CS 6530: Advanced Database Systems Fall 2023

## Lecture 14 Query optimization

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# So, what is query optimization and how does it work?



## **Meet Query Optimization**

- Basic Idea:A given LQP could have several possible<br/>PQPs with very different runtime performance
- Goal (Ideal): Get the optimal (fastest) PQP for a given LQP
- Goal (Realistic):FGOOD LOCK WITH THATPs!Image: Self State of Control of the integration of the integrate

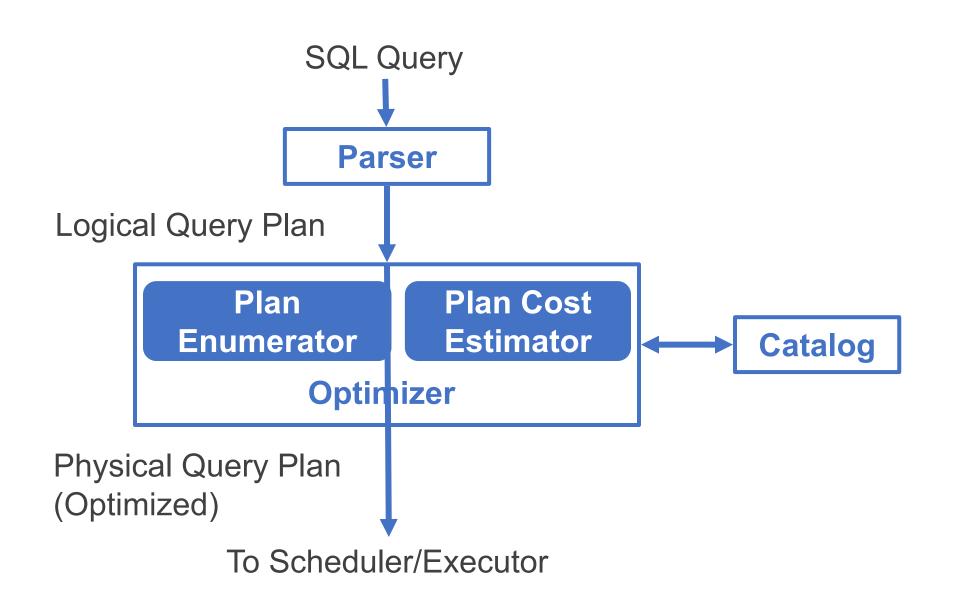


- Overview of Query Optimizer
- Physical Query Plan (PQP)
   Concept: Pipelining
   Mechanism: Iterator Interface
- Enumerating Alternative PQPs
   Logical: Algebraic Rewrites
   Physical: Choosing Phy. Op. Impl.
- Costing PQPs



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#### **Overview of Query Optimizer**



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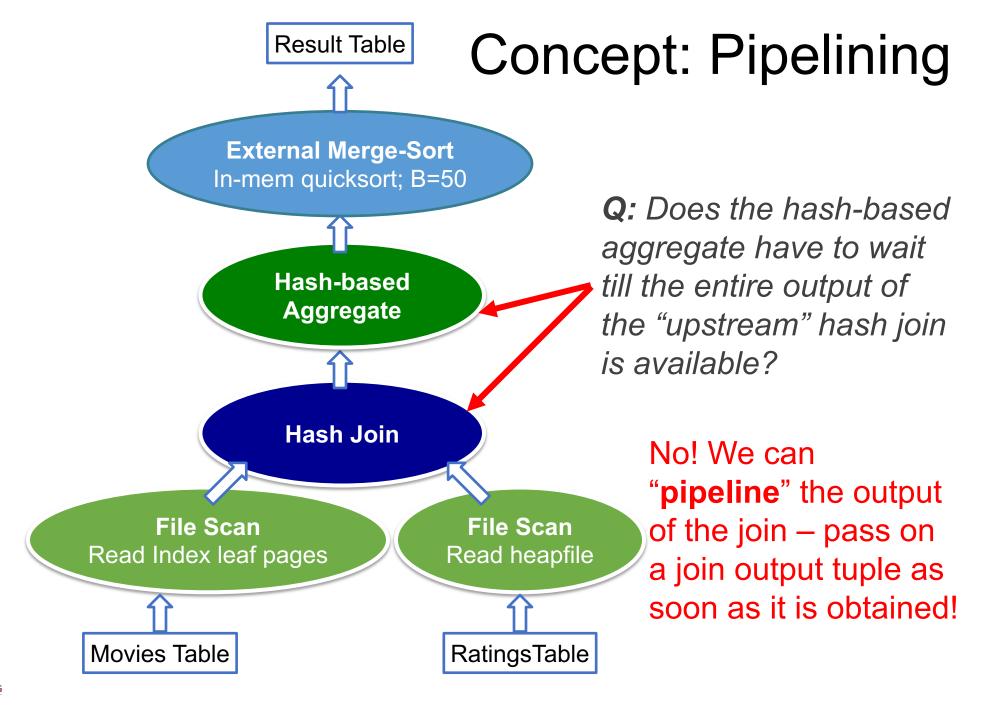
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## **Concept: Pipelining**

Basic Idea:

Do not force "downstream" physical operators to wait till the entire output is available

**Benefits:** 

File Scan Hash Join Hash-based Aggregate

Display output to the user incrementally

**CPU Parallelism in multi-core systems!** 

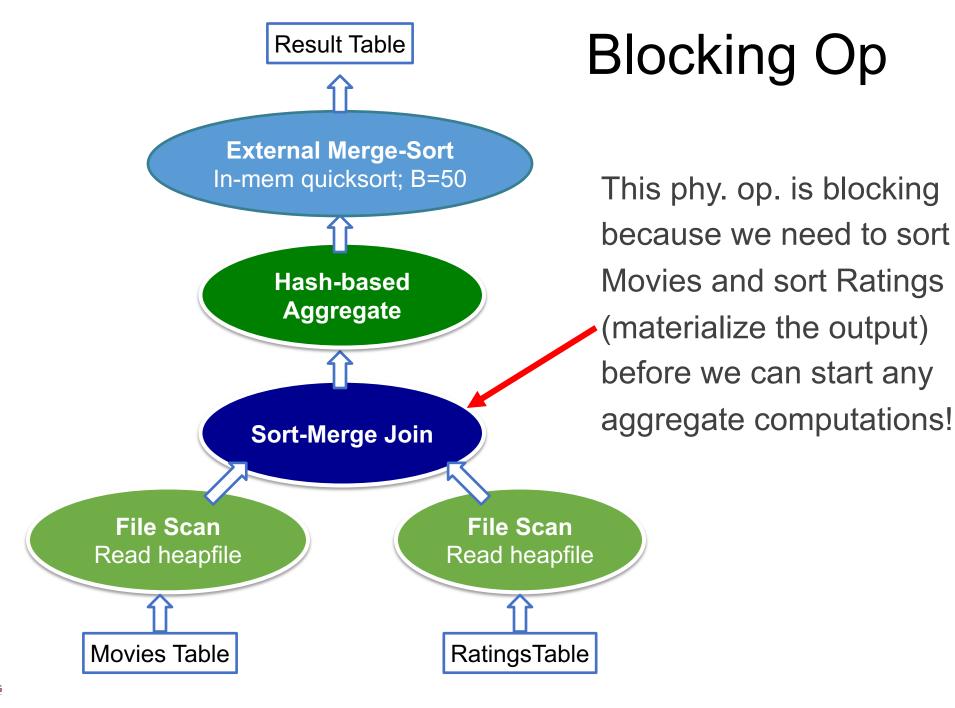
Tuples



## **Concept: Pipelining**

- Crucial for PQPs with workflow of many phy. ops.
- Common feature of almost all RDBMSs
- Works for many operators: SCAN, HASH JOIN, etc.
  - **Q:** Are all physical operators amenable to pipelining?
    - No! Some may "stall" the pipeline: "Blocking Op"
  - A blocking op. requires its output to be **Materialized** as a temporary table
    - Usually, any phy. op. involving <u>sorting</u> is blocking!





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#### Mechanism: Iterator Interface

- Software API to process PQP; makes pipelining easy to impl.
- Enables us to abstract away individual phy. op. impl. details
- Three main functions in usage interface of each phy. op.:
  - Open():Initialize the phy. op. "state", get argumentsAllocate input and output buffers
  - GetNext(): Ask the phy. op. impl. to "deliver" next output tuple; pass it on; if blocking, wait
  - Close(): Clear phy. op. state, free up space



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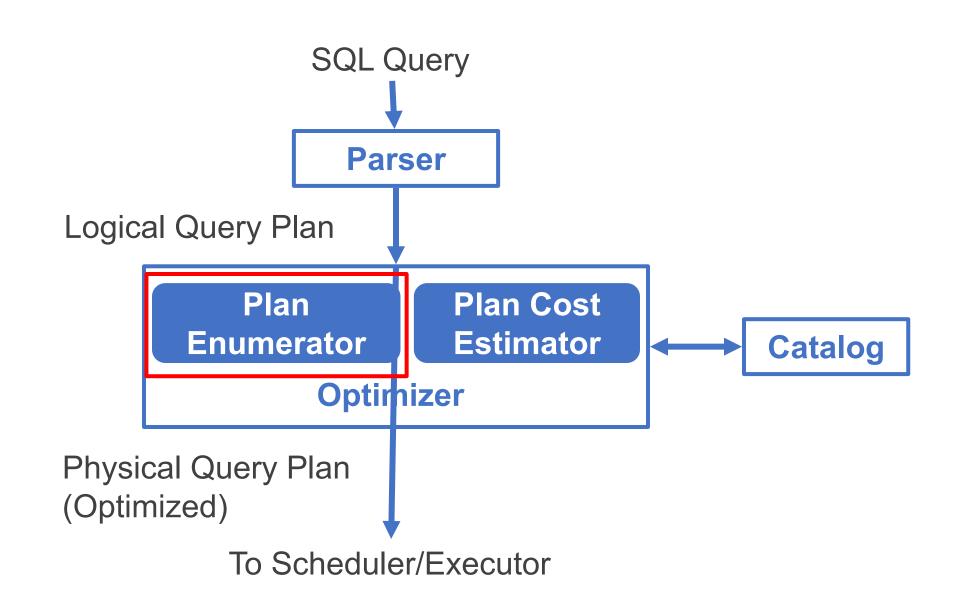
Costing PQPs



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#### **Overview of Query Optimizer**





## **Enumerating Alternative PQPs**

Plan Enumerator explores various PQPs for a given LQP

- Challenge: Space of plans is huge! How to make it feasible?
- RDBMS Plan Enumerator has **Rules** to help determine what plans to enumerate, and also consults **Cost models**
- Two main sources of Rules for enumerating plans:

Logical: Algebraic Rewrites:

Use relational algebra <u>equivalence</u> to rewrite LQP itself!

Physical: Choosing Phy. Op. Impl.:

Use different phy. op. impl. for a given log. op. in LQP



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#### Algebraic Rewrite Rules

- Rewrite a given RA query in to another that is <u>equivalent</u> (a logical property) but might be <u>faster</u> (a physical property)
   RA operators have some formal properties we can exploit
- ♦ We will cover only a few rewrite rules:
  - Single-operator Rewrites
    - **Unary** operators
    - **Binary** operators
  - **Cross-operator** Rewrites



### **Unary Operator Rewrites**

lpha Key unary operators in RA:  $\sigma~\pi$ 

lpha Commutativity of  $\sigma$ 

$$\sigma_{p_1}(\sigma_{p_2}(\mathbf{R})) = \sigma_{p_2}(\sigma_{p_1}(\mathbf{R}))$$

 $\diamond$  Cascading of  $\sigma$  $\sigma_{p_1}(\sigma_{p_2}(\ldots \sigma_{p_n}(\mathbf{R})\ldots)) = \sigma_{p_1 \wedge p_2 \wedge \cdots \wedge p_n}(\mathbf{R})$ 

♦ Cascading of  $\pi$   $A_i \subseteq A_{i+1} \forall i = 1 ... (n-1)$  $\pi_{A_1}(\pi_{A_2}(... \pi_{A_n}(\mathbf{R})...)) = \pi_{A_1}(\mathbf{R})$ 

**Q:** Why are cascading rewrites beneficial?



#### **Binary Operator Rewrites**

- ♦ Key binary operator in RA:
- $\diamond$  Commutativity of  $\bowtie$   $R \bowtie S = S \bowtie R$
- $\ \ \, \hbox{Associativity of } \boxtimes \quad (R \bowtie S) \bowtie T = R \bowtie (S \bowtie T)$

**Q:** Why are these properties beneficial?

**Q:** What other binary operators in RA satisfy these?



#### **Cross-Operator Rewrites**

 $\diamond$  Commuting  $\sigma$  and  $\pi$  $A \subseteq B$  $\sigma_{p(A)}(\pi_B(R)) = \pi_B(\sigma_{p(A)}(R))$  $\diamond$  Combining  $\sigma$  and imes $\sigma_p(R \times S) = R \bowtie_p S$ "Pushing the select"  $A \subseteq R.*$  $\sigma_{p(A)}(R \bowtie S) = \sigma_{p(A)}(R) \bowtie S$  $\sigma_{p(A)}(R \times S) = \sigma_{p(A)}(R) \times S$  $\diamond$  Commuting  $\pi$  with imes and  $\bowtie$  $\pi_A(R \times S) = \pi_{A \cap R_*}(R) \times \pi_{A \cap S_*}(S) \quad B \subset A$  $\pi_A(R \bowtie_{p(B)} S) = \pi_{A \cap R_*}(R) \bowtie_{p(B)} \pi_{A \cap S_*}(S)$ 

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## Choosing Phy. Op. Impl.

♦ Given a (rewritten) LQP, pick phy. op. impl. for each log. op.

Recall various RA op. impl. with their I/O (and CPU costs)

- $\sigma$  File scan vs Indexed (B+ Tree vs Hash)
- $\pi$  Hashing-based vs Sorting-based vs Indexed

M BNLJ vs INLJ vs SMJ vs HJ

etc. 
$$Q:$$
 With algebraic  
 $\pi_B(\sigma_{p(A)}(R) \bowtie S)$  rewrites?!  
3 options 3 options 4 options = **36** PQPs!



## Phy. Op. Impl.: Other Factors

- Are the indexes clustered or unclustered?
- Are there multiple matching indexes? Use multiple?
- Are index-only access paths possible for some ops?
- Are there "interesting orderings" among the inputs?
- Would sorted outputs benefit downstream ops?
- Estimation of <u>cardinality</u> of intermediate results!
- How best to reorder multi-table joins?

Query optimizers are complex beasts!

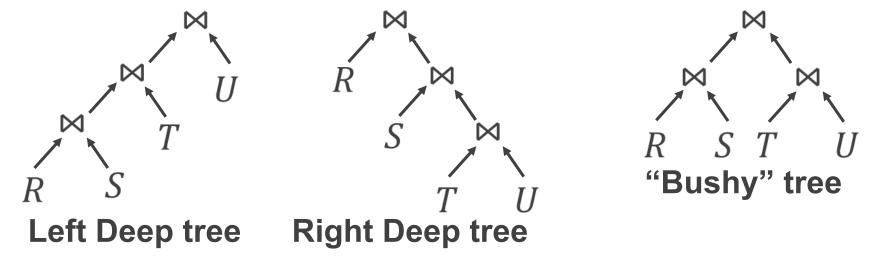
Still a hard, open research problem!



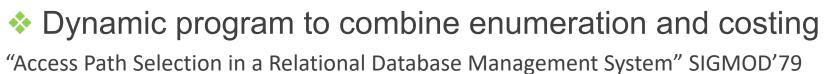
## Phy. Op. Impl.: Join Orderings

Since joins are associative, exponential number of orderings!

 $R \bowtie S \bowtie T \bowtie U$ 



- Almost all RDBMSs consider only left deep join trees Enables easy pipelining! Why?
- Interesting orderings" idea from System R optimizer paper



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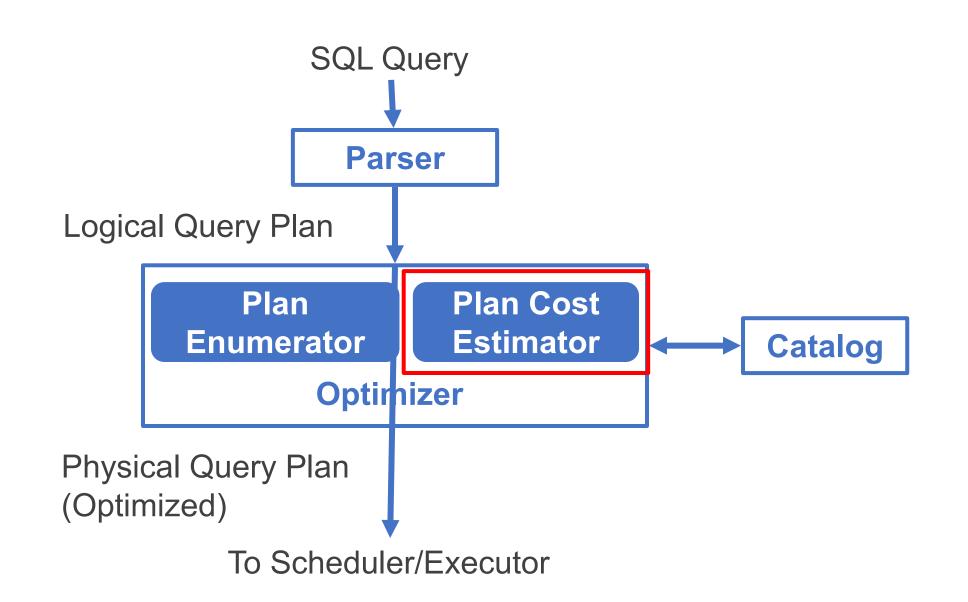
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Costing PQPs





#### **Overview of Query Optimizer**





#### Costing PQPs

- For each PQP considered by the Plan Enumerator, the Plan Cost Estimator computes "Cost" of the PQP Weighted sum of I/O cost and CPU cost (Distributed RDBMSs also include Network cost)
   Challenge: Given a PQP, compute overall cost
- Issues to consider:

Pipelining vs. blocking ops; cannot simply add costs!

Cardinality estimation for intermediate tables!

**Q:** What statistics does the catalog have to help?



### Costing PQPs

Most RDBMSs use various heuristics to make costing tractable; so, it is approximate!

Example: Complex predicates

 $\sigma_{p_1 \wedge p_2}(R)$  Suppose selectivity of  $p_1$  is 5% and selectivity of  $p_2$  is 10%

*Q. What is the selectivity of*  $p_1 \land p_2$ ? Not enough info!

But, most RDBMSs use the **independence** heuristic!

Selectivity of conjunction = Product of selectivities

Thus, ≈ 0.05 \* 0.1 = 0.005, i.e., 0.5%

## **Query Optimization: Summary**

Plan Enumerator and Cost Estimator work in lock step: **Rules** determine what PQPs are enumerated Logical: Algebraic rewrites of LQP Physical: Op. Impl. and ordering alternatives **Cost models** and **heuristics** help cost the PQPs Still an active research area! Parametric Q.O., Multi-objective Q.O., Multi-objective parametric Q.O., Multiple Q.O., Online/Adaptive Q.O., Dynamic re-optimization, etc.

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#### **Introducing Materialized Views**

♦ A View is a "virtual table" created with an SQL query

A Materialized View is a physically instantiated/stored view

Example:RatingIDStarsRateDateUIDMIDUIDNameAgeJoinDateMIDNameYearDirector

SELECT AVG(Stars)

FROM Ratings R, Movies M, Users U

WHERE R.MID = M.MID AND R.UID = U.UID

M.Director = "Christopher Nolan" AND

U.Age >= 20 AND U.Age < 30;

 $\gamma_{AVG(Stars)}(R \bowtie \sigma_{Director="Christopher Nolan"}(M) \bowtie \sigma_{20 \le Age < 30}(U))$ Requires file scans of R, M, and U and, say, hash joins



#### Materialized Views Example

Example:RatingIDStarsRateDateUIDMIDUIDNameAgeJoinDateMIDNameYearDirector

 $\gamma_{AVG(Stars)}(R \bowtie \sigma_{Director="Christopher Nolan"}(M) \bowtie \sigma_{20 \leq Age < 30}(U))$ 

- CREATE MATERIALIZED VIEW NolanRatings AS
- SELECT RatingID, Stars, UID, MID
- FROM Ratings R, Movies M
- WHERE R.MID = M.MID AND

**M.Director** = "Christopher Nolan"; Creates a subset of R with ratings for only Nolan's movies  $V \leftarrow \pi_{RatingID,Stars,UID,MID}(R \bowtie \sigma_{Director}="Christopher Nolan"(M))$ 



#### Materialized Views Example

Example:RatingIDStarsRateDateUIDMIDUIDNameAgeJoinDateMIDNameYearDirector

 $\gamma_{AVG(Stars)}(R \bowtie \sigma_{Director="Christopher Nolan"}(M) \bowtie \sigma_{20 \leq Age < 30}(U))$ 

Given the materialized view V, RDBMS optimizer can automatically *rewrite* to use V to avoid scans of R and M  $V \leftarrow \pi_{RatingID,Stars,UID,MID}(R \bowtie \sigma_{Director="Christopher Nolan"}(M))$  $\gamma_{AVG(Stars)}(V \bowtie \sigma_{20 \leq Age < 30}(U))$ 

Likely much faster since V is likely much smaller than R, but this depends on data statistics; leave it to optimizer! *Q:* How did DBA know to materialize a view for Nolan ratings?



#### Materialized View Maintenance

Example:RatingIDStarsRateDateUIDMIDUIDNameAgeJoinDateMIDNameYearDirector

We are given this materialized view V over R and M

 $V \leftarrow \pi_{RatingID,Stars,UID,MID}(R \bowtie \sigma_{Director="Christopher Nolan"}(M))$ 

**Q:** What if new ratings are inserted to R for Nolan's movies?

- RDBMS will automatically "trigger" updates to V
- Such updates are called Materialized View Maintenance
- 2 alternatives: Recompute whole view from scratch vs

**Incremental View Maintenance** (IVM)



Basic Idea:Recomputing V from scratch may be an overkill<br/>Try to *incrementally* update parts that change

$$V = Q(D) \qquad V' = Q(D')$$

D' can be the outcome of inserts and/or deletes to D

- Q can be a unary query or involve multiple tables
- Computing V' may require inserts and/or deletes to V; realized as algebraic rewrite rules at LQP level
- Whether or not IVM of V is feasible and/or efficient depends on form of Q, nature of updates to D, data statistics, etc.



We will focus only on inserts to D triggering inserts to V

**Unary IVM for insertions:** 

 $R' = R \cup \Delta R$  — Newly inserted tuples Select:  $V \leftarrow \sigma_{SelectCondition}(R)$  $V' = V \cup \sigma_{SelectCondition}(\Delta R)$ Can be just an *append* (union with "bag" semantics) Project:  $V \leftarrow \pi_{ProjectionList}(R)$  $V' = V \cup \pi_{ProjectionList}(\Delta R)$ Requires full set union with V for deduplication Select and Project can be composed and reordered as before



**Unary IVM for insertions:** 

 $R' = R \cup \Delta R$  — Newly inserted tuples Group By Agg:  $V \leftarrow \gamma_{AggList,Agg(Y)}(R)$ 

Feasibility of IVM Depends on Agg() function! Rewrite rules exist for SUM, COUNT, and MIN/MAX over bags AVG not possible in general; needs deeper system changes

$$V' = \gamma_{AggList,SUM(Y)} (V \cup \gamma_{AggList,SUM(Y)} \Delta R)$$
$$V' = \gamma_{AggList,SUM(Y)} (V \cup \gamma_{AggList,COUNT(Y)} \Delta R)$$
$$V' = \gamma_{AggList,MIN(Y)} (V \cup \gamma_{AggList,MIN(Y)} \Delta R)$$

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Join IVM for insertions:

Assume no duplicate inserts

 $V \leftarrow A \bowtie B \qquad \begin{array}{c} A' = A \cup \Delta A \\ B' = B \cup \Delta B \end{array}$ 

$$V' = V \cup (\Delta A \bowtie B') \cup (A' \bowtie \Delta B)$$

Alternatively, we can just append the output of the following query to V (union below is just append too):

$$(\Delta A \bowtie B') \cup (A' \bowtie \Delta B) - (\Delta A \bowtie \Delta B)$$

IVM for complex queries compose such op-level rewrites



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