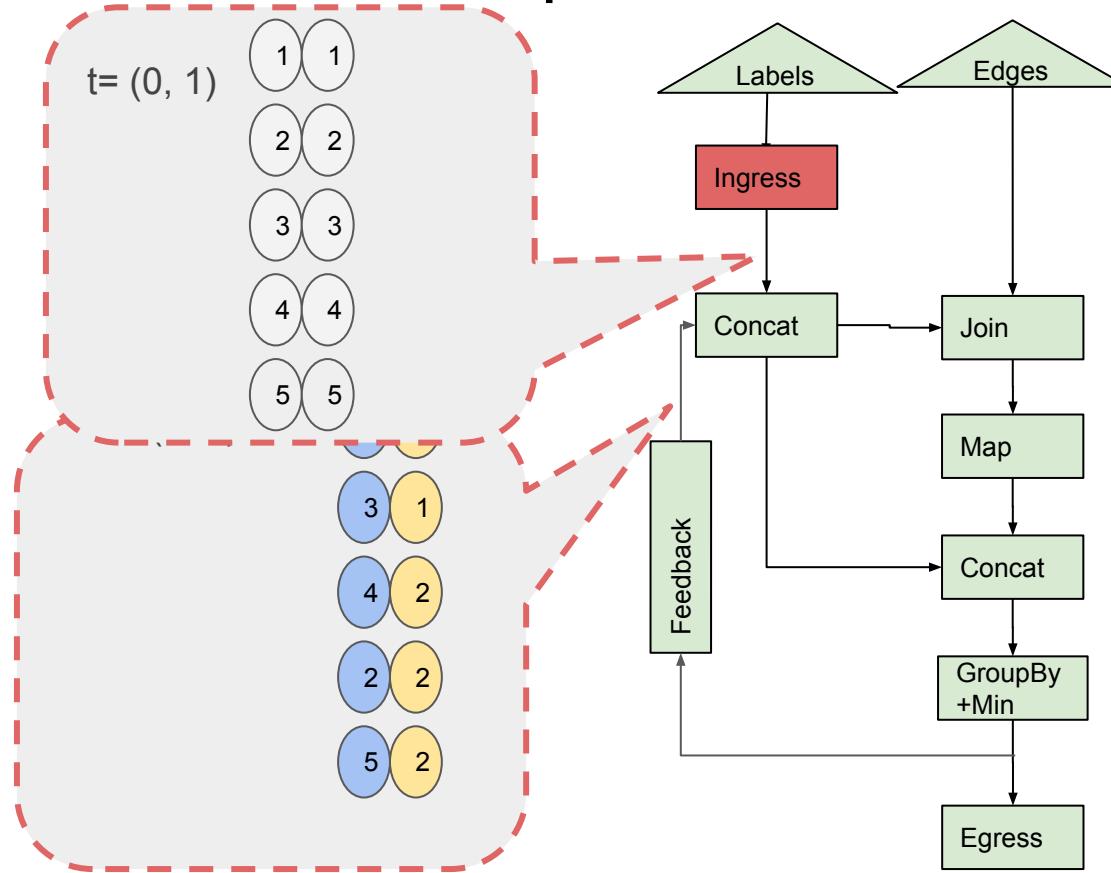
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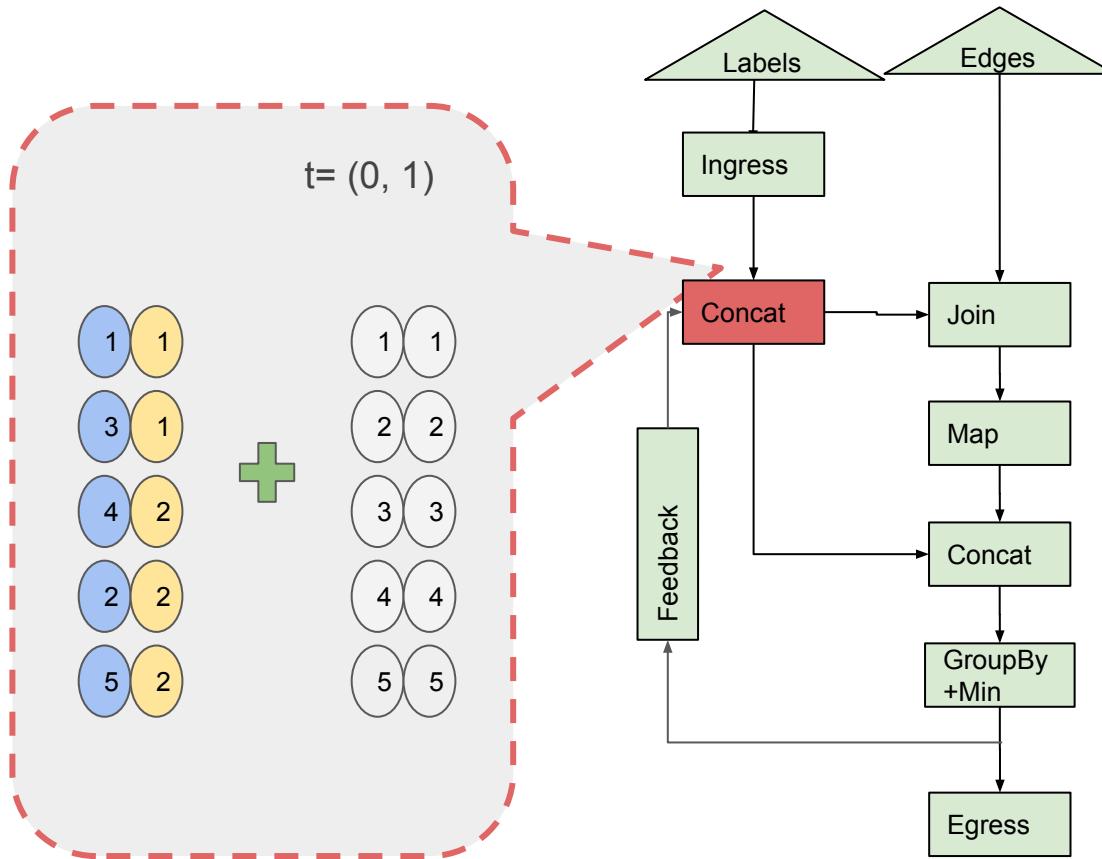
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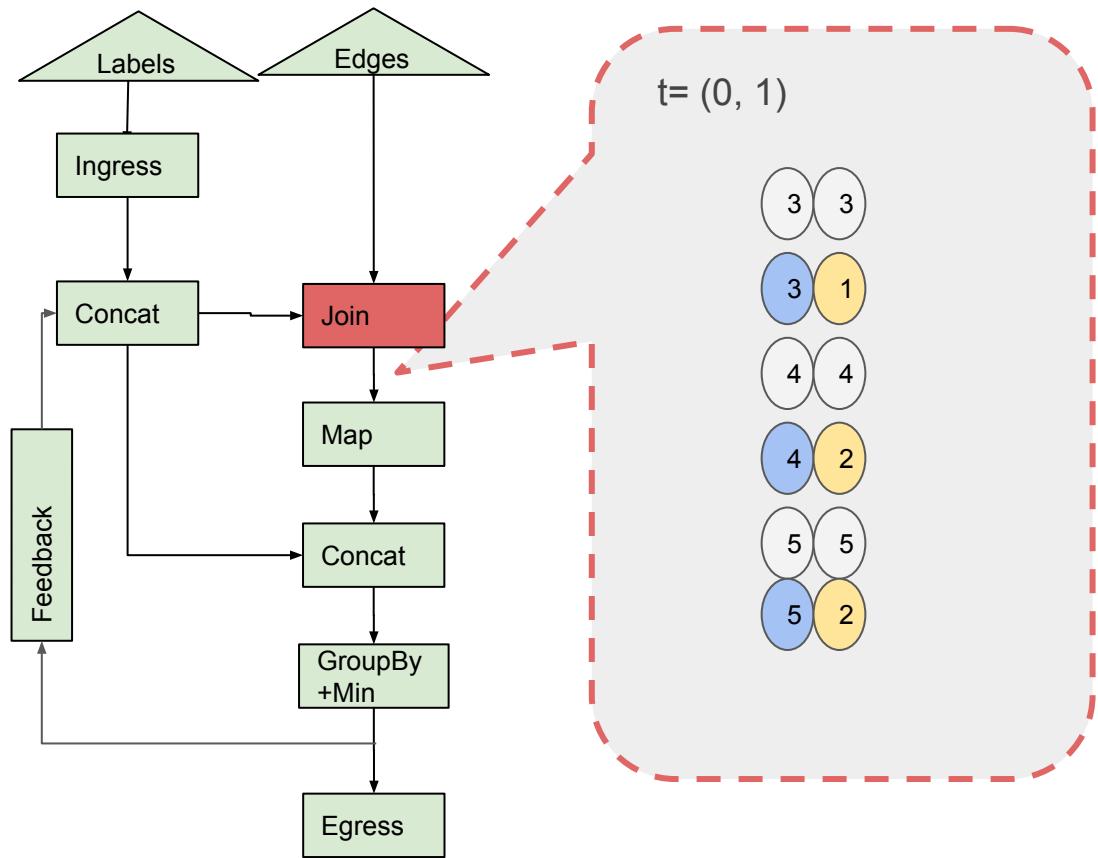
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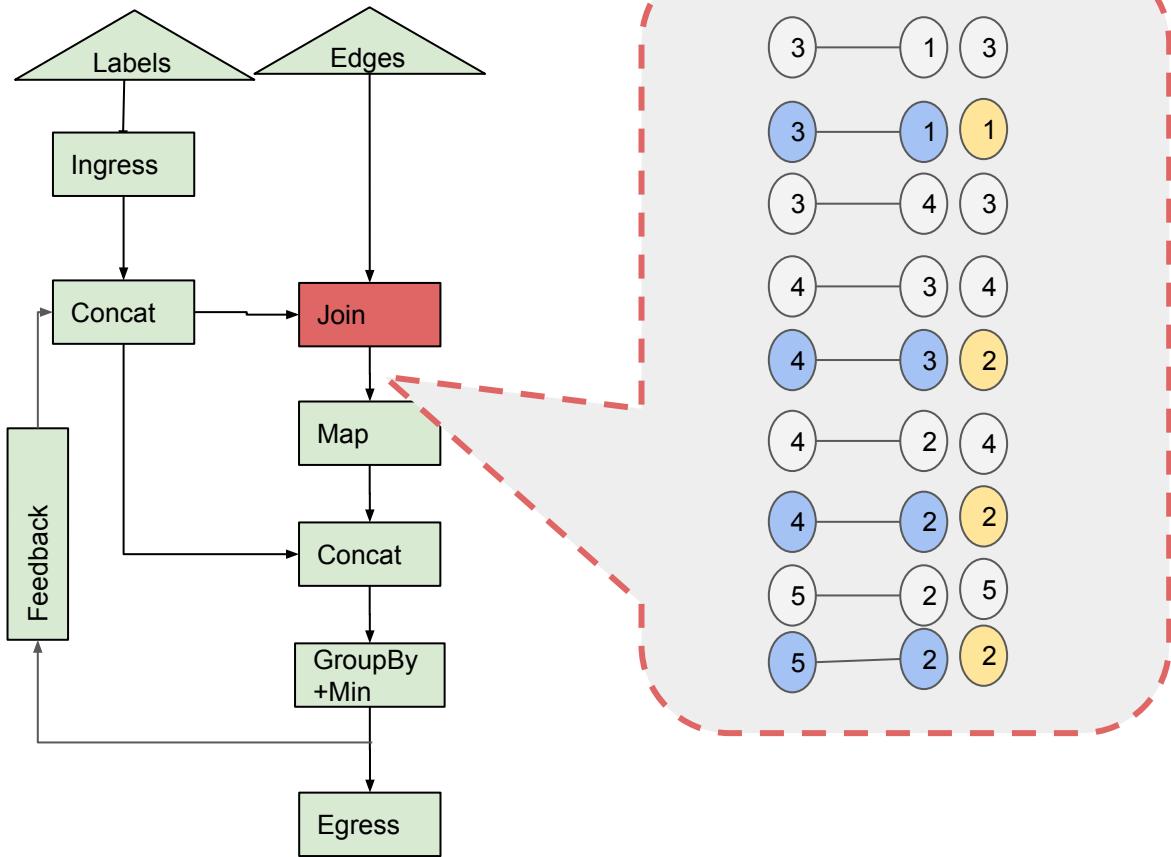
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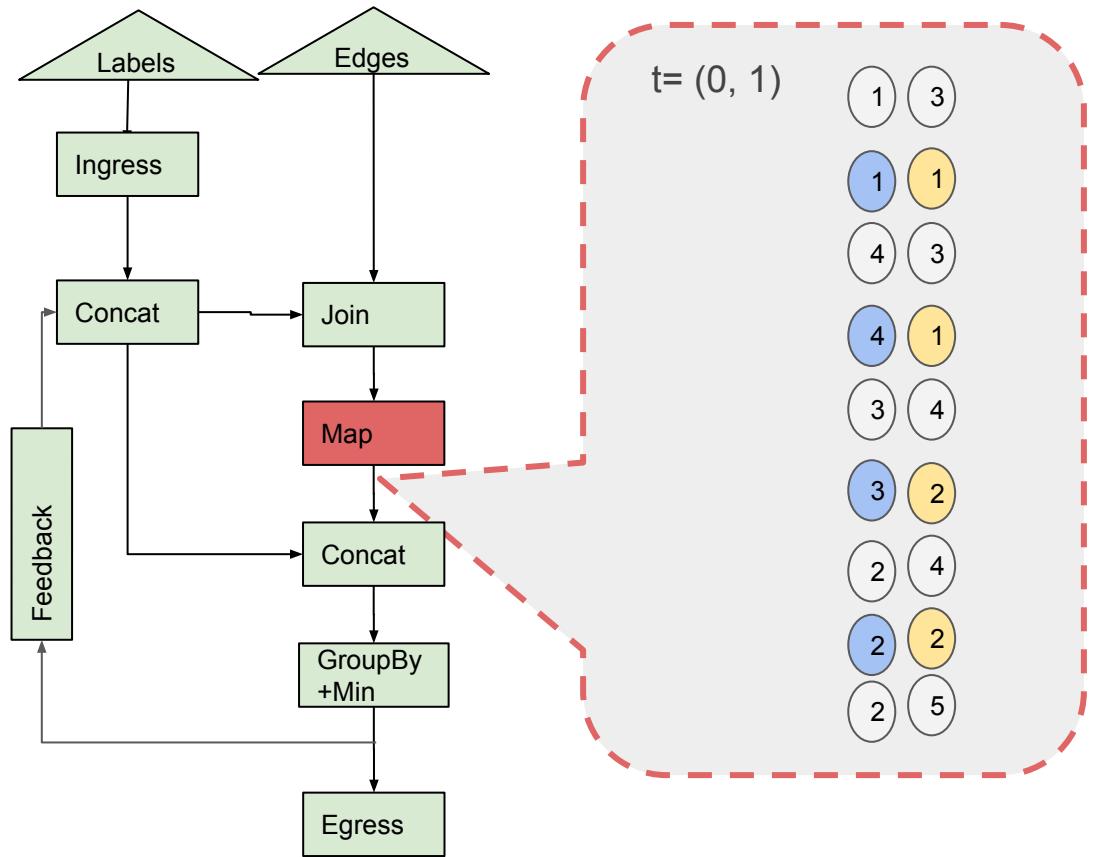
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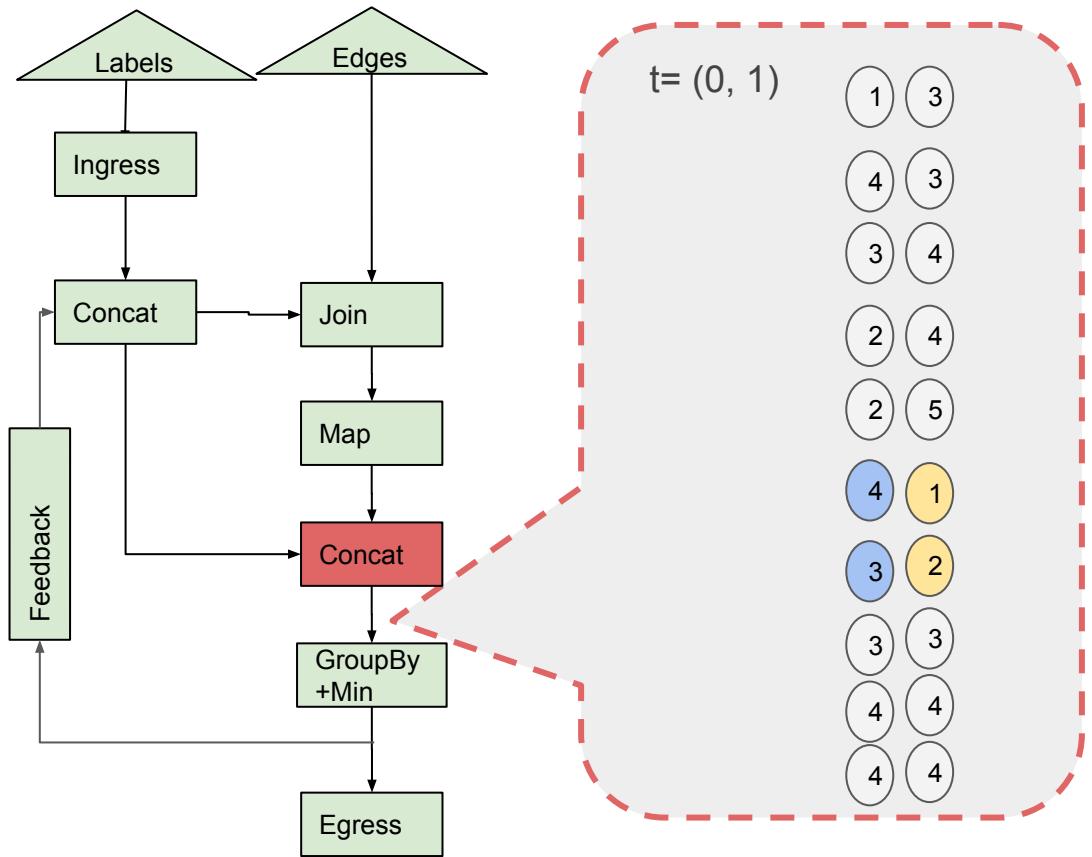
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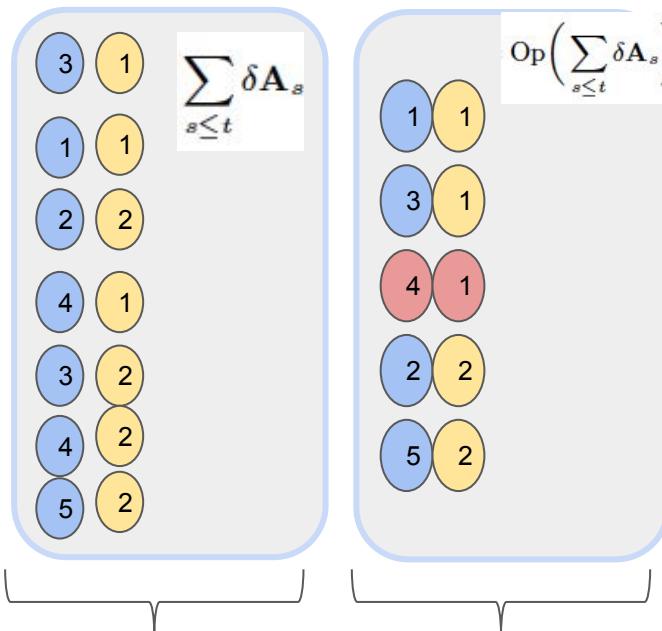
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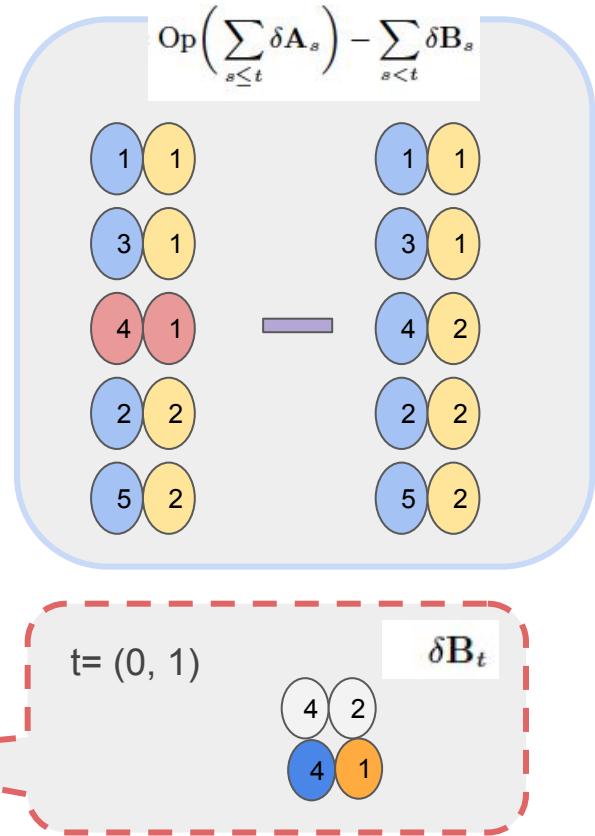
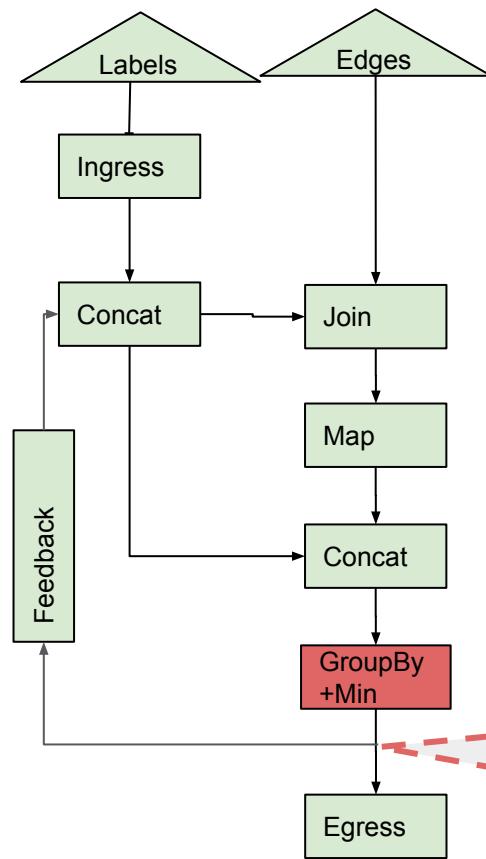


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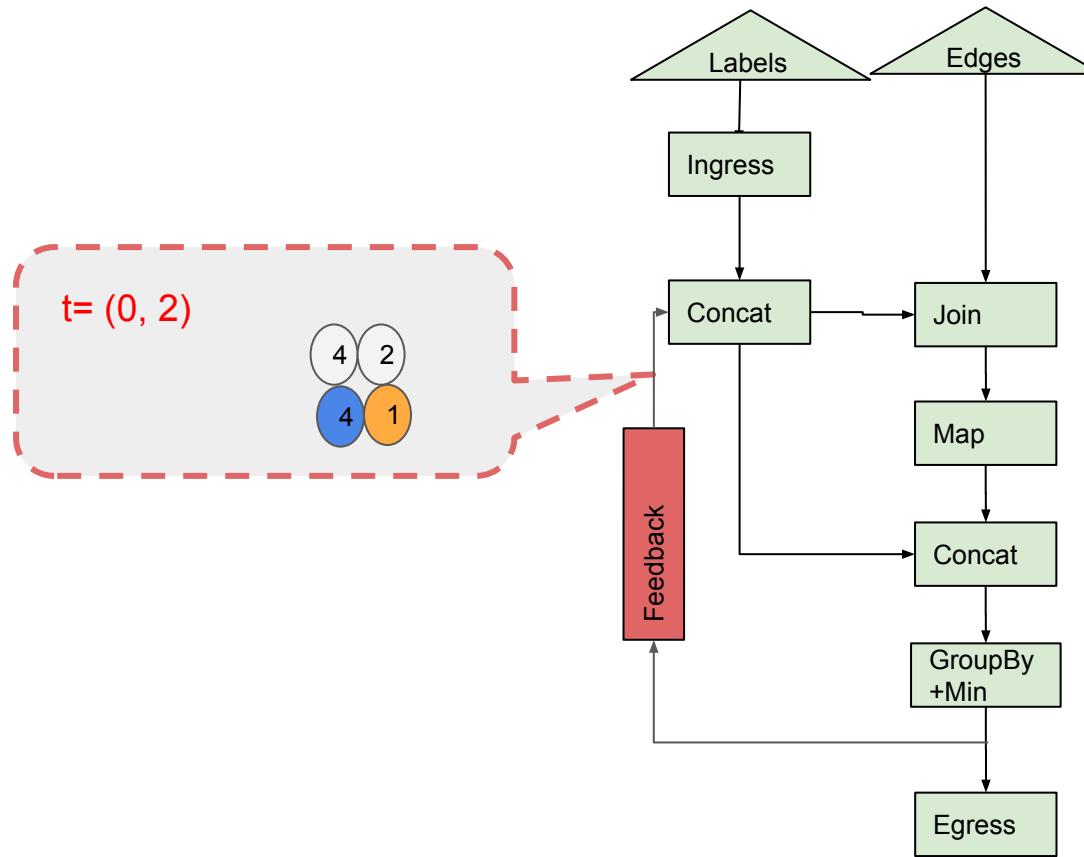


Cumulative Input
from concat

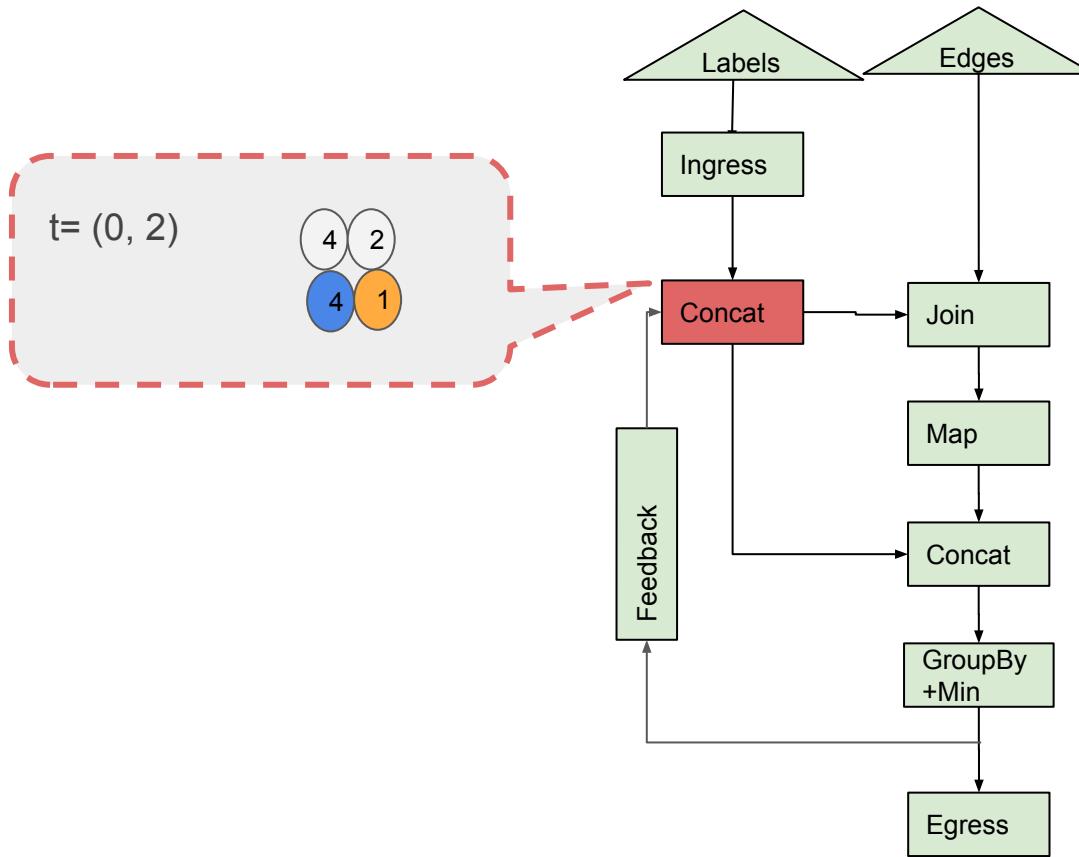
Groupby + Min



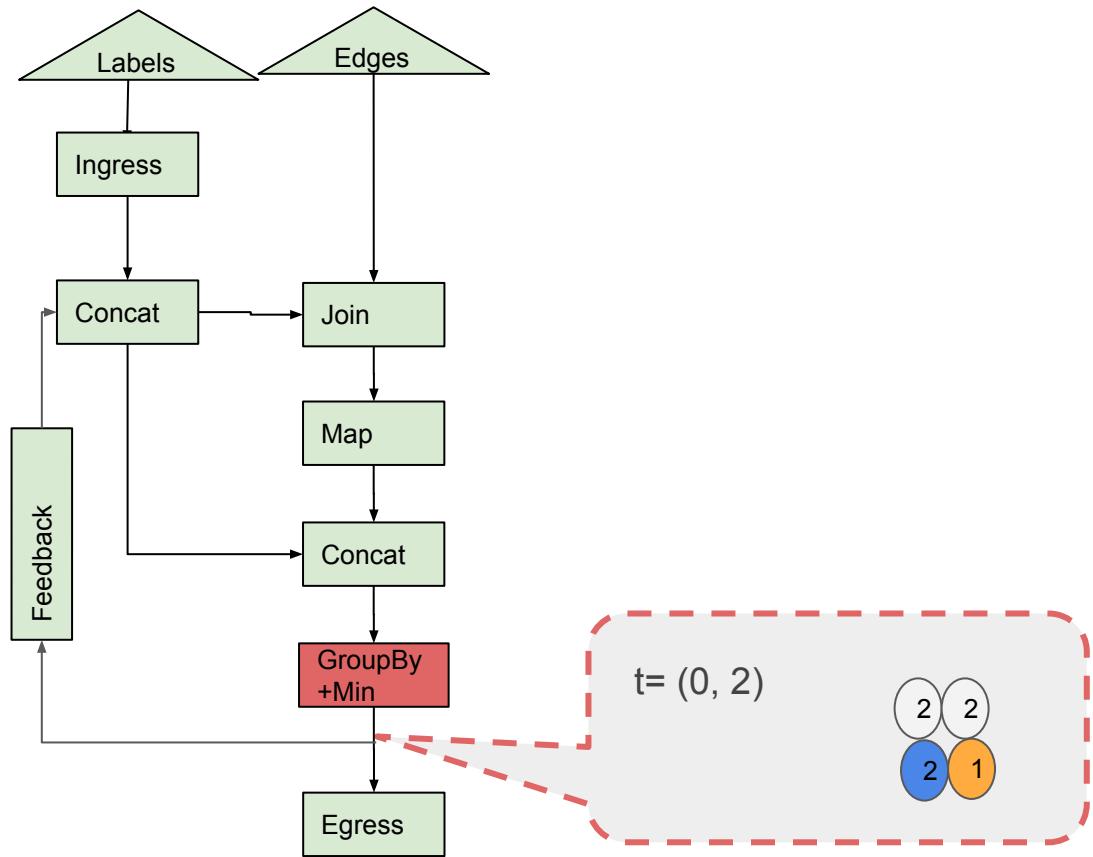
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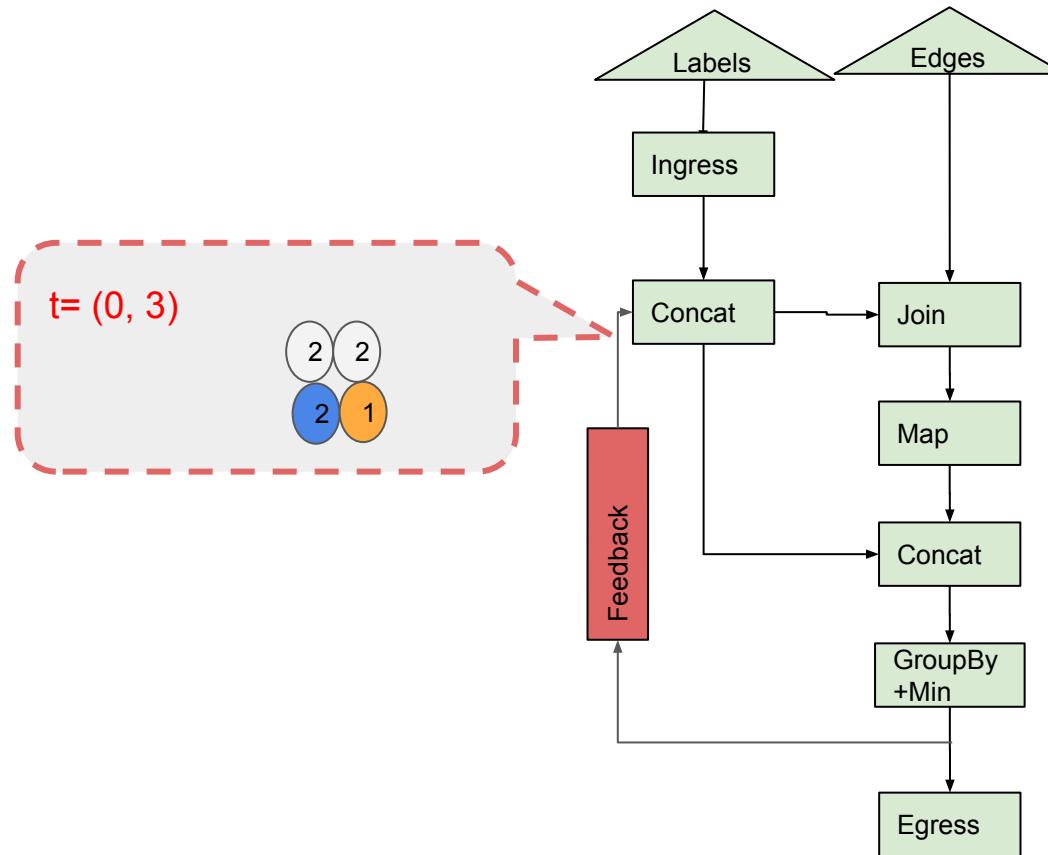
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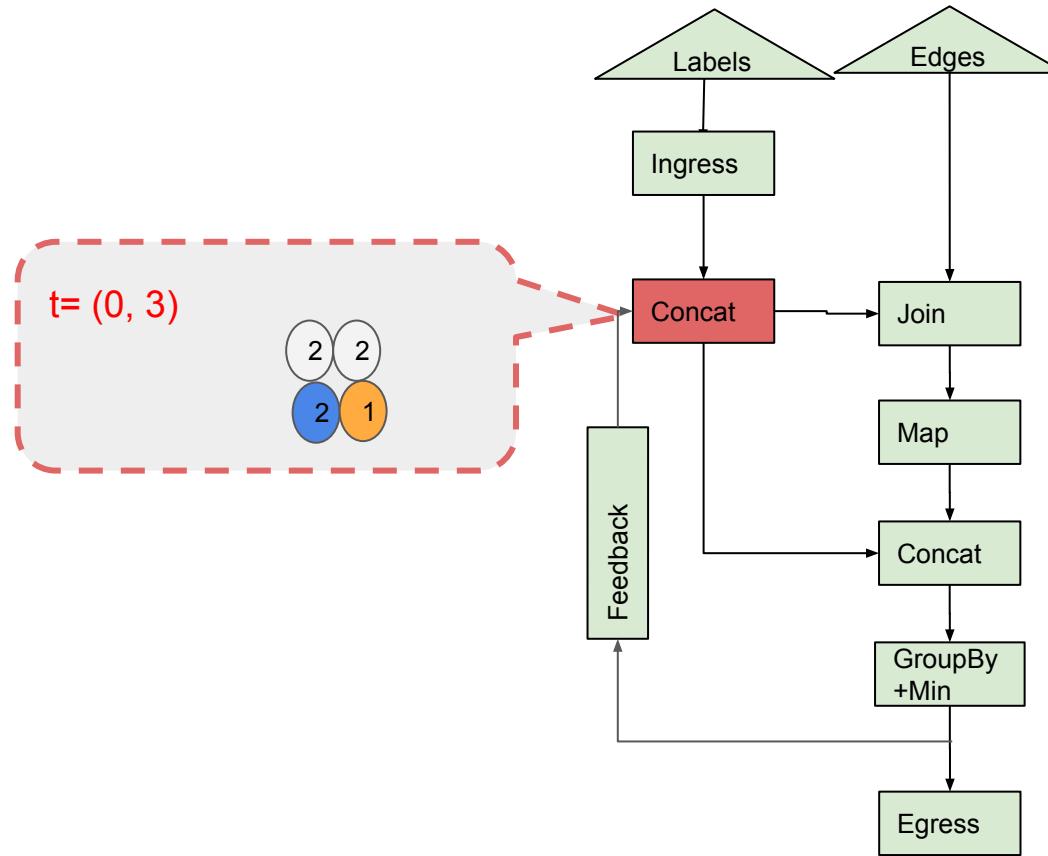
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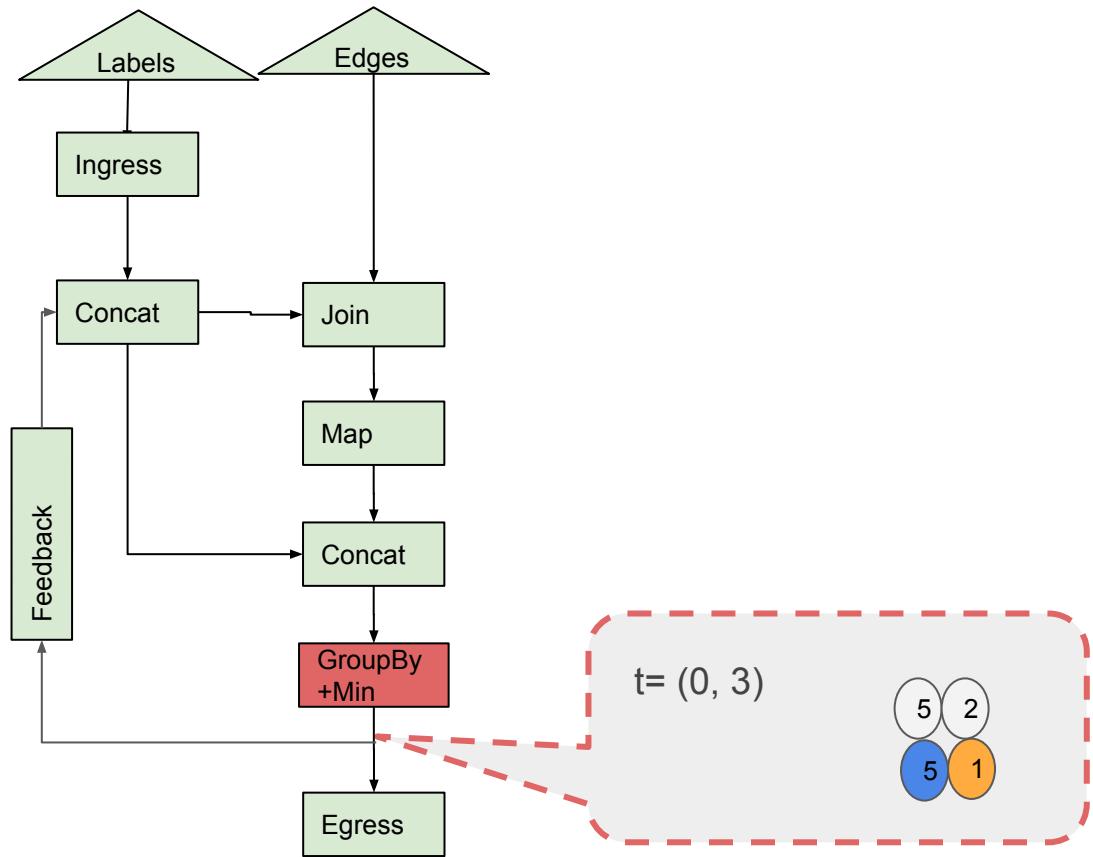
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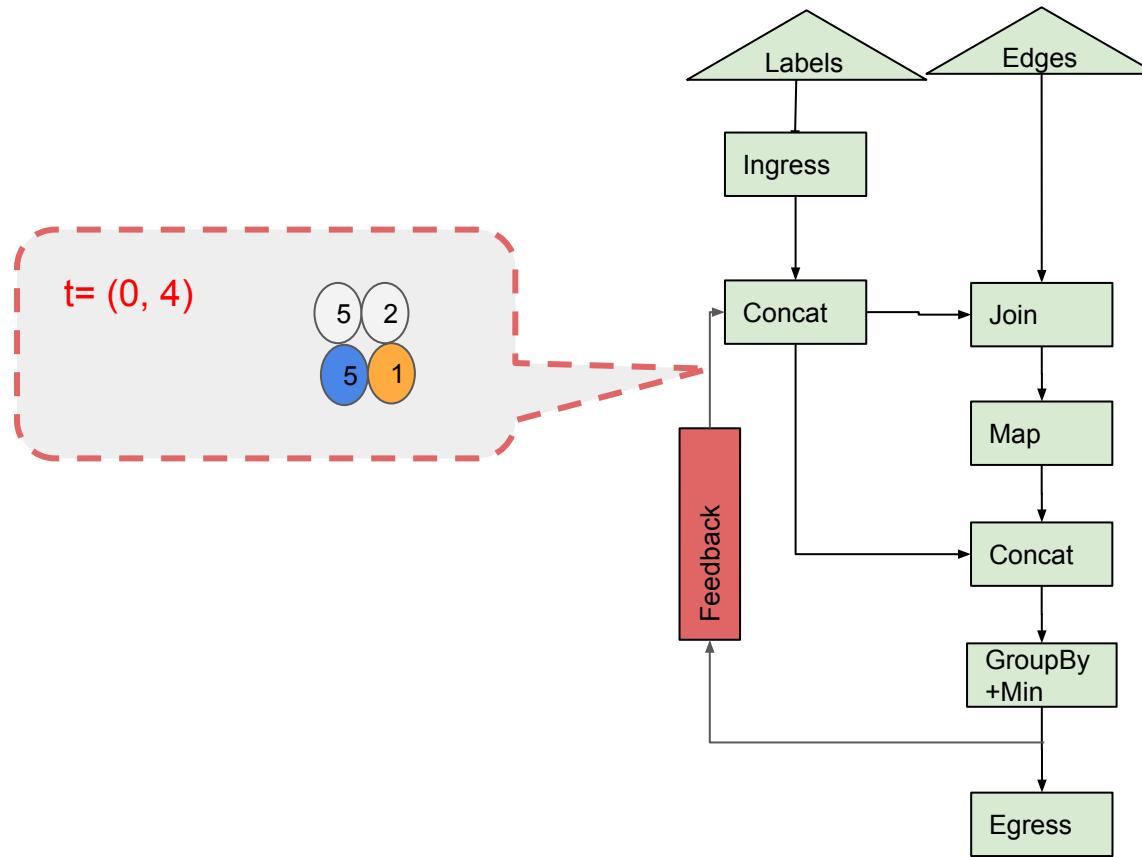
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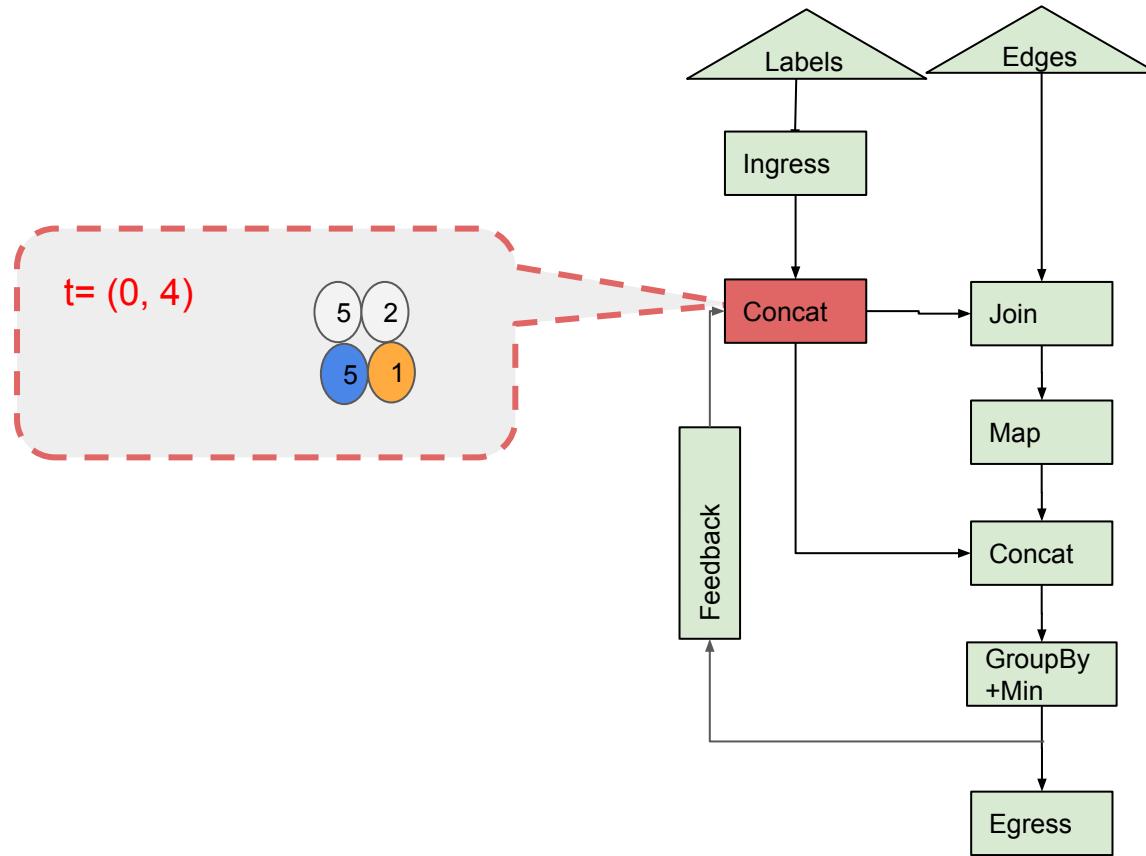
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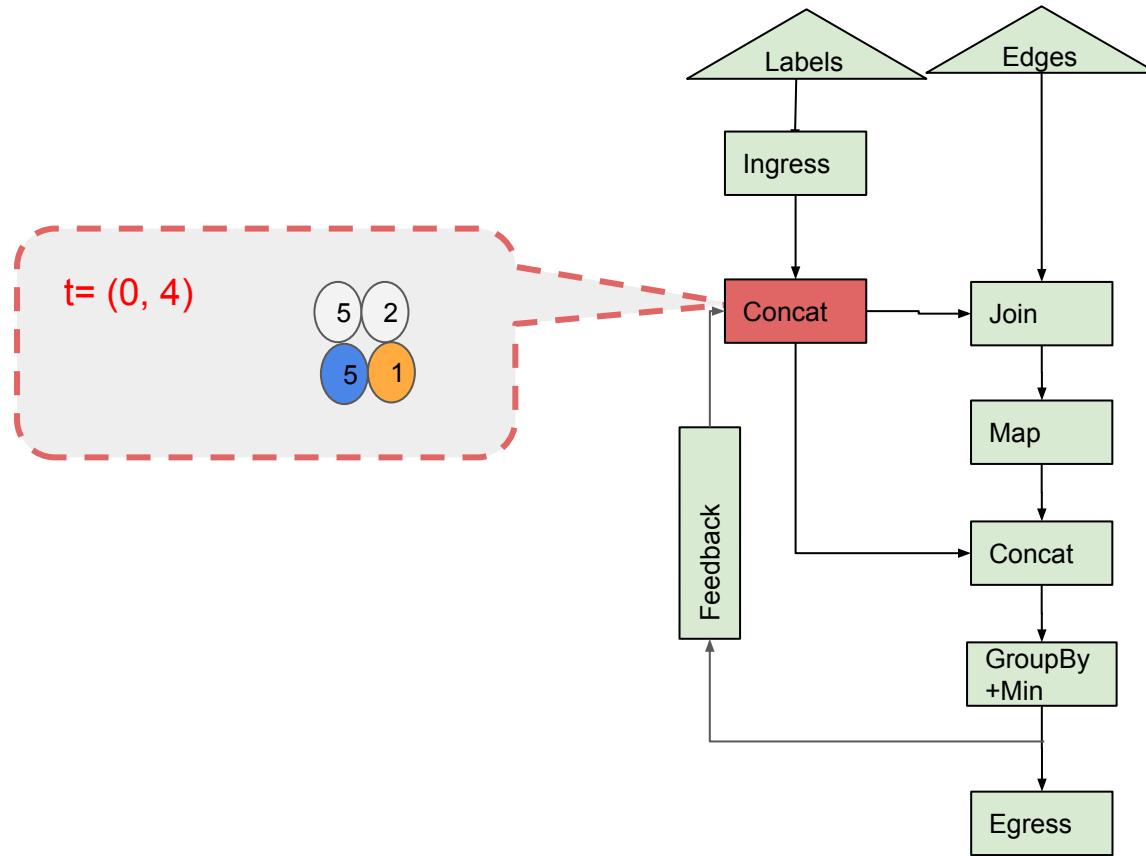
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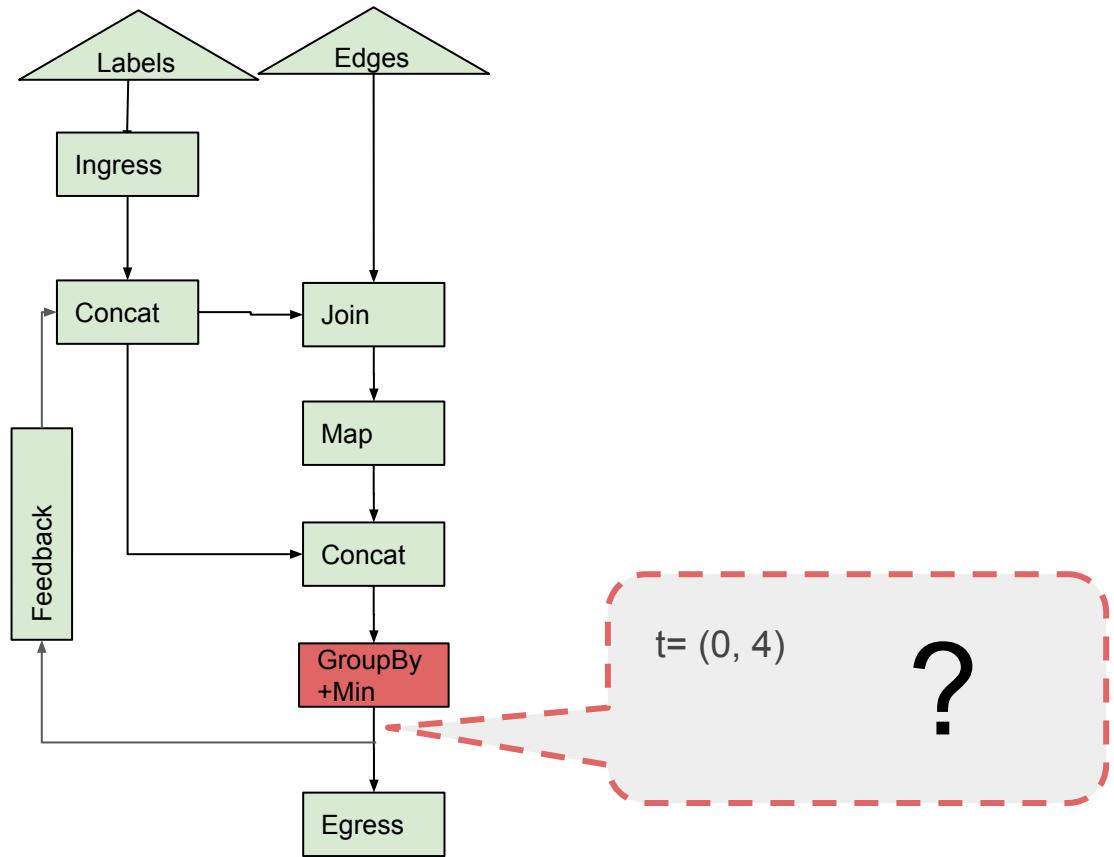
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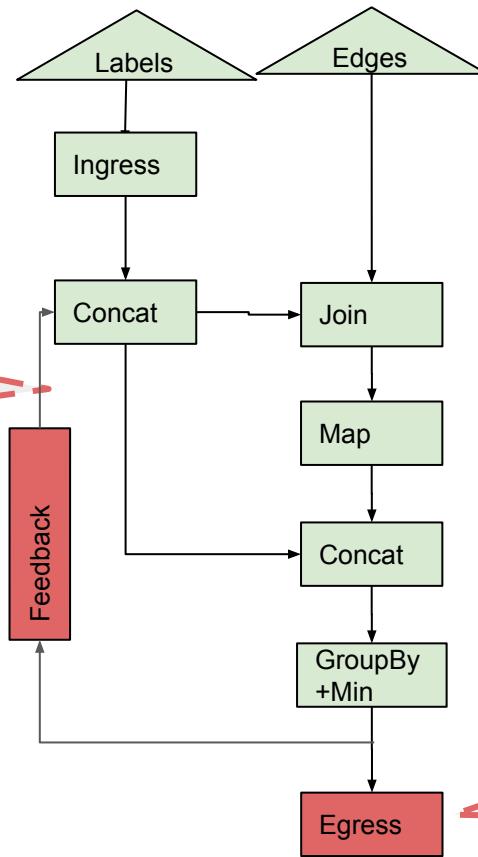
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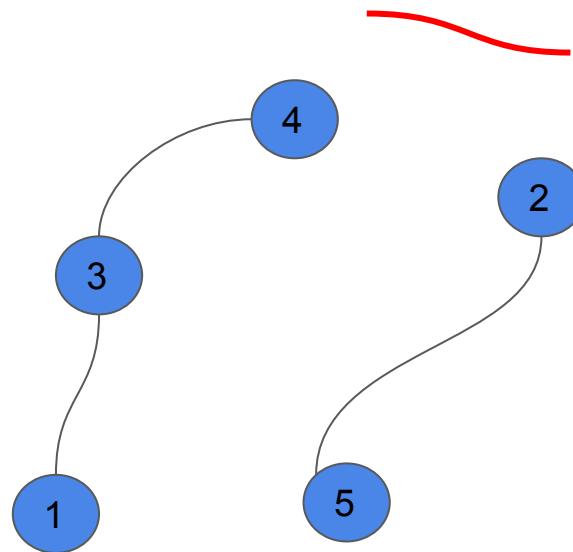
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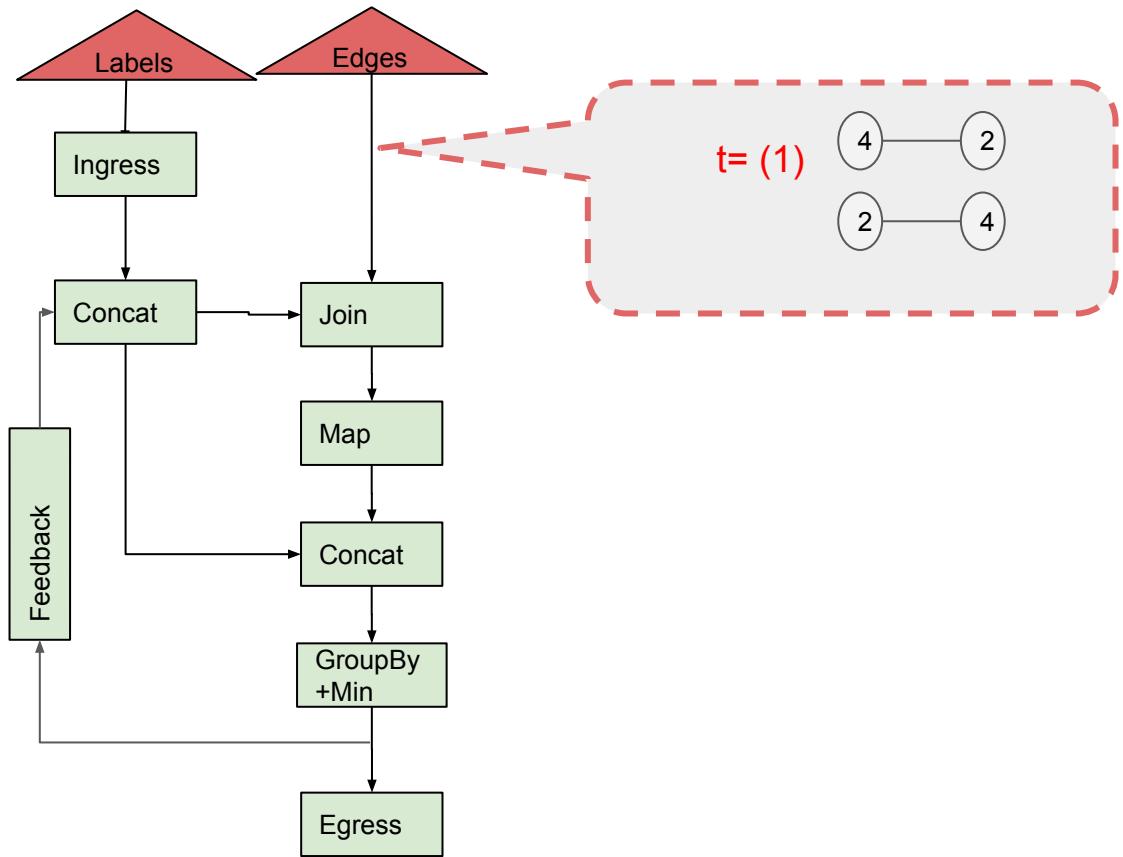


Changes to Connected Graph - I

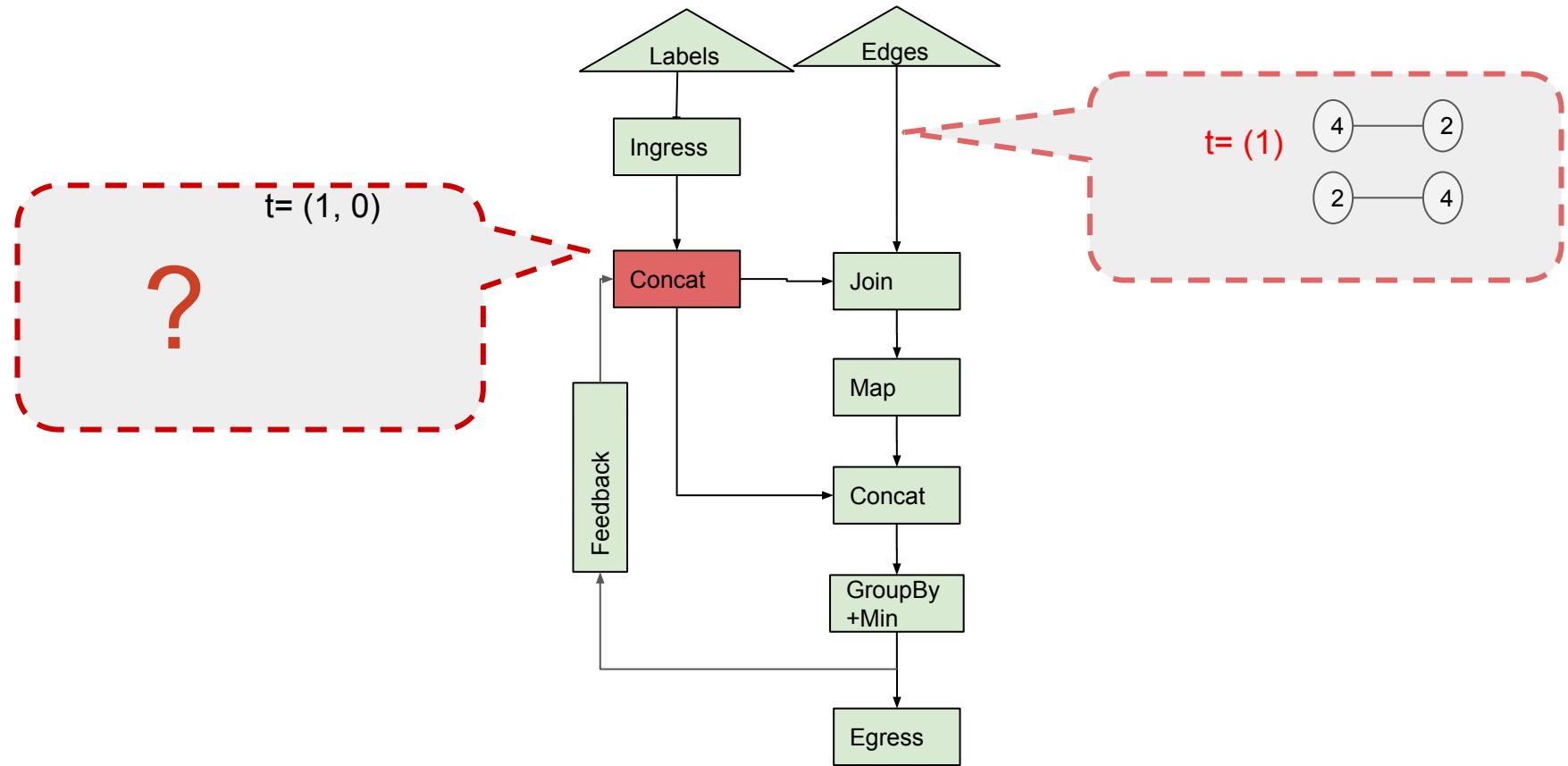


Remove Undirected Edge

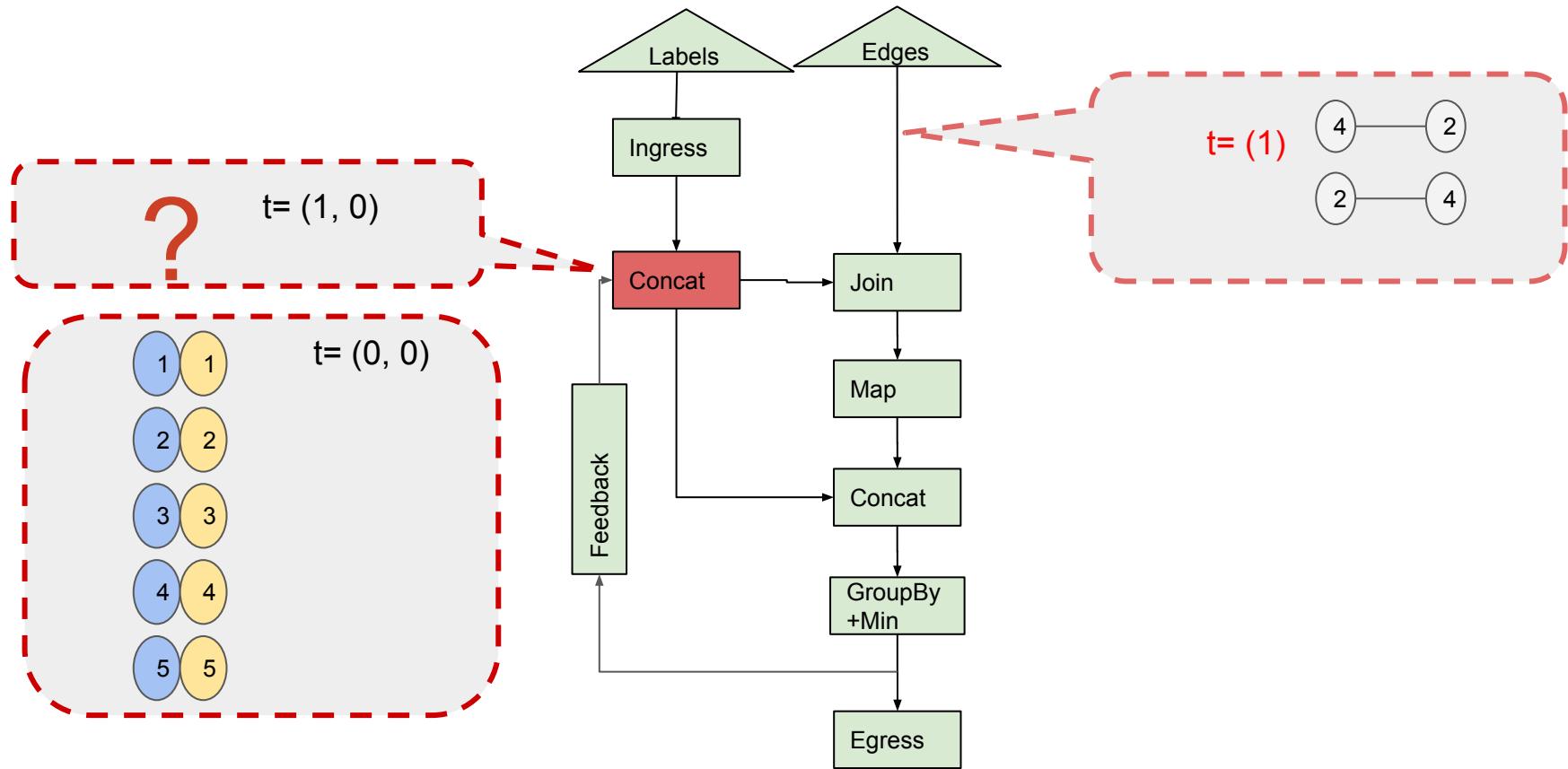
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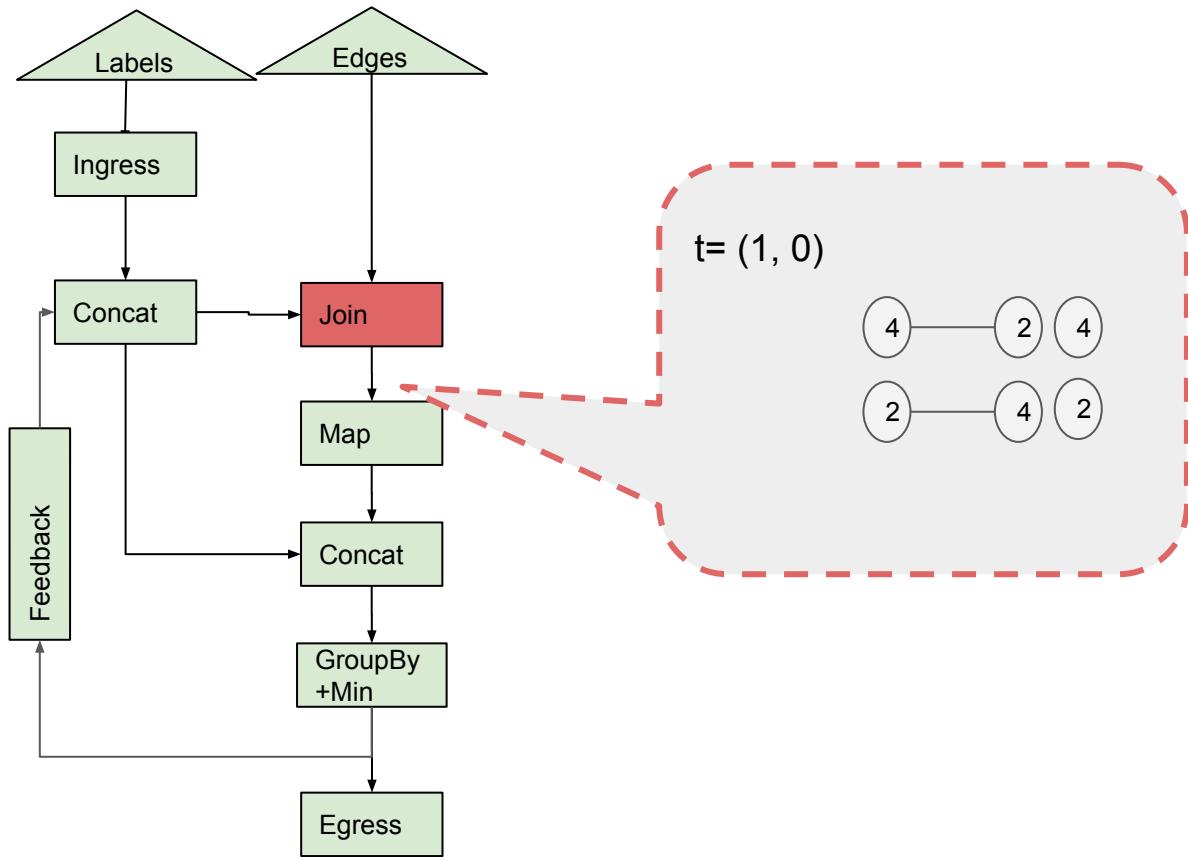
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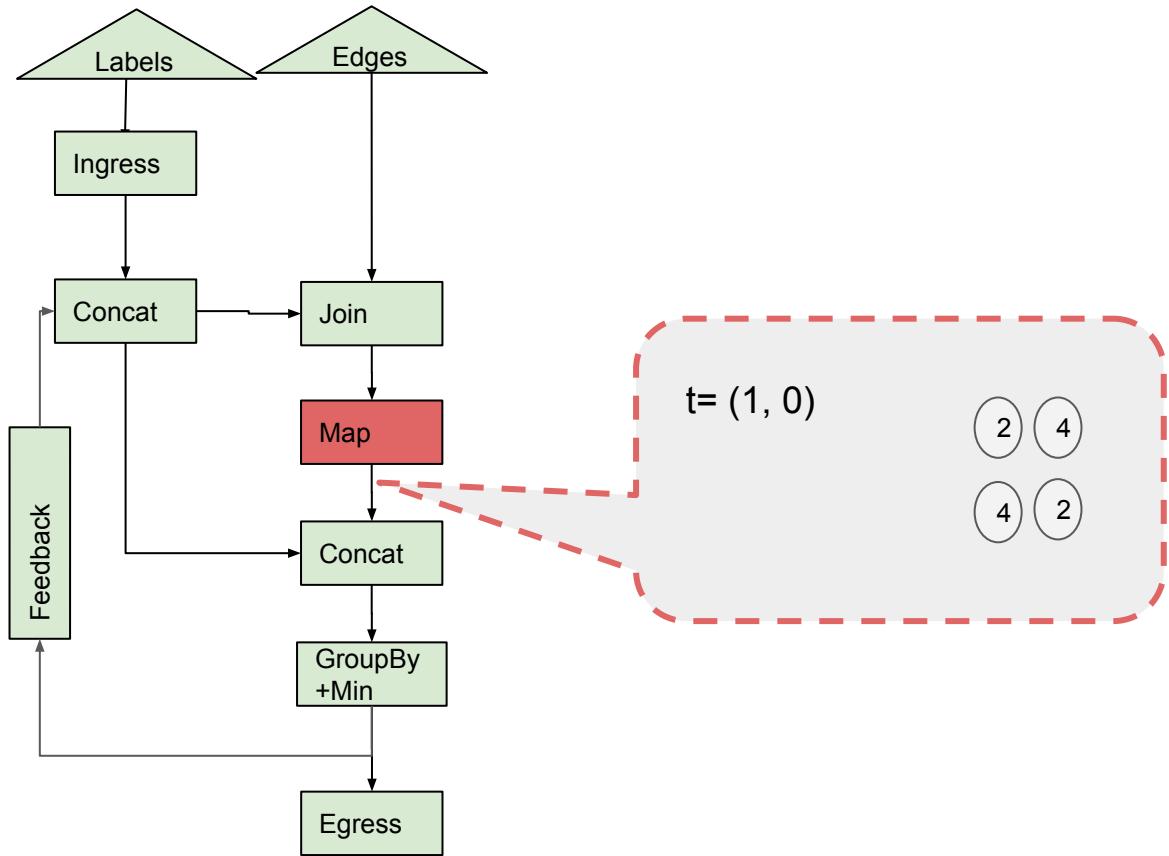
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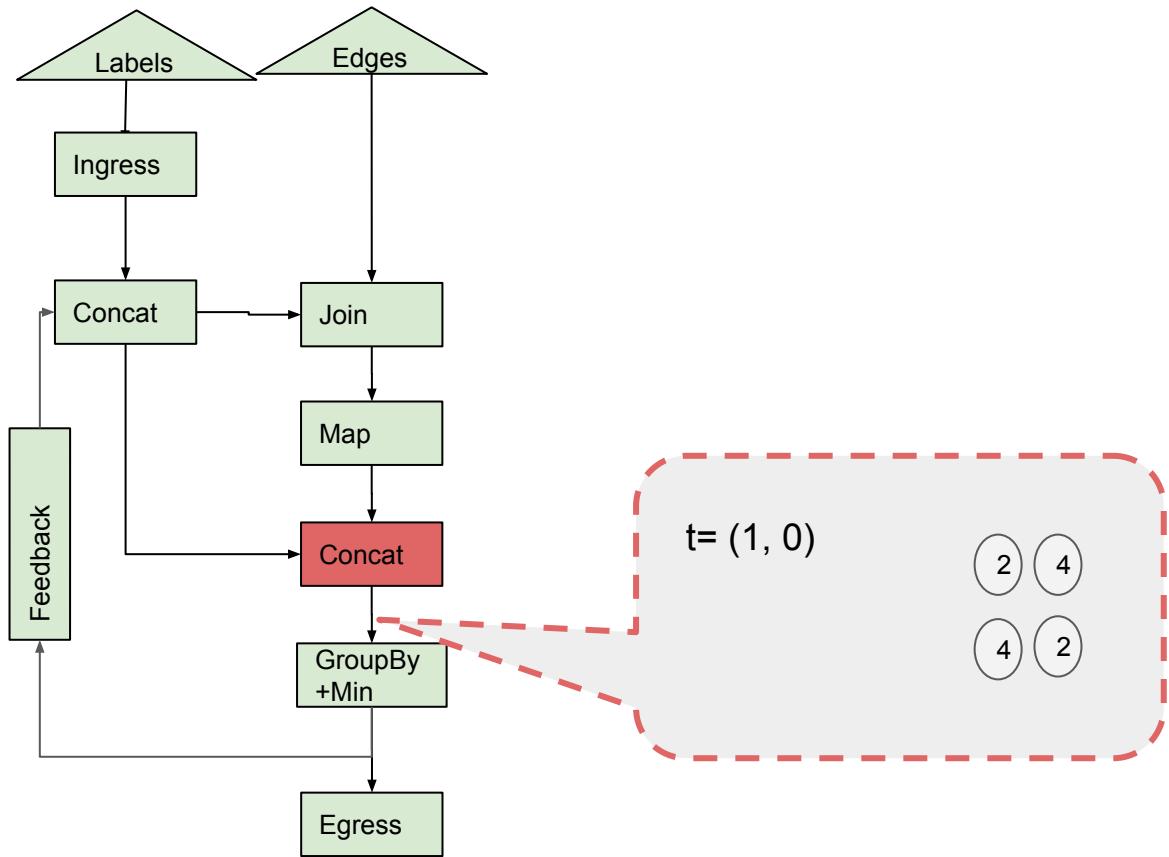
Changes to Connected Graph - I



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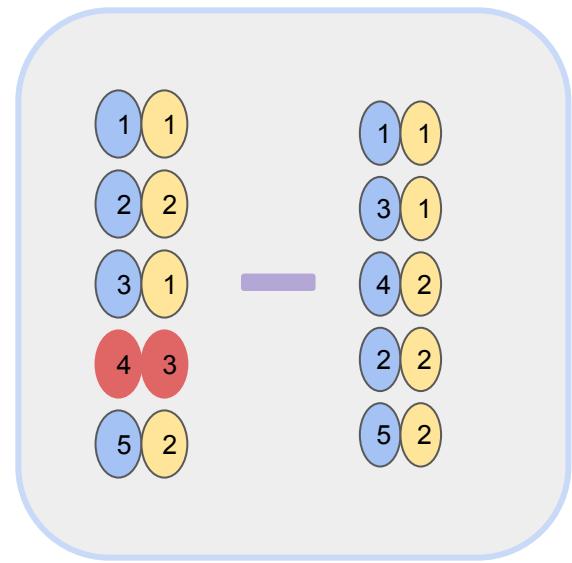
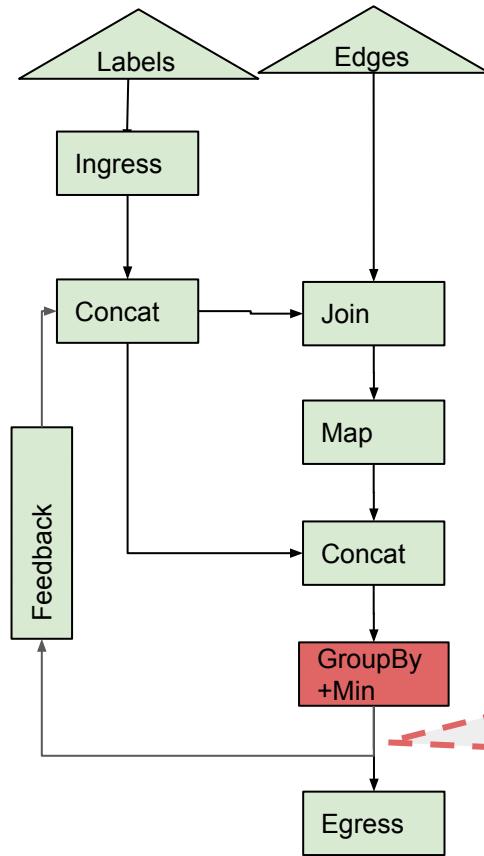
Changes to Connected Graph - I

$t=(0, 0)$ $t=(1, 0)$



Cumulative Input
from concat

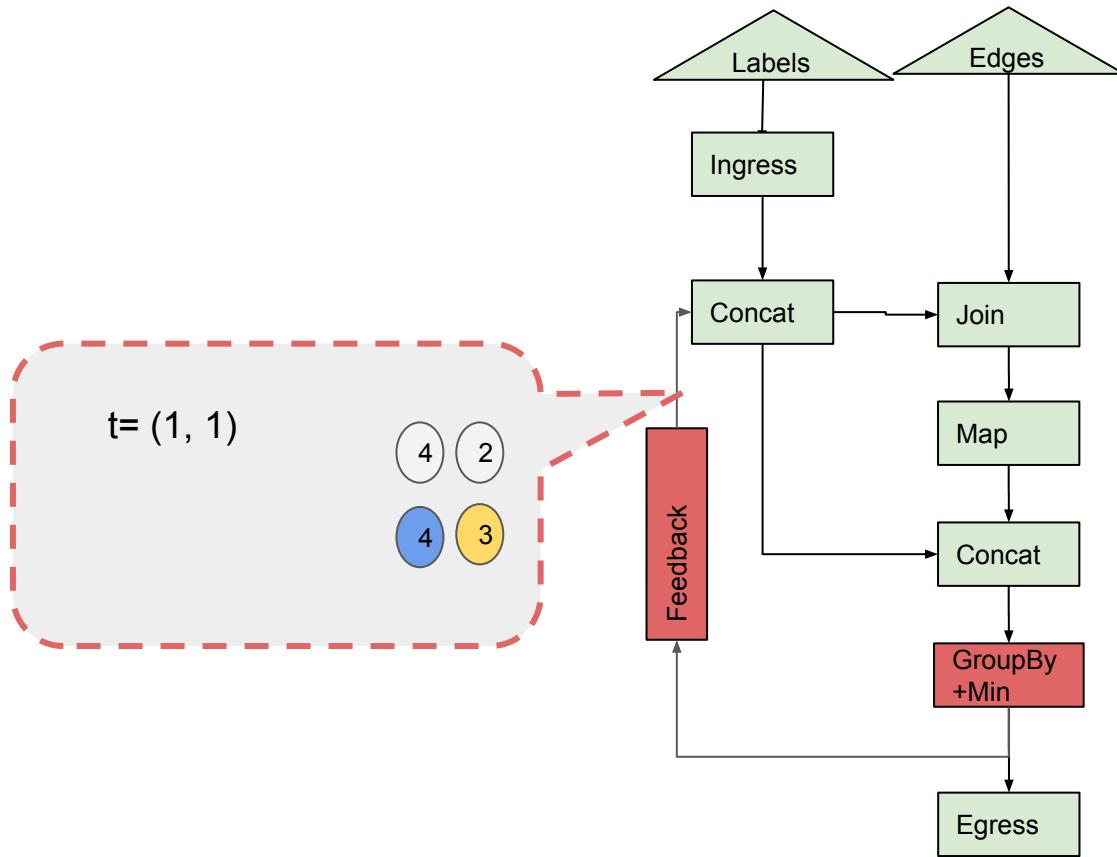
Groupby + Min



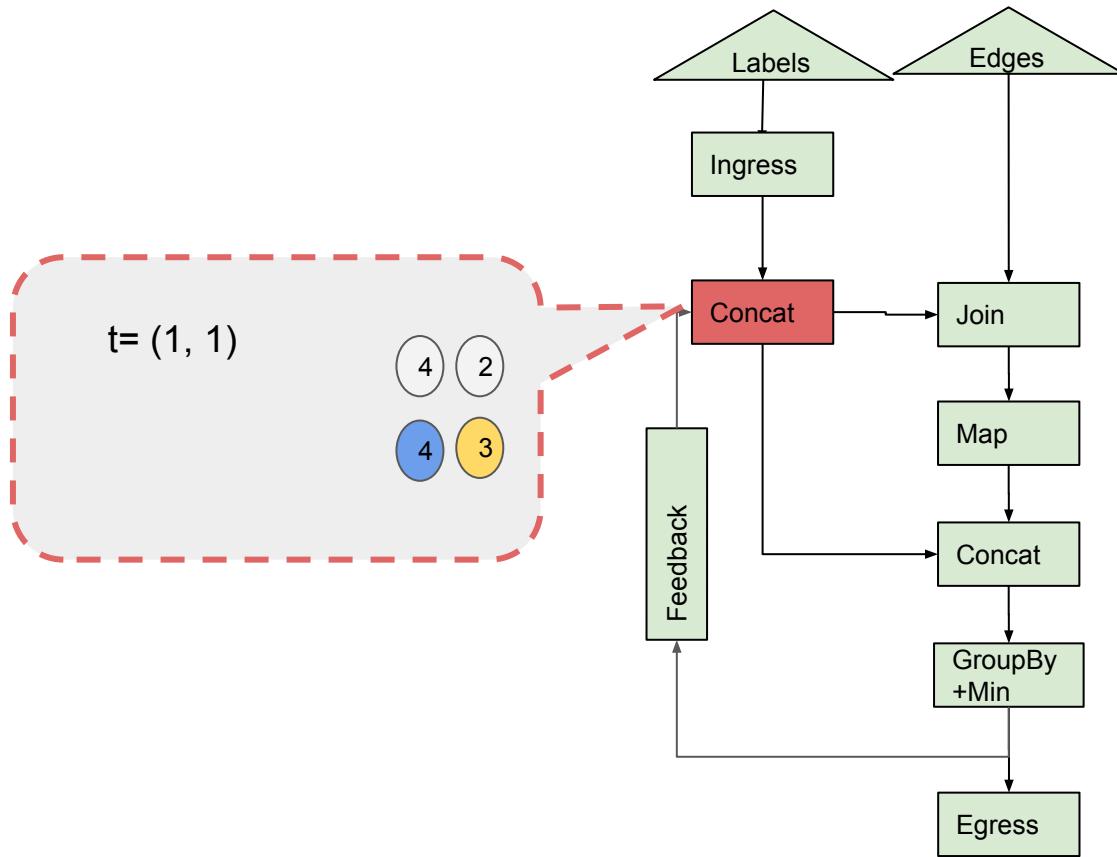
$t= (1, 0)$



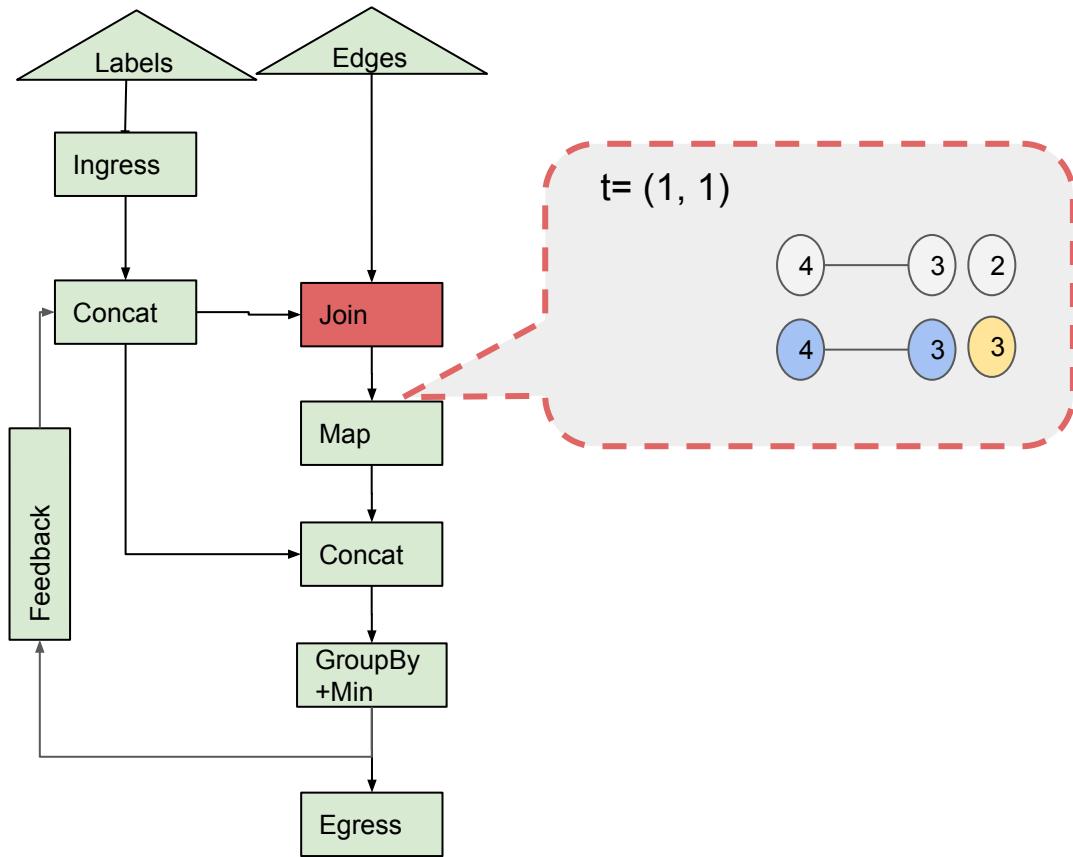
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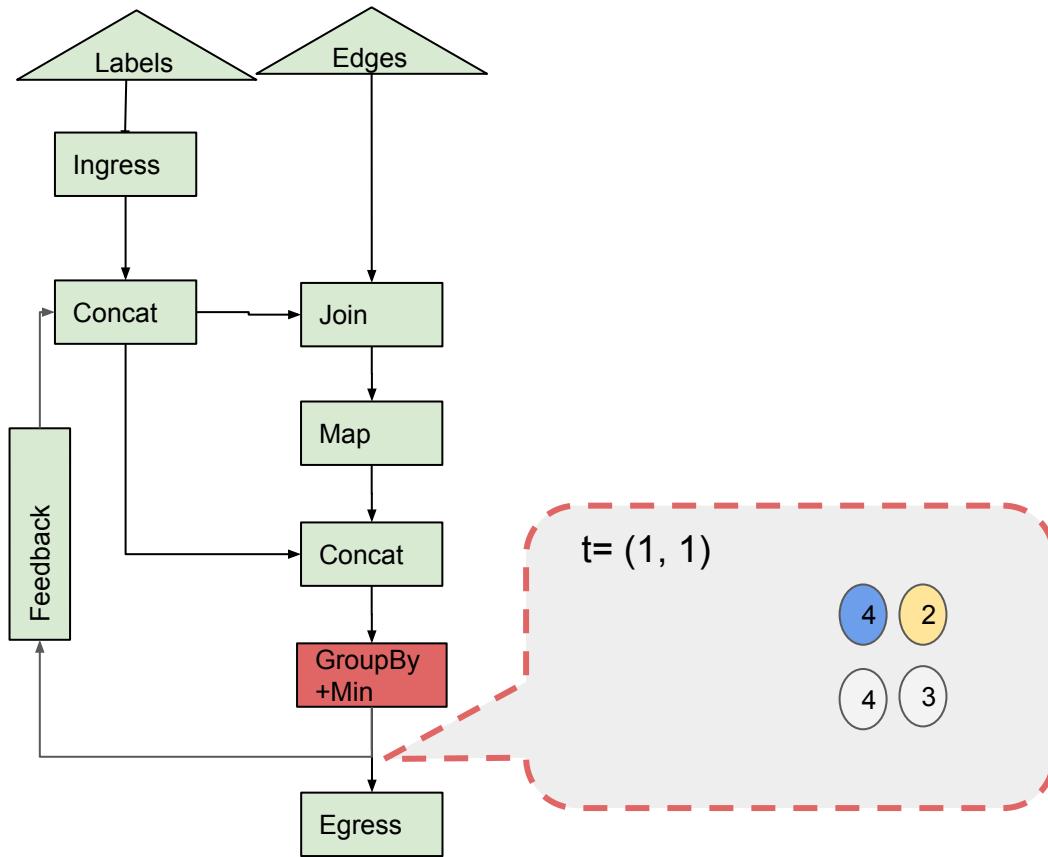
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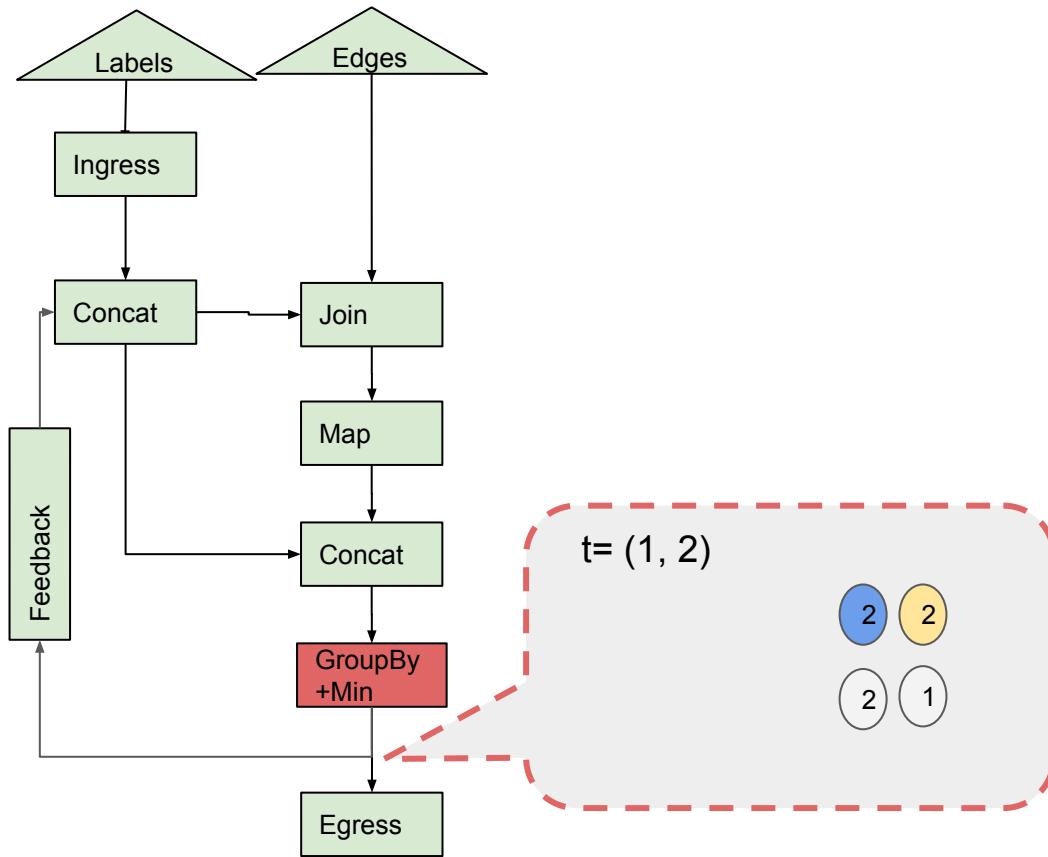
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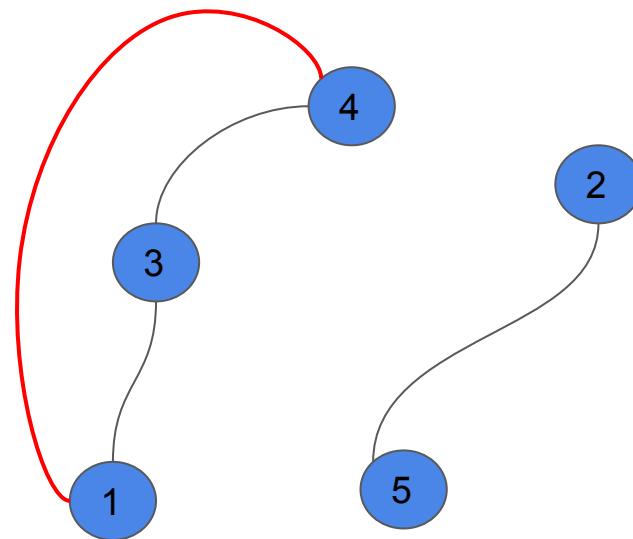


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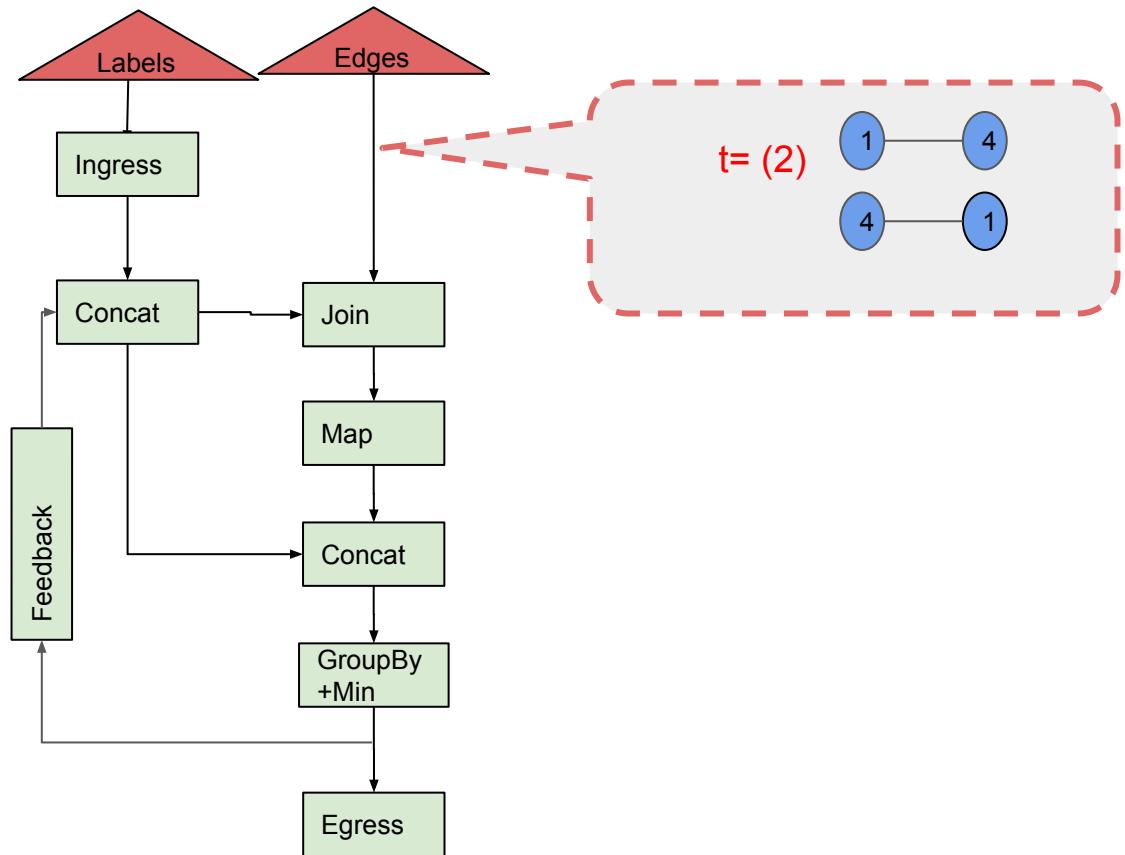


Changes to Connected Graph - II

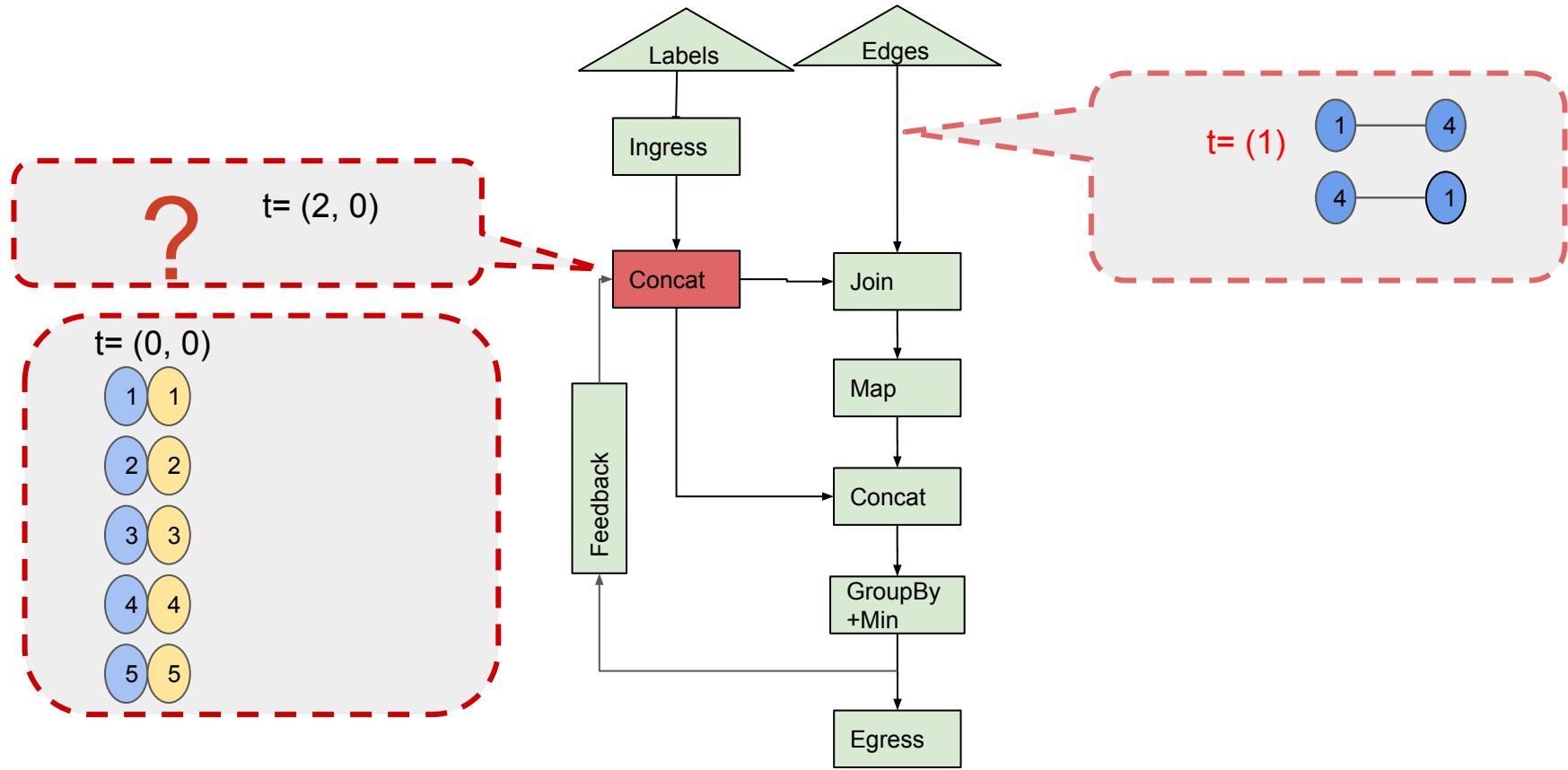
Add Undirected Edge



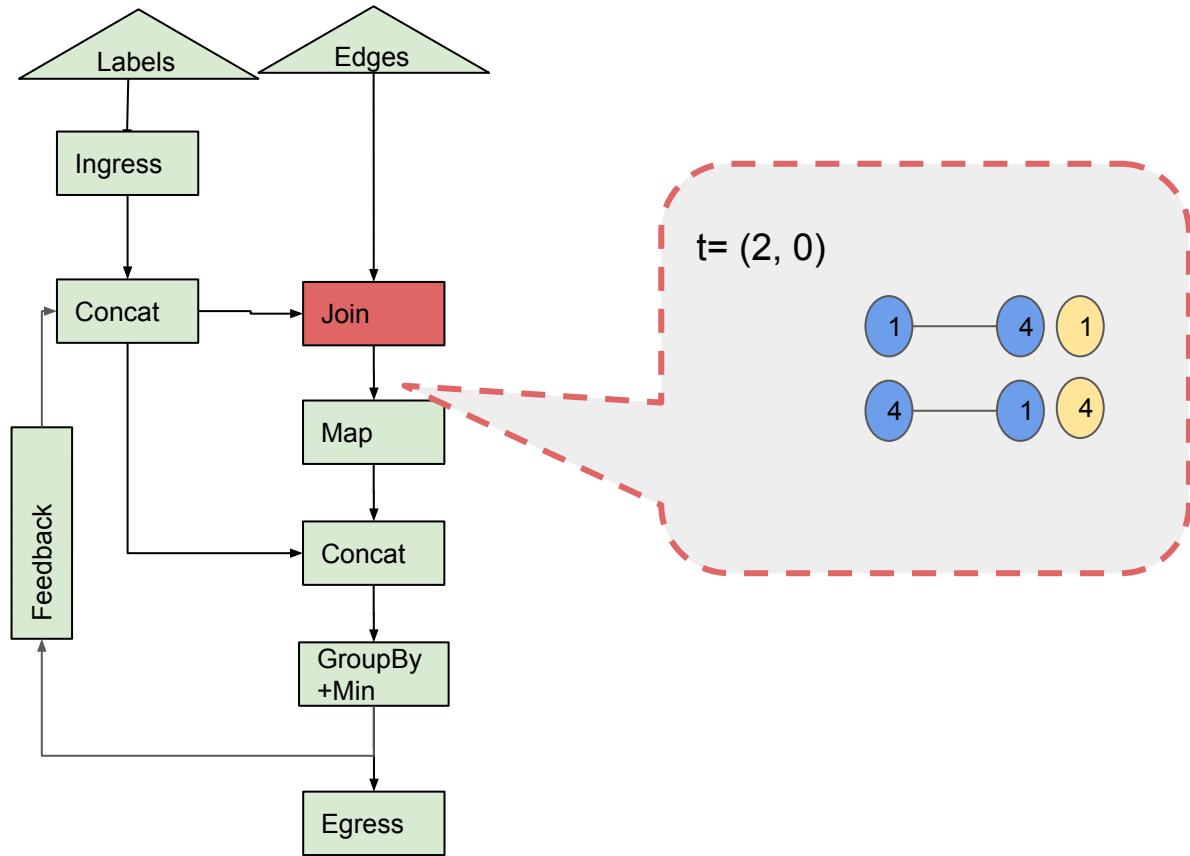
Changes to Connected Graph - II



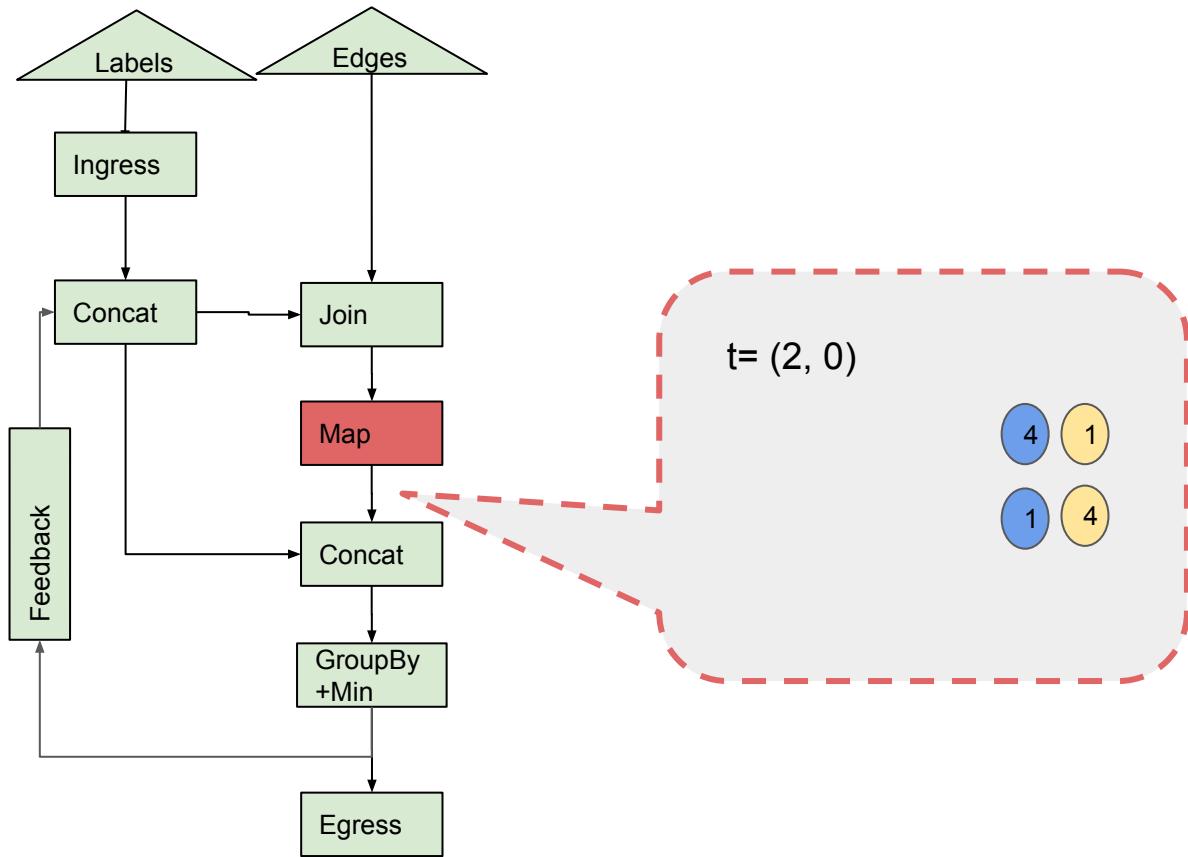
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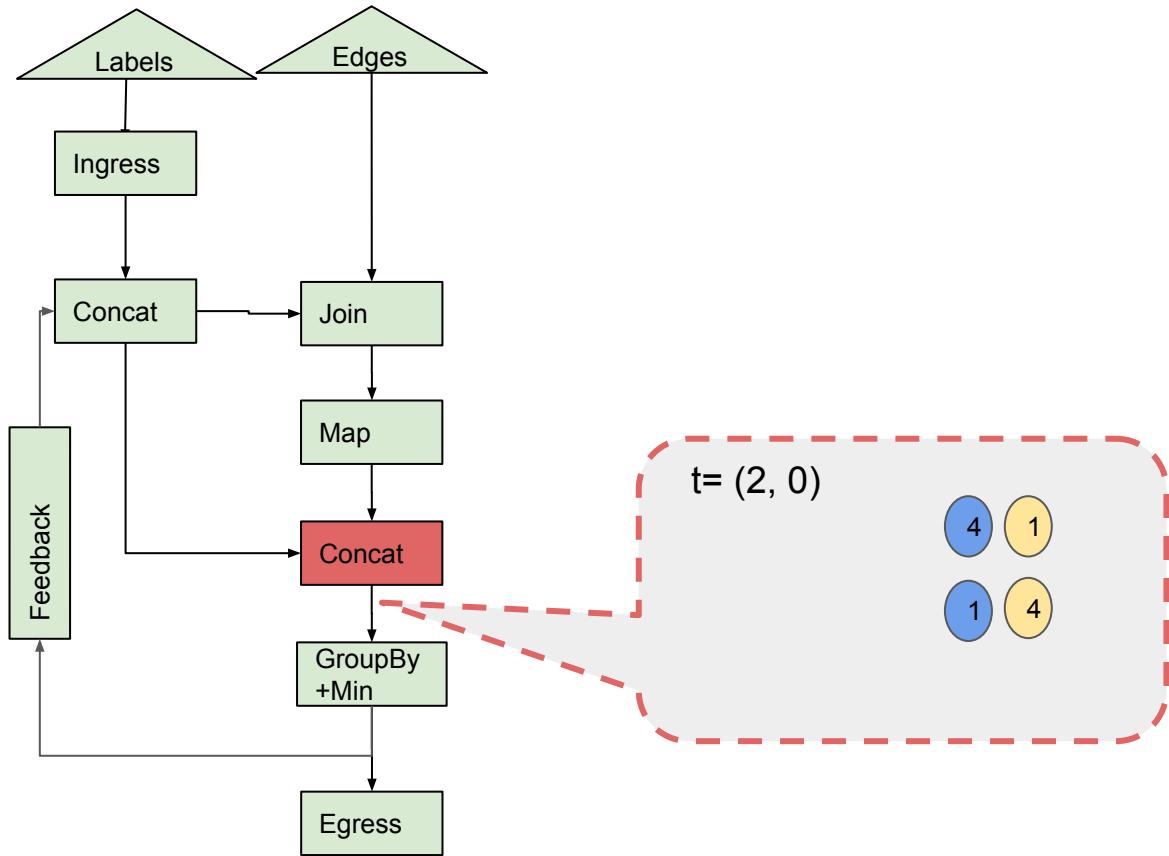
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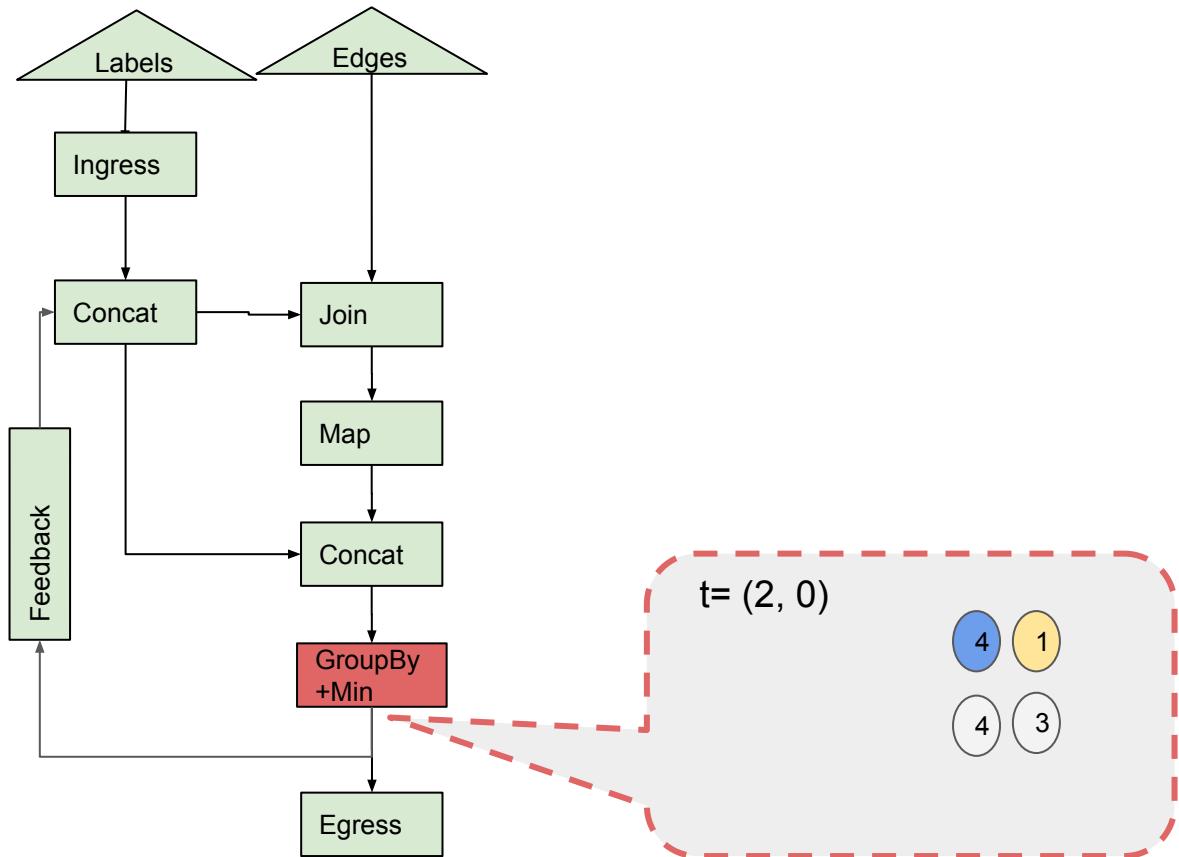
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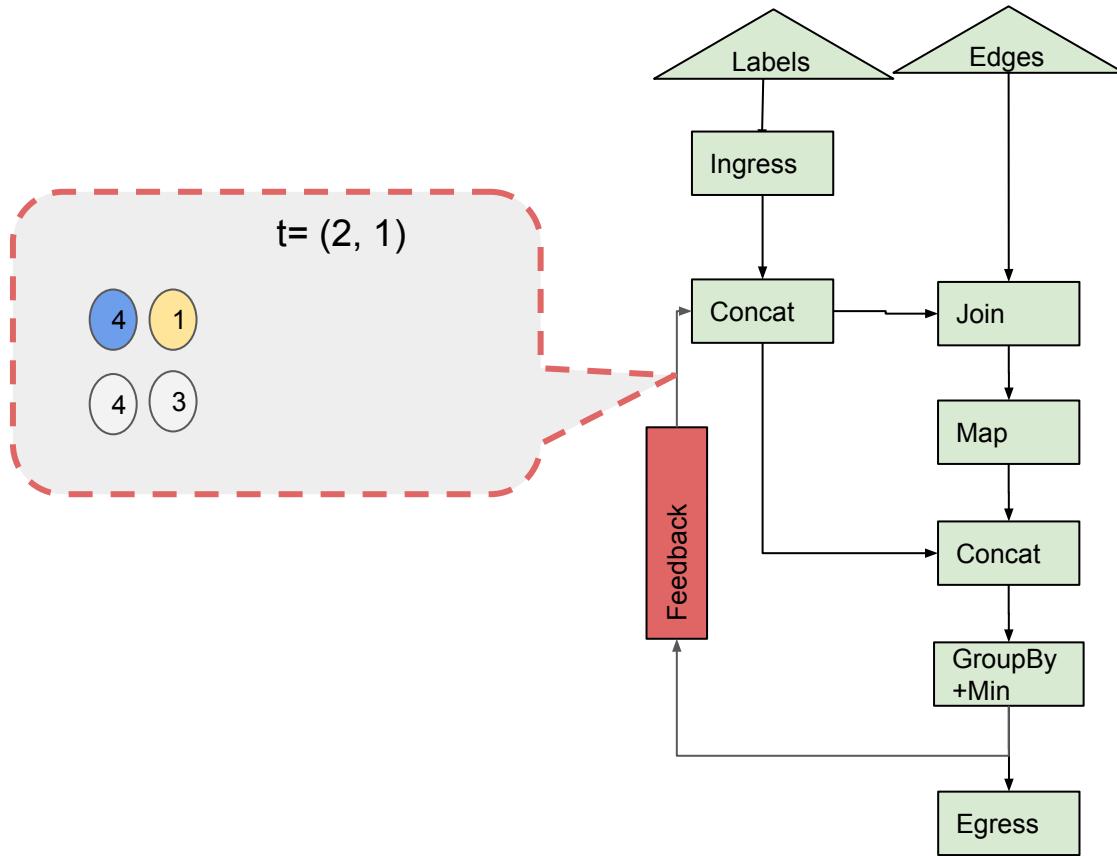
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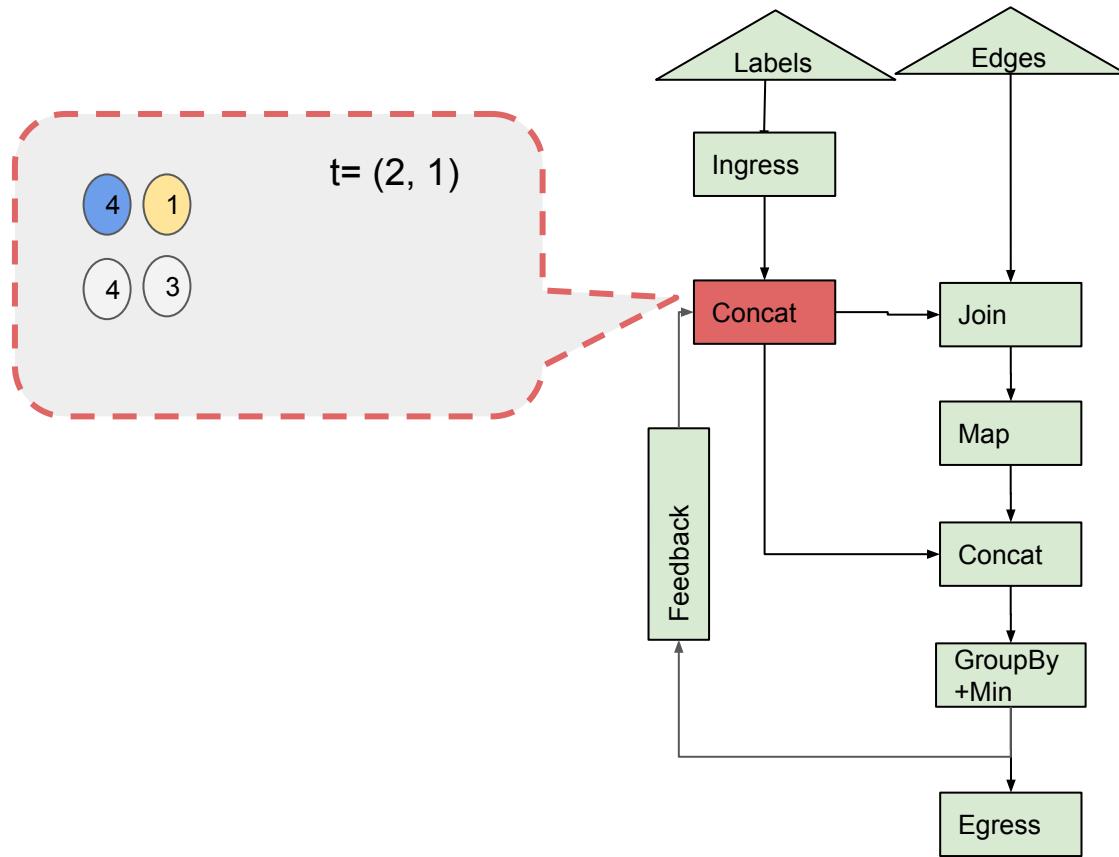
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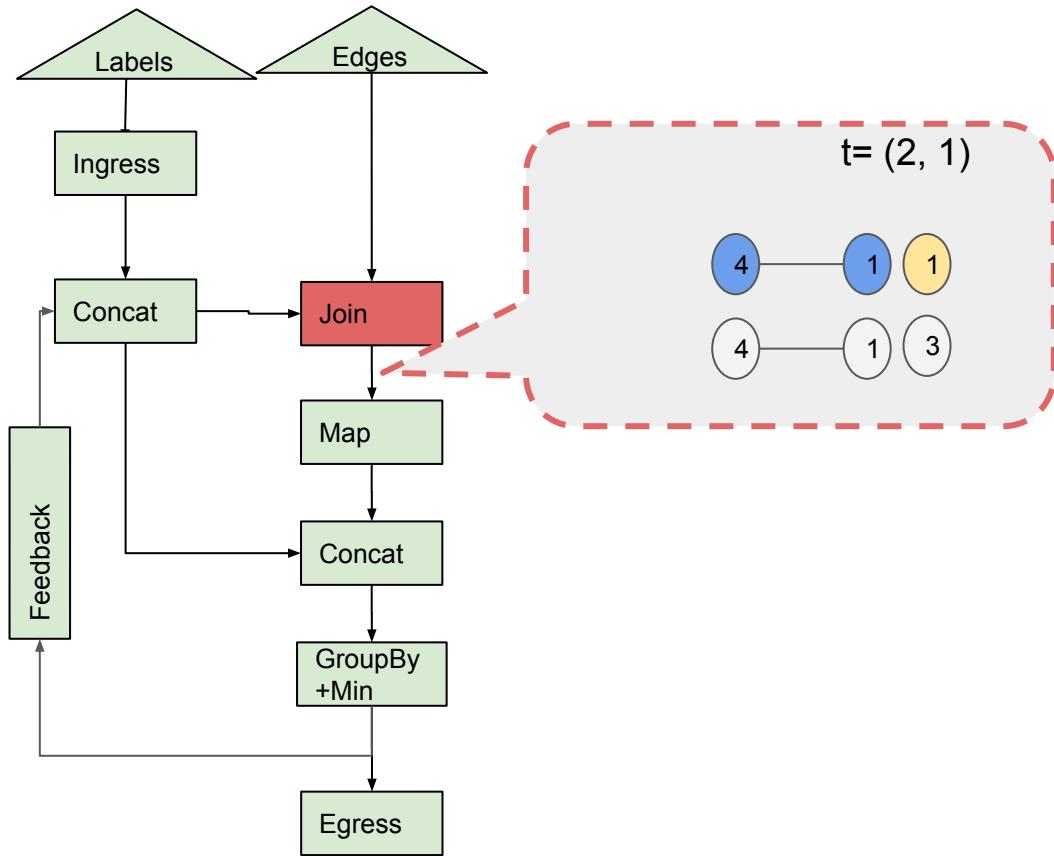
Changes to Connected Graph - II



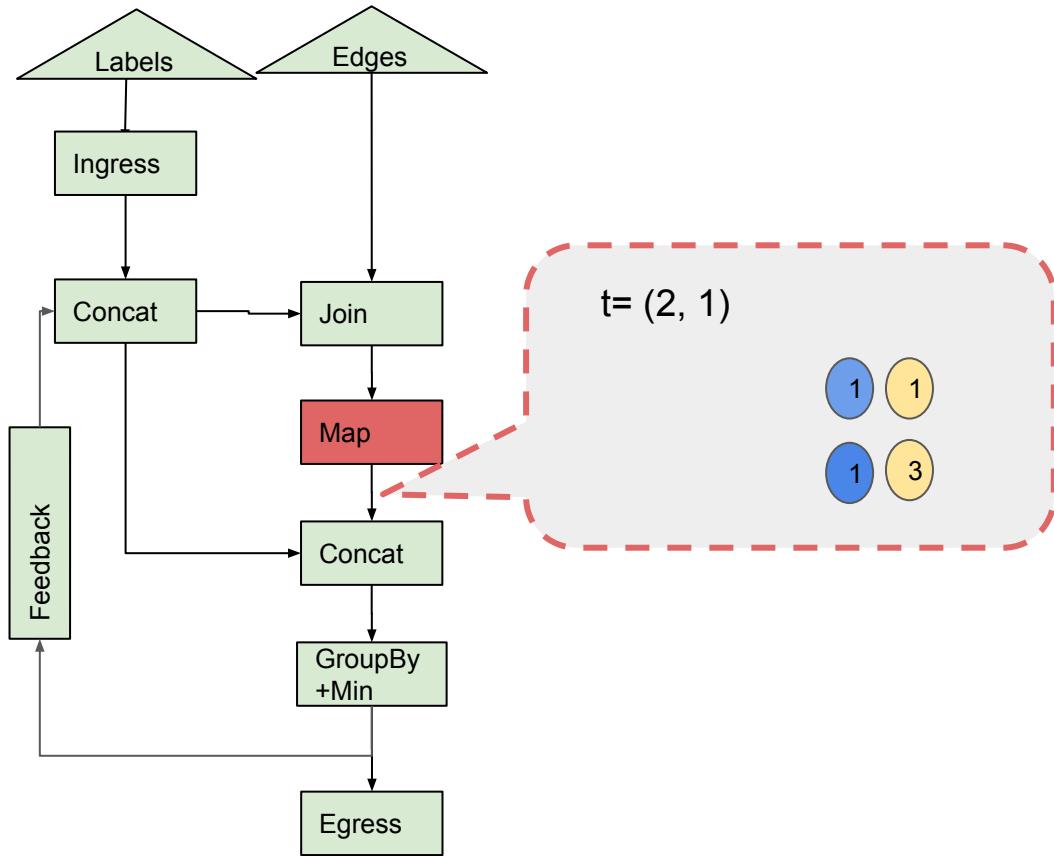
Changes to Connected Graph - II



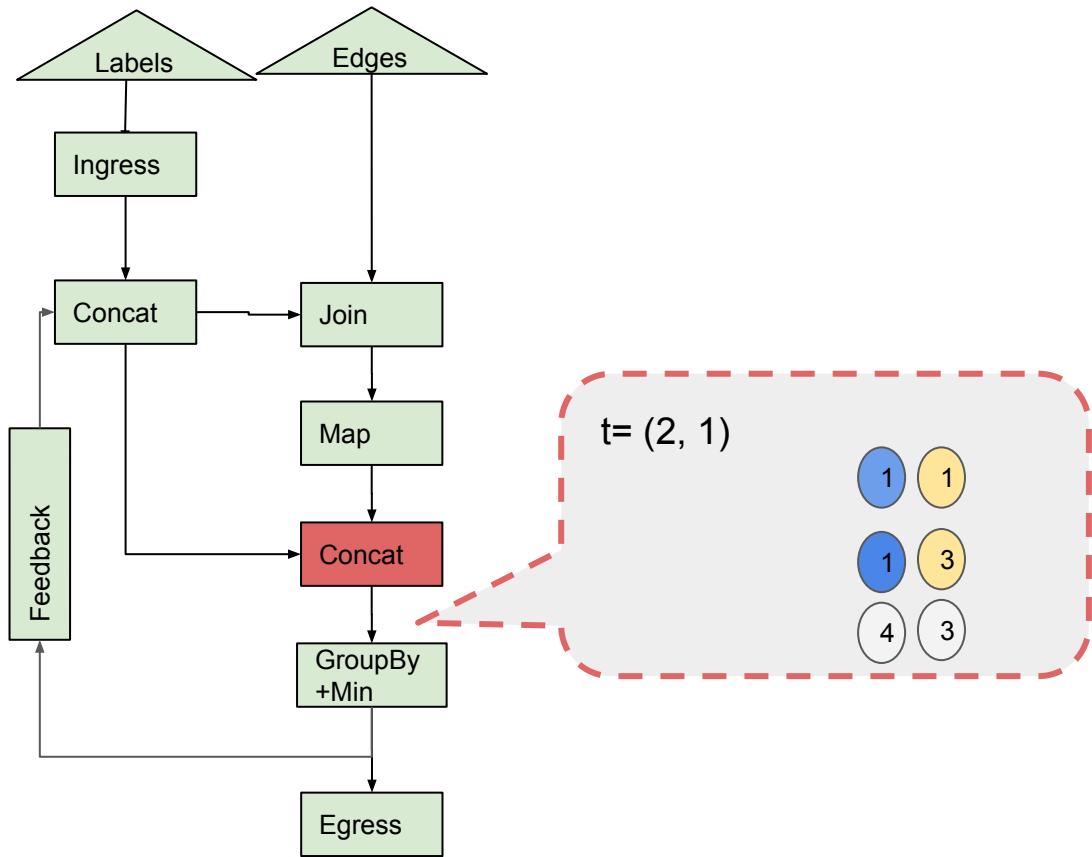
Changes to Connected Graph - II



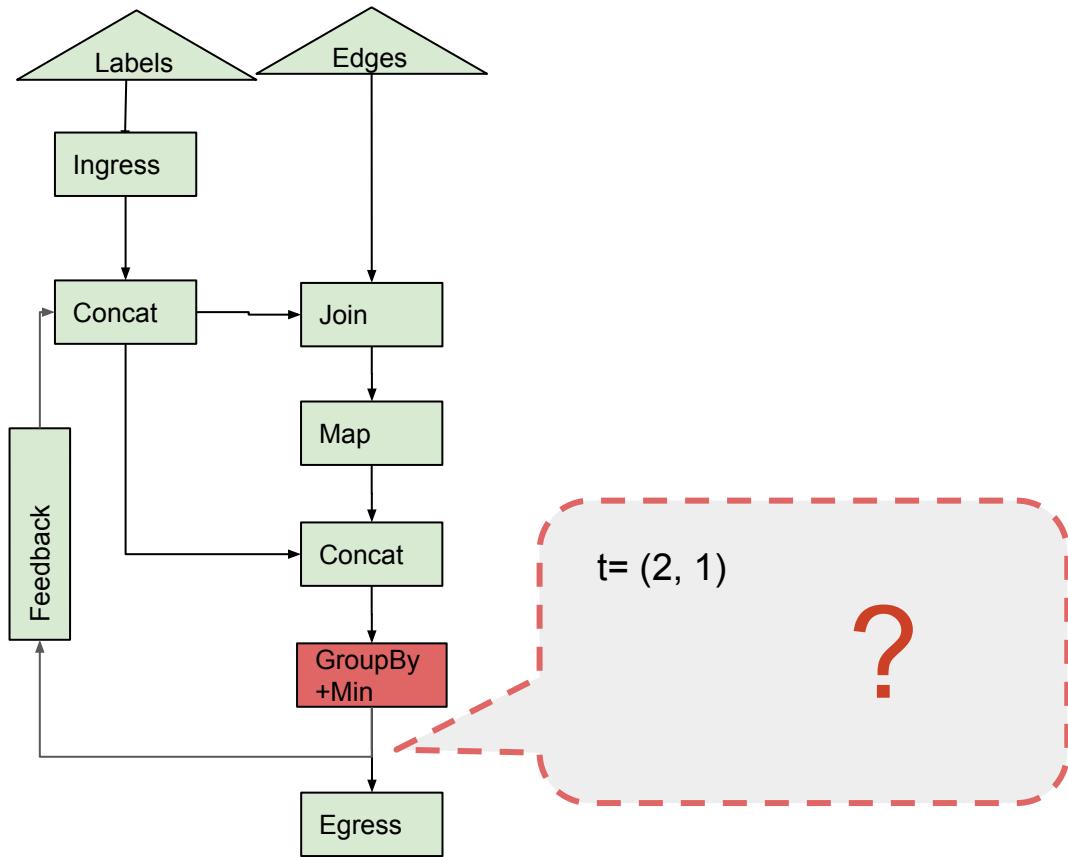
Changes to Connected Graph - II



Changes to Connected Graph - II



Changes to Connected Graph - II



Discussion

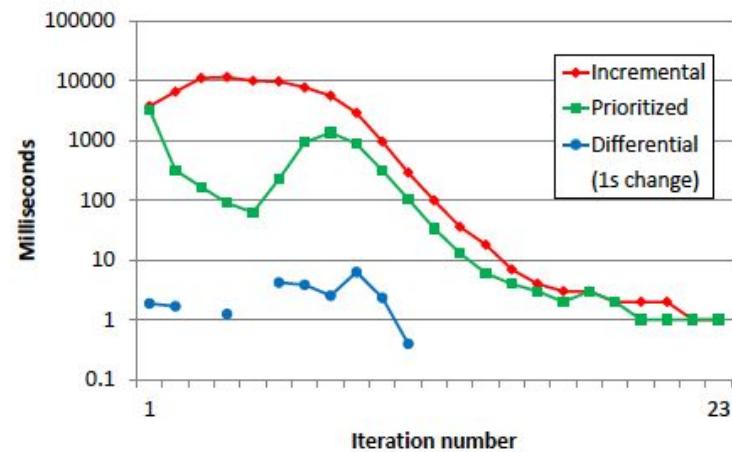
Tradeoffs in Iterative Systems

How do you deal with new data when you are iterating with old data?

- How much state to keep (Memory)
 - Do you keep all data in memory
 - What about intermediate calculations
 - Incremental View Maintenance
- How much work to do
 - Do everything from the beginning
 - Do work only in the nodes where new data came in

Iterative vs Differential Dataflow

- The flexibility of partial Ordering.
 - Iterative Ordering - $(i_1, j_1) \leq (i_2, j_2)$ iff $i_1 \leq i_2$ and $j_1 \leq j_2$.
 - Lexicographic Ordering - $(i_1, j_1) \leq (i_2, j_2)$ if $i_1 < i_2$ or $i_1 = i_2$ and $j_1 \leq j_2$.
 - Programmer can choose the partial ordering.
- Communication via Diffs
 - Only the diffs are sent around as messages
 - Nodes on both sides know the previous calculations



Discussion

- Is the memory for performance tradeoff justified?

Thank You