

Join on GPUs

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Roadmap

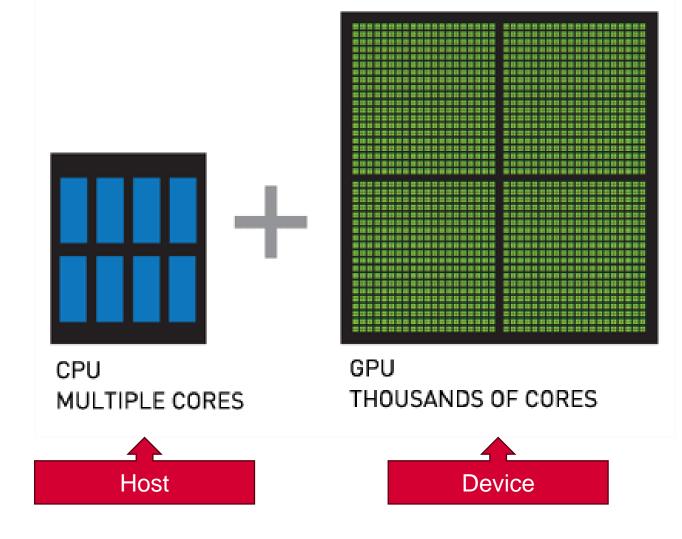
- Introduction to GPU
- GPGPU
- Recap to Join operation
- Parallel join
- Off-the-shelf parallel join
- Parallel hash join



Introduction to GPU

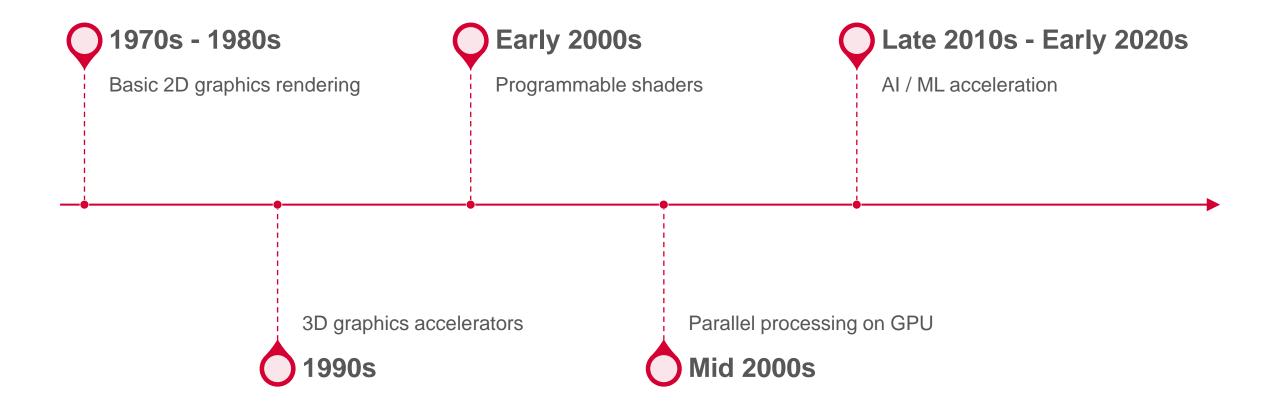
GPU

- Graphics processing unit (GPU)
 accelerates graphics and data processing
- Work together with CPU
- GPU is designed for parallel processing
- Use cases:
 - ✓ Graphics and video rendering
 - ✓ Gaming
 - ✓ Machine learning, AI, Deep learning
 - ✓ Scientific computing
- Major manufacturers: Nvidia, AMD, Intel





Advancements in GPU





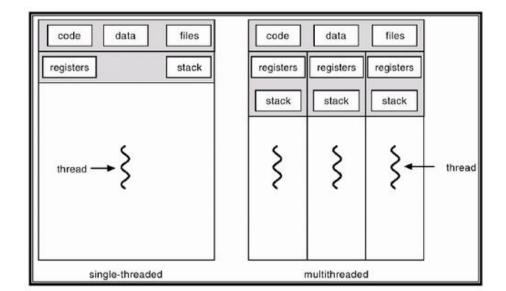
CPU vs GPU (A Sample Machine)

CPU

- 13th Gen Intel® Core™ i9-13900H
- 14 cores (6 P-cores + 8 E-cores)
- Total 20 threads
- Suitable for serial workloads
- Access to system memory (RAM)

GPU

- NVIDIA GeForce RTX 4070, 8 GB GDDR6
- 5888 CUDA cores
- Total 94,208 threads
- Suitable for parallel workloads
- Access to dedicated VRAM

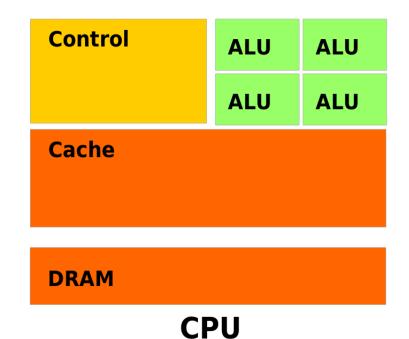


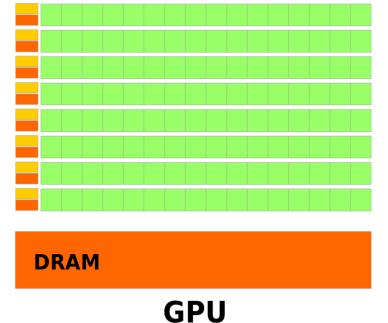


GPGPU

GPGPU

- General Purpose computing using GPU
- Influenced the scientific computing paradigms
- Offers thousands of cores
- Power efficiency TFlop per Watt









GPGPU Advantages

Massive parallel processing: Scientific simulations

Efficient large dataset handling: Machine learning algorithms

Real-time processing: Gaming and streaming

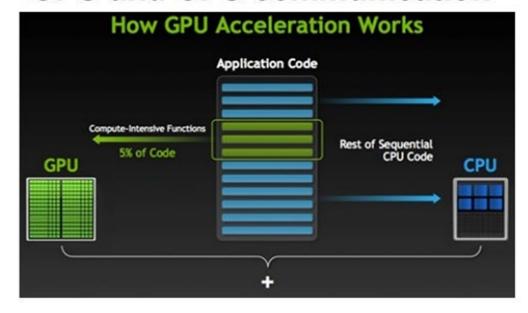
Accelerated financial modeling: Risk assessment and pricing



GPU Programming Model

- CUDA proprietary to Nvidia GPUs but most mature and established
- **HIP** targets AMD GPUs
- SYCL open standard for cross-platform portability
- DPC++ Intel's implementation of SYCL
- OneAPI Intel's unified programming model across devices

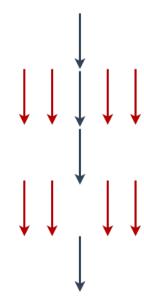
GPU and CPU communication





CUDA Programming Model

- Globally Sequential Locally Parallel programming pattern
- Invokes parallel kernels that execute across a set of threads
- CUDA spawns the threads from a hierarchy of grid (3D) and block (3D)
- Each thread executes an instance of the kernel
- Supports C/C++, Fortan, Python



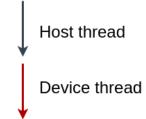
Sequential Execution (Program initialization)

Parallel Execution
Host and Device runs in parallel

Sequential Execution

Parallel Execution
Host waits for GPU completion

Sequential Execution (Program termination)





GPGPU Challenges

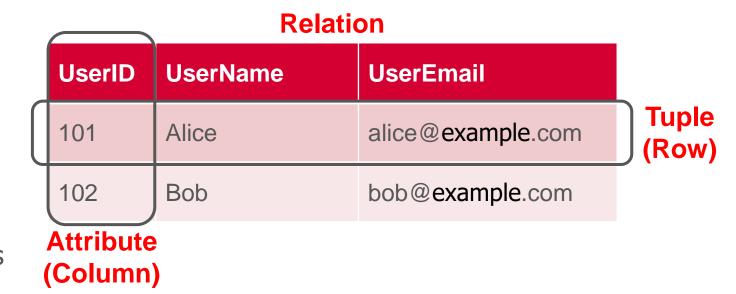
- Algorithm adaptation for GPU: Sequential to parallel
- Parallelism synchronization: Putting barrier
- Memory management: Host to device and device to host data transfer
- Portability: Portability to different GPU devices



Recap to Join operation

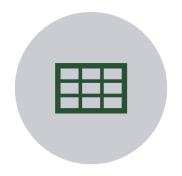
Recap to Relational Data

- Relation: 2-dimensional structure
- Attribute: Represents characteristics
- Row: Represents unique record
- Join (⋈): Combines data from relations
- Projection (Π): Select specific columns





Why Join is Important?







FIND PATTERNS IN DATA



CLEAN DATA



CREATE NEW DATA SETS



User

| UserID | UserName | UserEmail |
|--------|----------|-------------------|
| 101 | Alice | alice@example.com |
| 102 | Bob | bob@example.com |
| 103 | Eve | eve@example.com |



| UserID | OrderTotal | Items |
|--------|------------|-------|
| 101 | 25.69 | 2 |
| 102 | 145.66 | 3 |
| 103 | 12.11 | 1 |
| 103 | 44.00 | 2 |



User

| UserID | UserName | UserEmail |
|--------|----------|-------------------|
| 101 | Alice | alice@example.com |
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Order



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| UserID | UserName | UserEmail | OrderTotal | Items |
|--------|----------|-------------------|------------|-------|
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| 101 | Alice | alice@example.com | 25.69 | 2 |
| 102 | Bob | bob@example.com | 145.66 | 3 |
| 103 | Eve | eve@example.com | 12.11 | 1 |



User (Outer Relation)

| UserID | UserName | UserEmail |
|--------|----------|-------------------|
| 101 | Alice | alice@example.com |
| 102 | Bob | bob@example.com |
| 103 | Eve | eve@example.com |



Order (Inner Relation)

| UserID | OrderTotal | Items |
|--------|------------|-------|
| 101 | 25.69 | 2 |
| 102 | 145.66 | 3 |
| 103 | 12.11 | 1 |
| 103 | 44.00 | 2 |





| UserID | UserName | UserEmail | OrderTotal | Items |
|--------|----------|-------------------|------------|-------|
| 101 | Alice | alice@example.com | 25.69 | 2 |
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User (Outer Relation)

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Order (Inner Relation)

| UserID | OrderTotal | Items |
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| 101 | 25.69 | 2 |
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| UserID | UserName | UserEmail | OrderTotal | Items |
|--------|----------|-------------------|------------|-------|
| 101 | Alice | alice@example.com | 25.69 | 2 |
| 102 | Bob | bob@example.com | 145.66 | 3 |
| 103 | Eve | eve@example.com | 12.11 | 1 |
| 103 | Eve | eve@example.com | 44.00 | 2 |



Duplicates on Join Result

User ⋈ Order

| UserID | UserName | UserEmail | OrderTotal | Items |
|--------|----------|-------------------|------------|-------|
| 101 | Alice | alice@example.com | 25.69 | 2 |
| 102 | Bob | bob@example.com | 145.66 | 3 |
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Π(_{UserName,UserEmail})(User ⋈ Order)

| UserName | UserEmail |
|----------|-------------------|
| Alice | alice@example.com |
| Bob | bob@example.com |
| Eve | eve@example.com |
| Eve | eve@example.com |



Parallel Join

How can we do join in parallel?

User (Outer Relation)

| UserID | UserName | UserEmail |
|--------|----------|-------------------|
| 101 | Alice | alice@example.com |
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Order (Inner Relation)

| UserID | OrderTotal | Items |
|--------|------------|-------|
| 101 | 25.69 | 2 |
| 102 | 145.66 | 3 |
| 103 | 12.11 | 1 |
| 103 | 44.00 | 2 |



Parallel Join ⋈

101

User (Outer Relation)

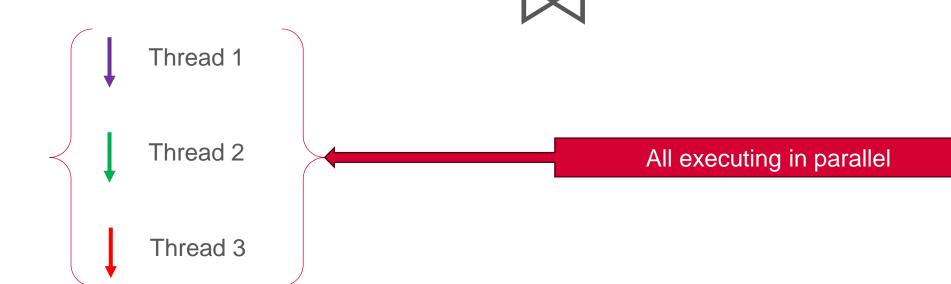
UserID UserName UserEmail alice@example.com Alice

bob@example.com Bob 102

eve@example.com 103 Eve

Order (Inner Relation)

| | UserID | OrderTotal | Items |
|-------------|--------|------------|-------|
| - | 101 | 25.69 | 2 |
| > | 102 | 145.66 | 3 |
| * | 103 | 12.11 | 1 |
| * | 103 | 44.00 | 2 |





Parallel Join



What: Perform relational join operation simultaneously on a number of processors or machines



When: Useful when input data is enormous and the join is computationally costly



How: Divide the data into partitions and assign each partition to a different processor



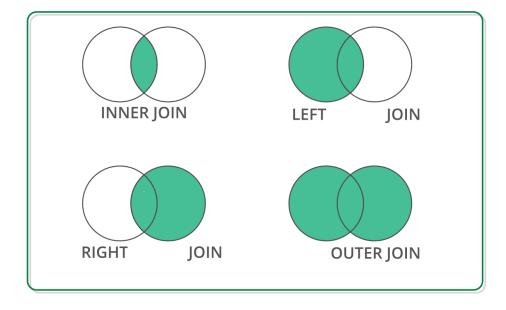
Off-the-shelf Parallel Join

Off-the-shelf Data Structure for Join Operation

DataFrame: 2D labeled tabular data structure



DataFrame has RA primitives APIs



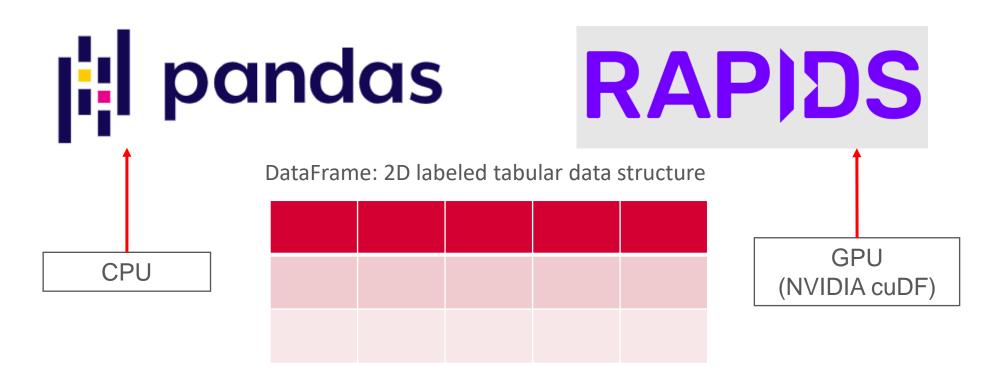


[•] Chen, D. Y. (2017). Pandas for everyone: Python data analysis. Addison-Wesley Professional.



[•] Singh, R. (2020, July 1). Merging DataFrames with Pandas: Pd.merge(). Medium. Retrieved April 8, 2023, from https://medium.com/swlh/merging-dataframes-with-pandas-pd-merge-7764c7e2d46d

Off-the-shelf Python Libraries



Both supports join operation with similar APIs



Reback, J., McKinney, W., Van Den Bossche, J., Augspurger, T., Cloud, P., Klein, A., ... & Seabold, S. (2020). pandas-dev/pandas: Pandas 1.0. 5. Zenodo.

[•] Chen, D. Y. (2017). Pandas for everyone: Python data analysis. Addison-Wesley Professional.

[•] Green, O., Du, Z., Patel, S., Xie, Z., Liu, H., & Bader, D. A. (2021, December). Anti-Section Transitive Closure. In 2021 IEEE 28th International Conference on High Performance Computing, Data, and Analytics (HiPC) (pp. 192-201). IEEE.

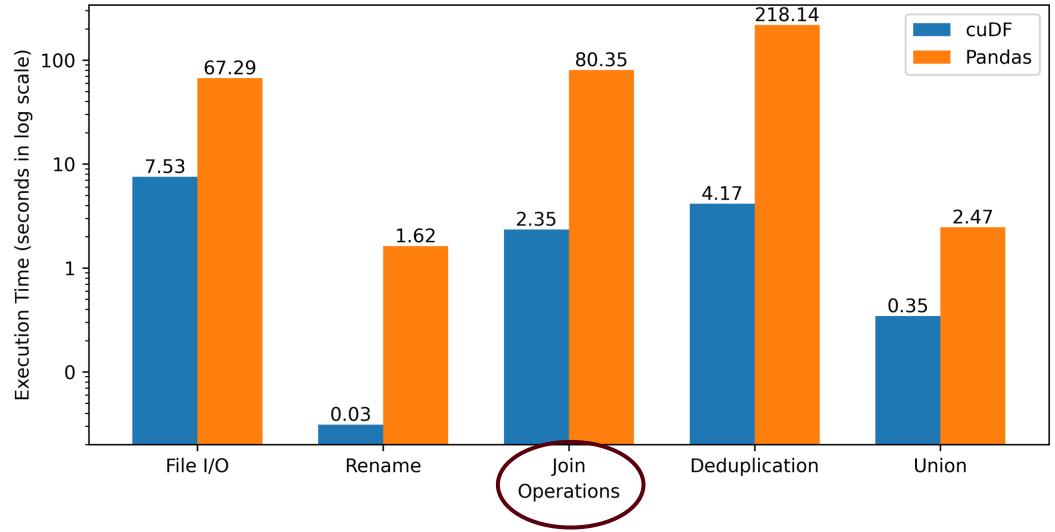
[•] Fender, A., Rees, B., & Eaton, J. RAPIDS cuGraph. In Massive Graph Analytics (pp. 483-493). Chapman and Hall/CRC.

CPU (Pandas) and GPU (cuDF)

```
CPU Environment
import pandas as pd
import cudf
                           GPU Environment
def get read csv(filename, method='cudf', n):
    column names = ['column 1', 'column 2']
   if method == 'df':
        return (pd. read_csv(filename, sep='\t', header=None,
                          names=column names, nrows=n)
    return (cudf).read_csv(filename, sep='\t', header=None,
                         names=column names, nrows=n)
def get join(relation 1, relation 2):
    column names = ['column 1', 'column 2']
    return relation 1.merge(relation 2, on=column names[0],
                            how="inner".
                            suffixes=(' relation 1', ' relation 2'))
```



Performance Improvement of using GPU





Parallel Hash Join

Parallel Join: Algorithms

Popular algorithms

Sort-Merge Join (SMJ)

Hash Join (HJ)

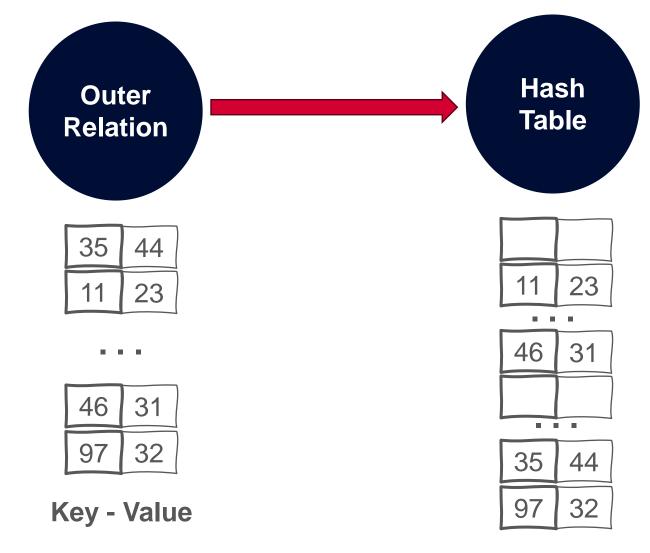


SMJ is suitable for small to medium-sized tables HJ is suitable for large tables



Chengxin Guo, Hong Chen, Feng Zhang, and Cuiping Li. Parallel hybrid join algorithm on gpu. 2019IEEE 21st International Conference on High Performance Computing and Communications; IEEE17th International Conference on Smart City; IEEE 5th International Conference on Data Science and Systems (HPCC/SmartCity/DSS), pages 1572–1579, 2019.

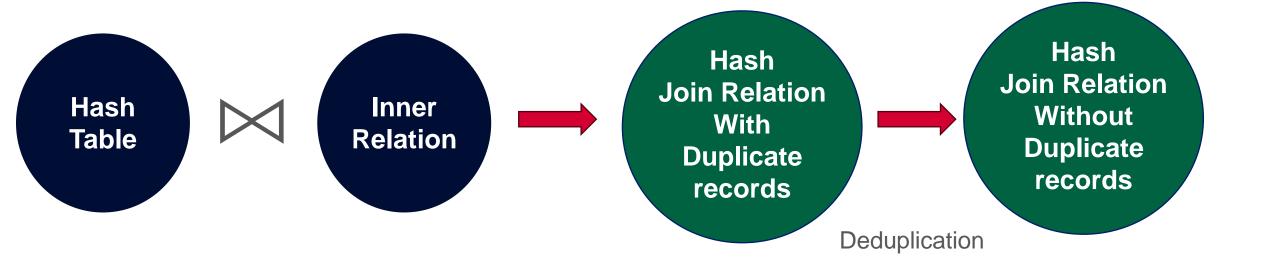
Hash Join Process





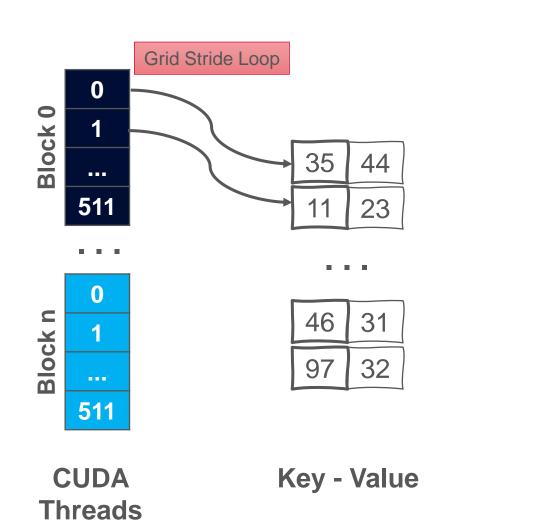
Key - Value

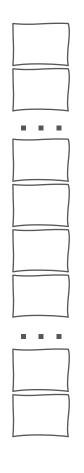
Hash Join Process





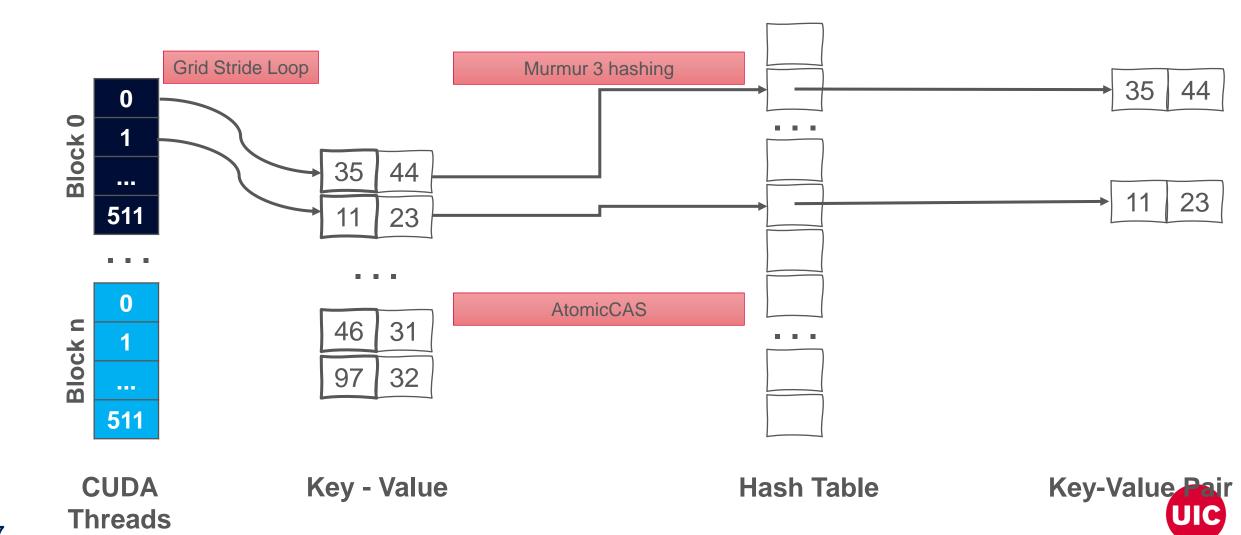
Hash Table (Open Addressing, Linear Probing)

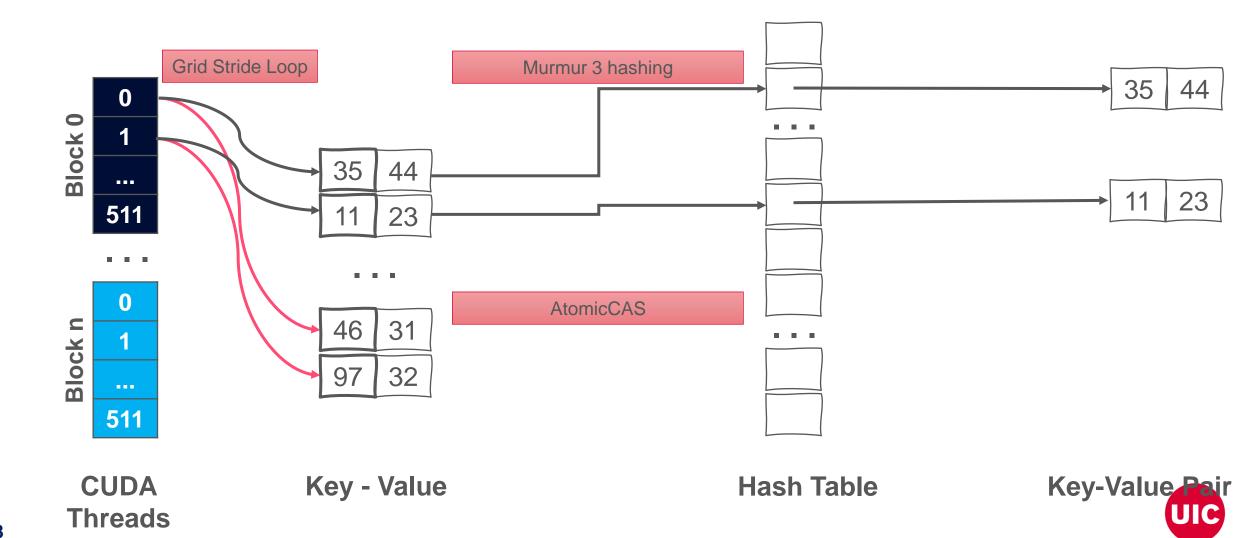


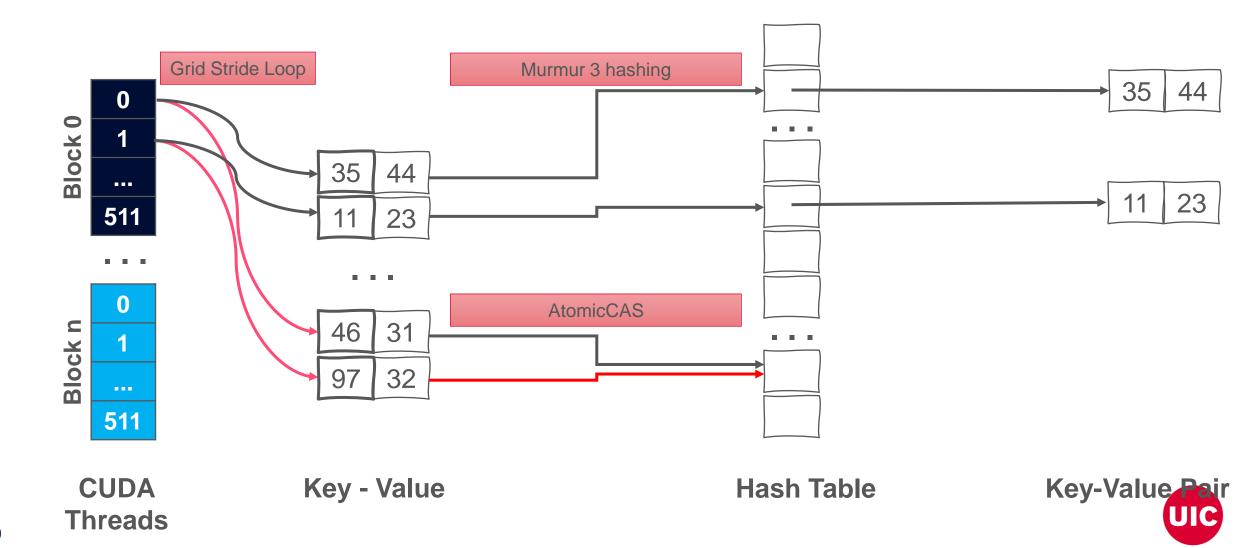


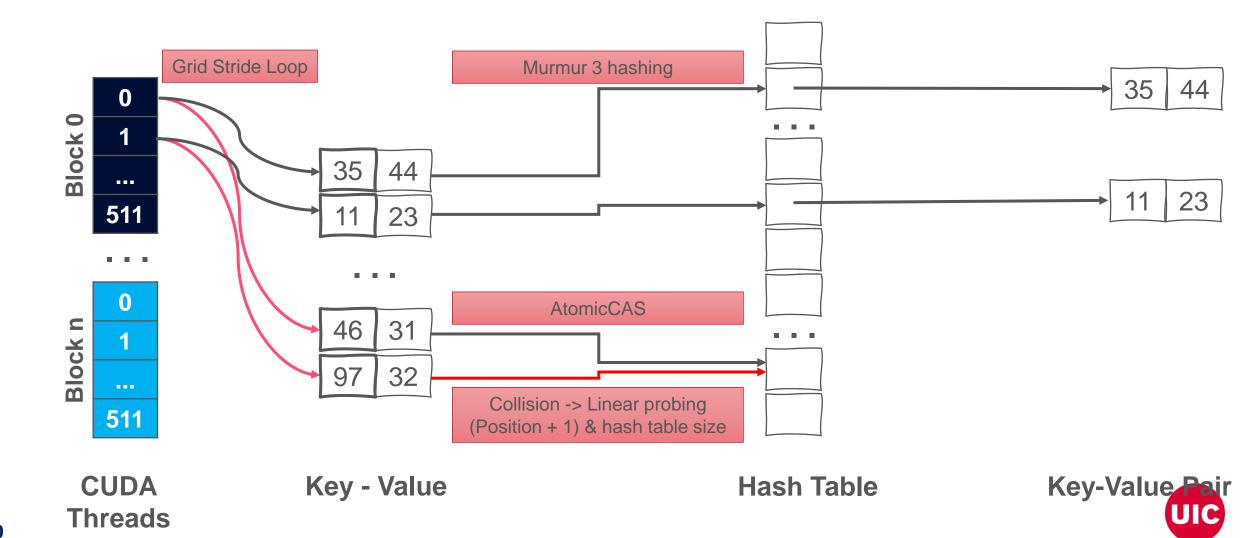


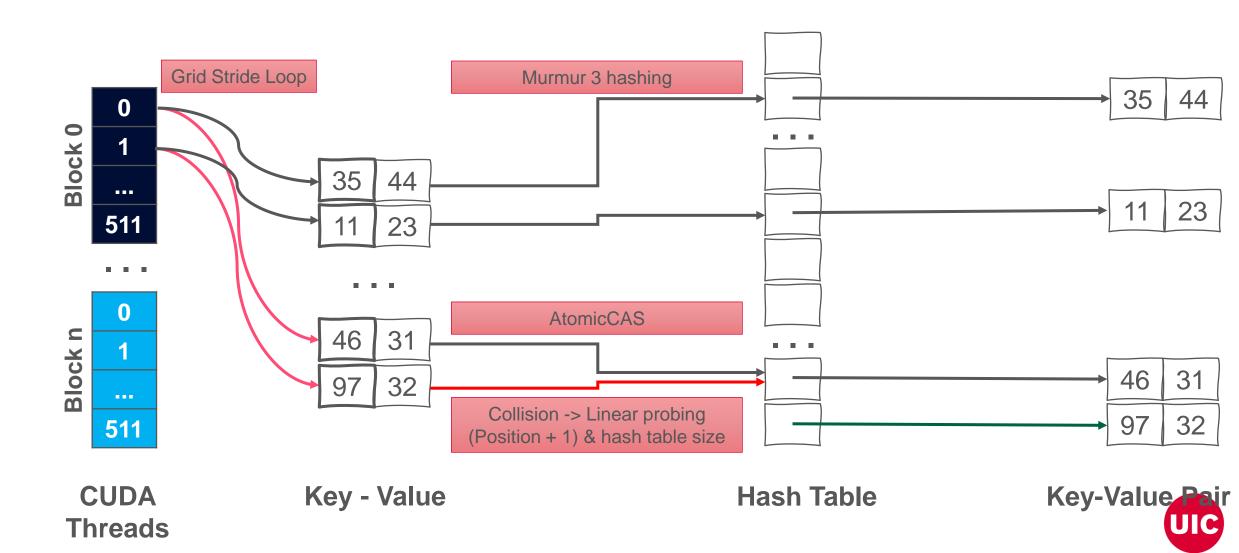




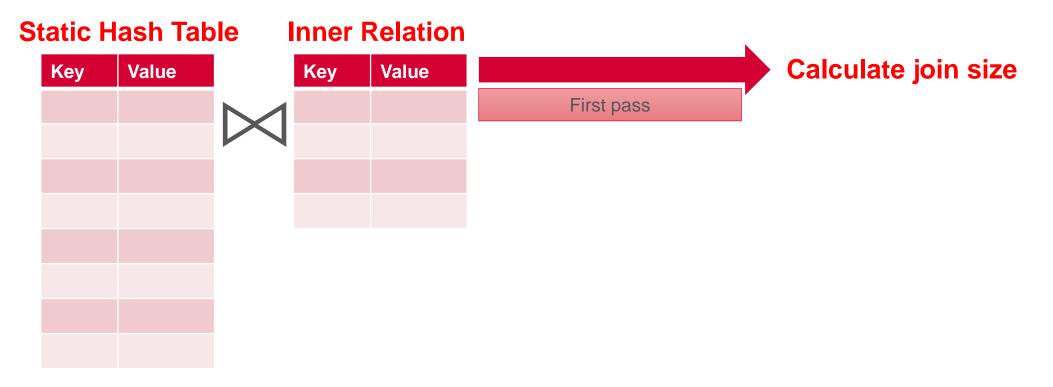






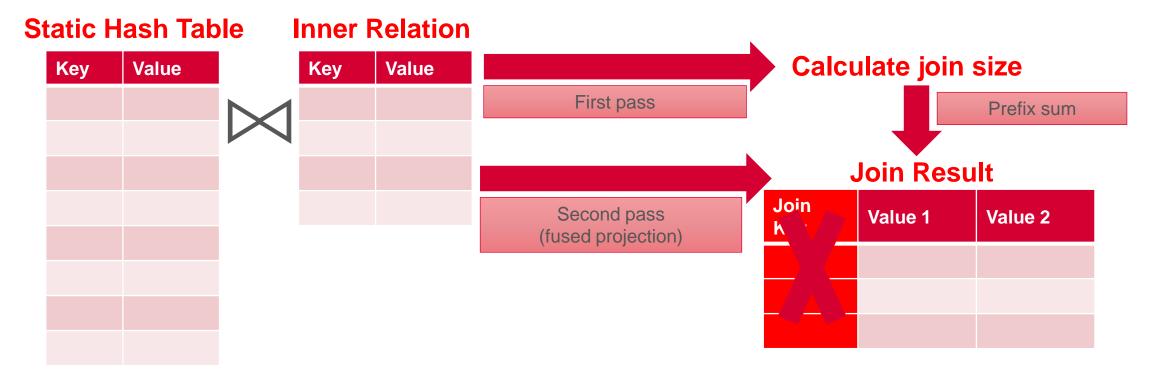


Performing Hash Join on GPU



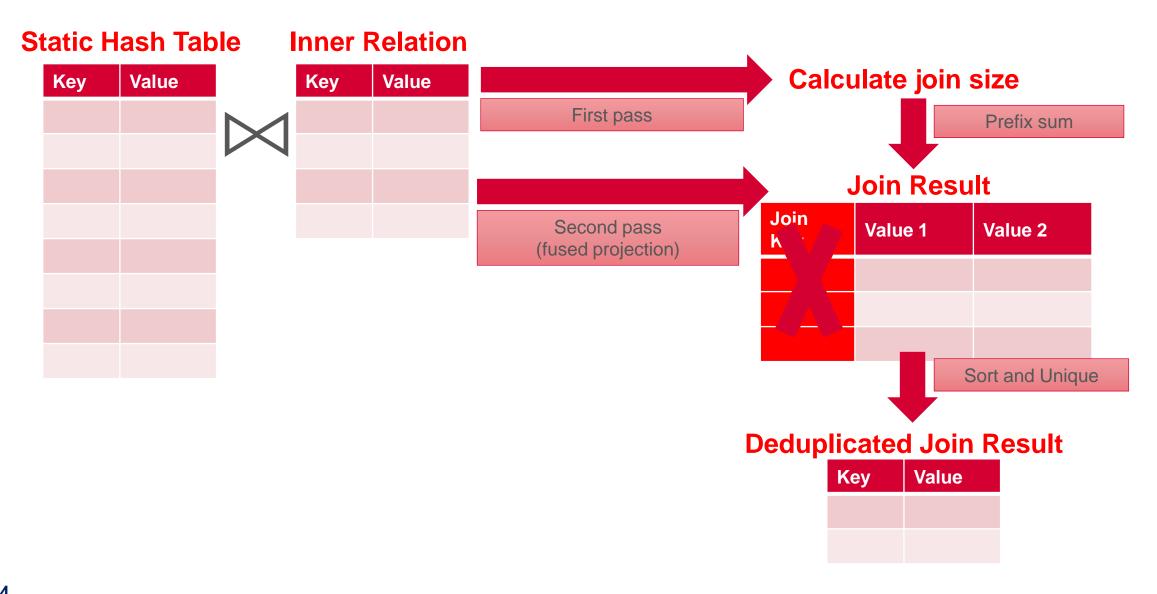


Performing Hash Join on GPU





Performing Hash Join on GPU





CUDA Advantages over cuDF

Fuse operations

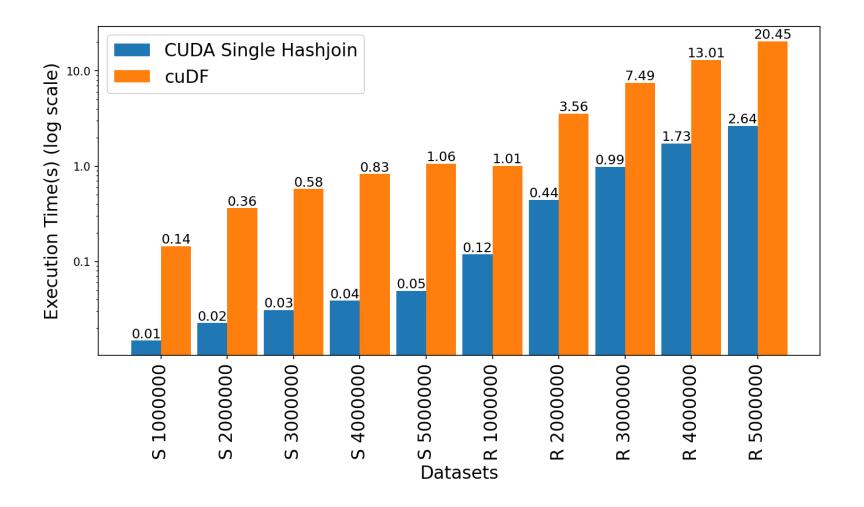
Thread-block configuration

Memory management

Optimize data structure



Join Performance Comparison: CUDA vs cuDF





Limitations



Limited to a single GPU that dictates scaling by available VRAM on the GPU

Memory overflow error for larger graphs

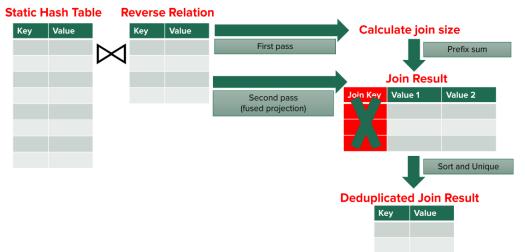
Open addressing based hash table causes memory overhead



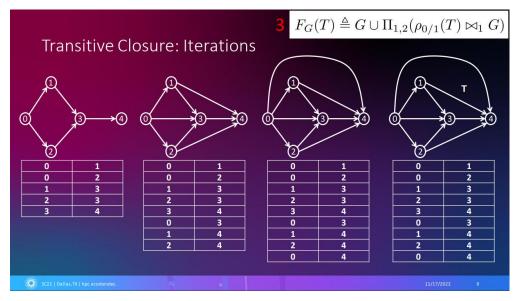
Publications

Shovon, A. R., Gilray, T., Micinski, K., & Kumar, S. (2023). Towards iterative relational algebra on the {GPU}. In 2023 USENIX Annual Technical Conference (USENIX ATC 23) (pp. 1009-1016).

Performing Hash Join on GPU



Shovon, A. R., Dyken, L. R., Green, O., Gilray, T., & Kumar, S. (2022, November). Accelerating Datalog applications with cuDF. In 2022 IEEE/ACM Workshop on Irregular Applications: Architectures and Algorithms (IA3) (pp. 41-45). IEEE.





Summary



GPU provides performance enhancement



Python based cuDF can be a head start to GPU programming



Low level CUDA has a learning curve but improves performance



