MassiveClicks

A Massively-parallel Framework for Efficient Click Models Training

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What is a Click Model?

1. Users interact with **search engines**.
2. **Clicks** on search results show **relevance**.
3. Relevance assessments help **improve search engines**[1].

[1] Filip Radlinski et al. "How Does Clickthrough Data Reflect Retrieval Quality?"

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Click

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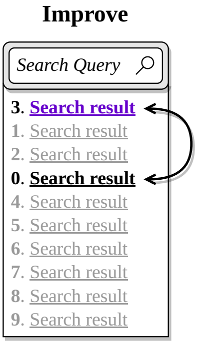

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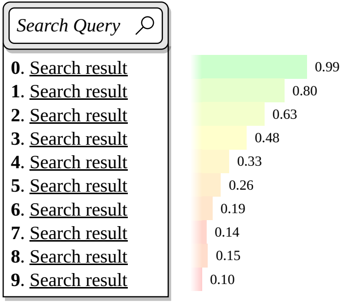
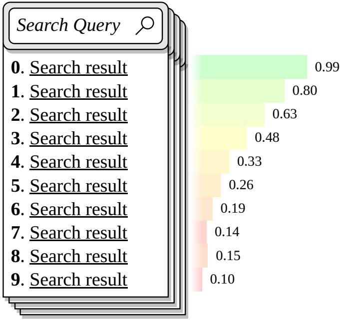
What is a Click Model?

A click model assigns a **click probability** to a search engine result page (SERP).



How is a Click Model built?

1. A search engine logs a user's clicks on a SERP inside a *click* log.
2. Click models use parameters to quantify relevance.
3. EM-based models (for example) are used to train these parameters using data from click logs.



Click logs from real-world search engines can be very large[2] making training expensive.

[2] https://www.internetlivestats.com/google-search-statistics/

Limitations of Existing Solutions

- **Training** EM-based models is **challenging due to the size** of click logs.
- **Existing tools** like *PyClick* are sequential and slow.
- ***ParClick***, though parallel, is limited to single-node multi-core systems.

MassiveClicks

A scalable multi-GPU solution to parallelize generic EM-based training algorithms for click models.

Why MassiveClicks?

— First multi-GPU, distributed click model training framework.

— Efficient GPU kernels and data-partitioning.

— Outperforms ParClick on GPUs/multi-node.

Requirements

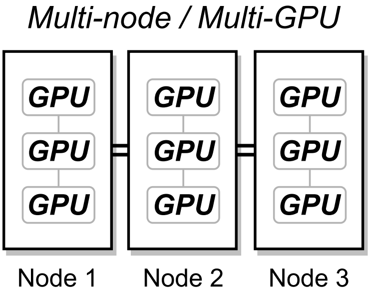
— Scalable EM-based training.

— Efficient, multi-GPU, multi-node distributed processing.

— General, adaptable framework.

MassiveClicks

A scalable multi-GPU solution to parallelize generic EM-based training algorithms for click models.



EM-based Click Models

Click models supported by MassiveClicks:	*Computational difficulty:*
• Position-based Model (PBM)	8 %
• Click Chain Model (CCM)	88 %
• Dynamic Bayesian Network model (DBN)	100 %
• User Browsing Model (UBM)	10 %

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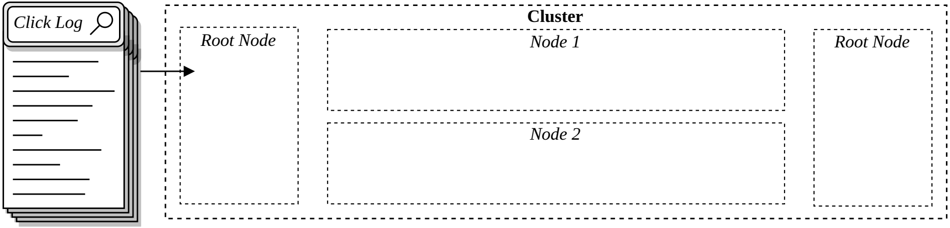
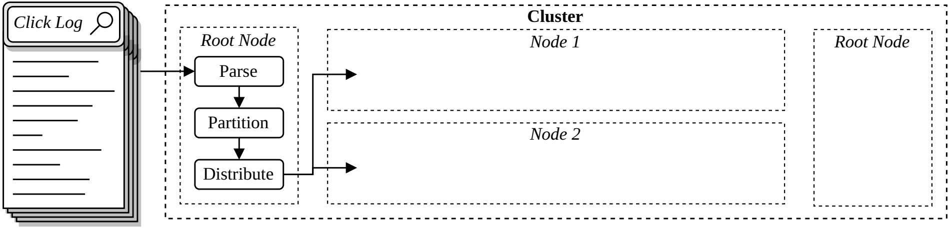
High-level Design



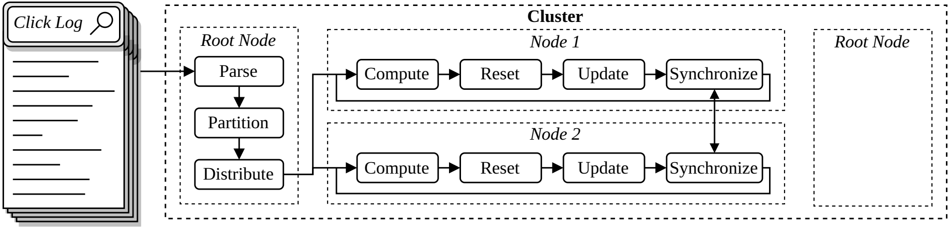
1. Read click log.

High-level Design



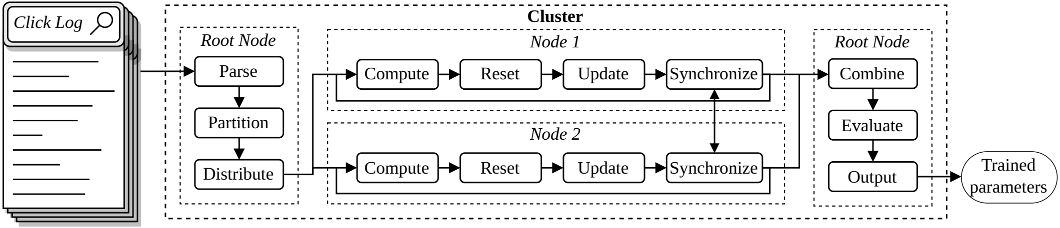
2. Preprocess input.

High-level Design



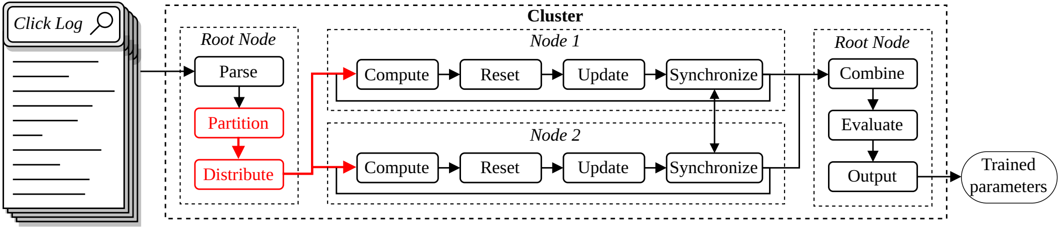
3. Estimate parameters.

High-level Design



4. Evaluate and output results.

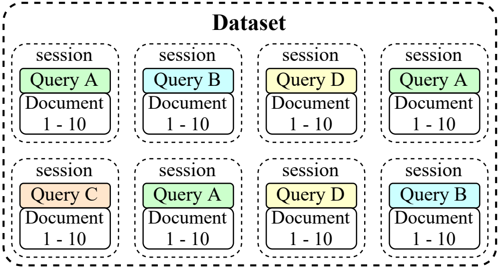
Data Distribution



Partitioning and distribution

Data Distribution

Constrain data distribution to **reduce communication** during parameter estimation. Sessions are *grouped by query*.



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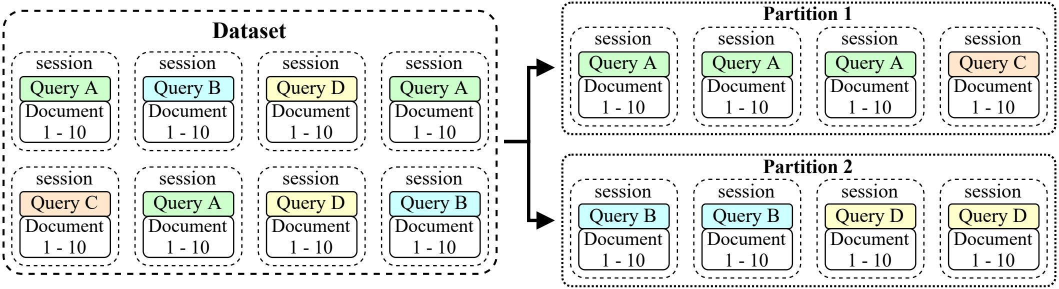


Data Distribution

Nodes *parse sessions independently* from root, ensuring dataset size isn't limited by the root node's memory.

Difficulties:

- Similar queries grouped on same node.
- Query IDs on other nodes unknown.
- IDs are inconsistent due to gaps.
- Variable query count per node.
- Differing memory available per node.

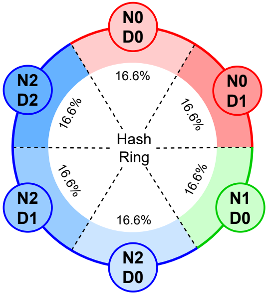
Desirable Characteristics:

- Minimize inter-node communication.

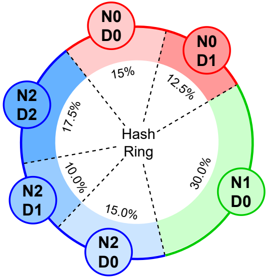
Data Distribution

Decide session distribution across nodes by adjusting *node ranges* on a *hash ring* based on some property, i.e., number of CUDA cores.

Uniform Distribution



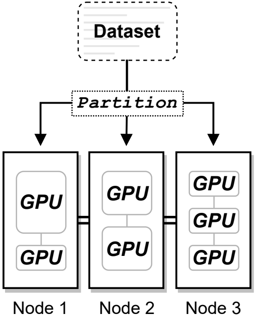
Property-Based Distribution



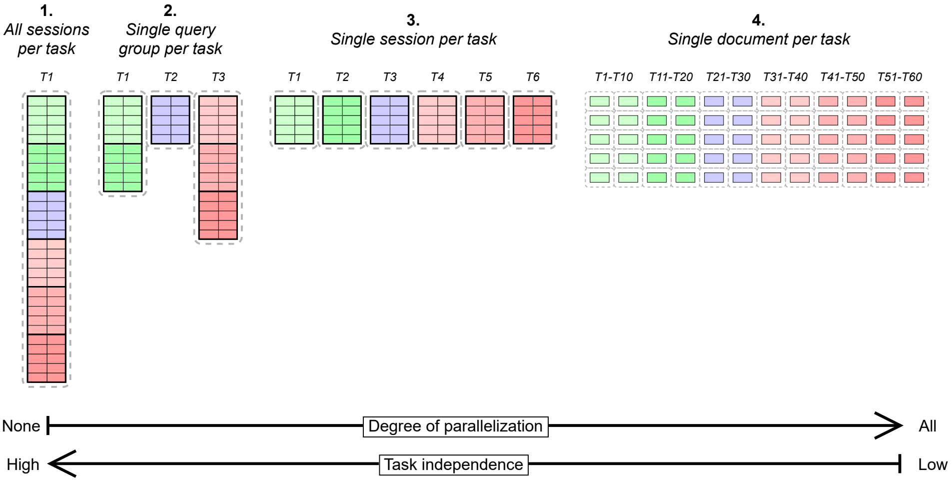
Data Distribution

Five partitioning policies:

- Round-robin
- Maximum-Utilization
- Proportional to:
  - Available Memory
  - CUDA-core Count
  - Theoretical Peak Performance



Session Distribution



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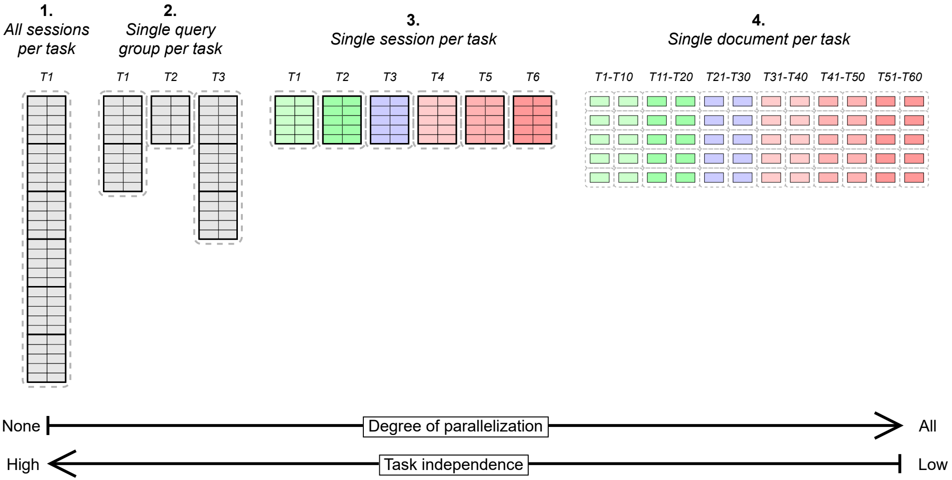

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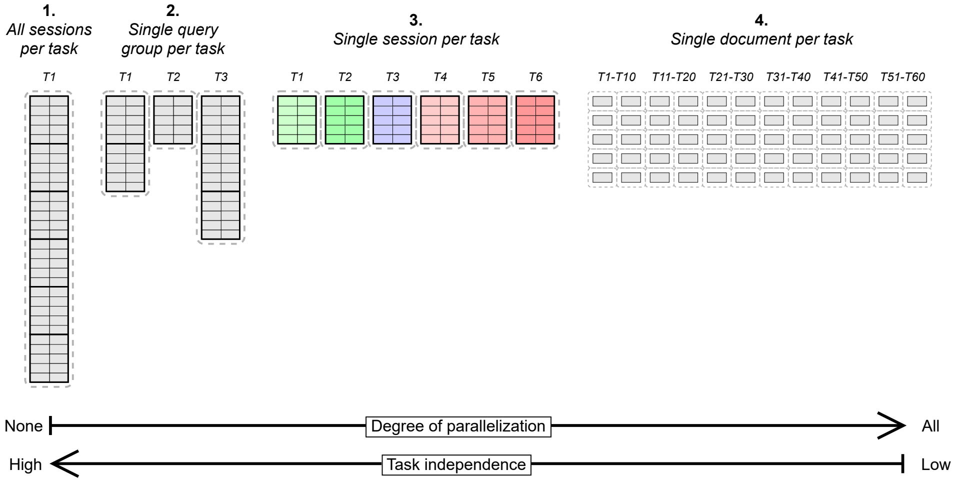
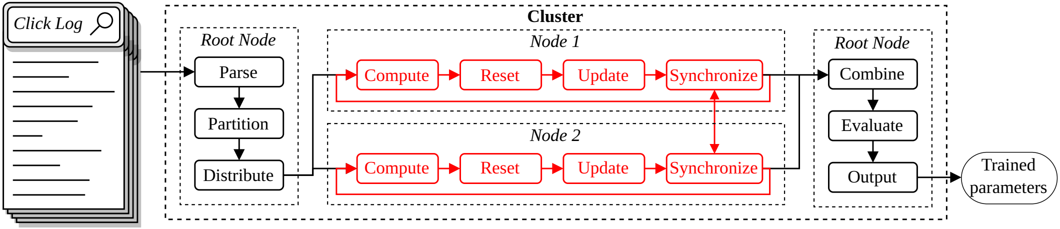


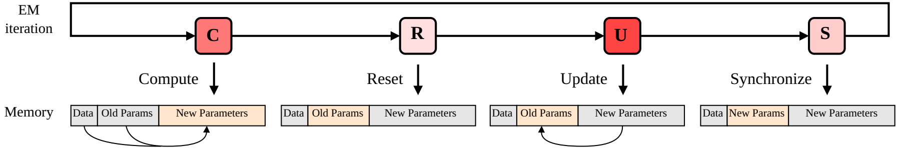
Parameter Estimation



Iterative parameter estimation

Parameter Estimation

EM-based parameter estimation is divided into four phases.



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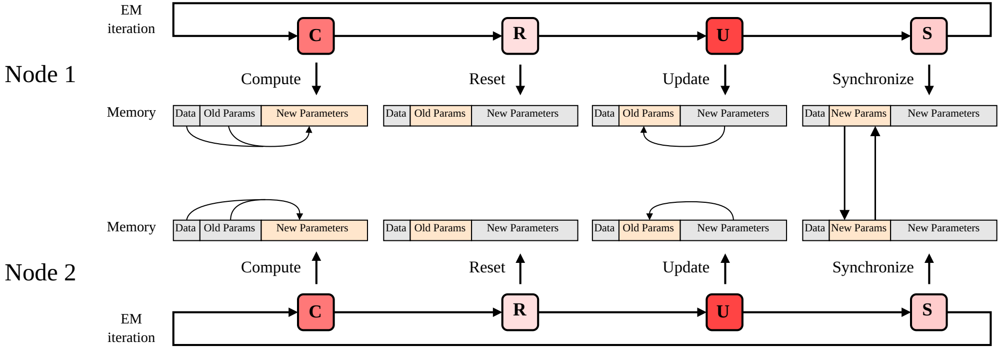
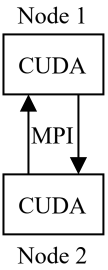


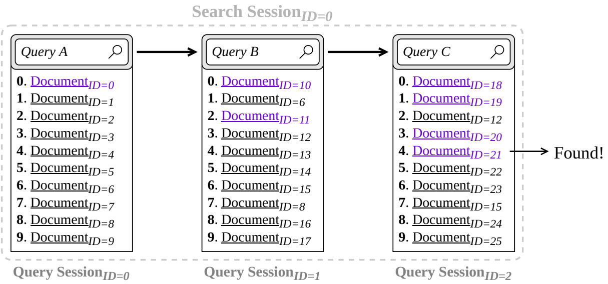
Multi-GPU/Multi-node Architectures

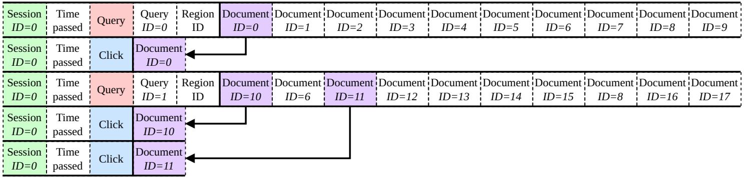
Programming models:

- **C++** framework.
- **CUDA** for (multi) GPU execution.
- **MPI** for multi-node communication.



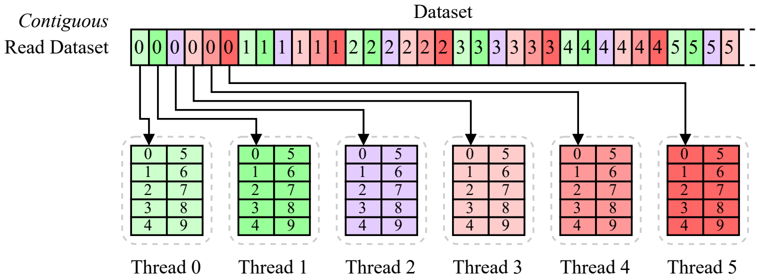
Click Log Layout





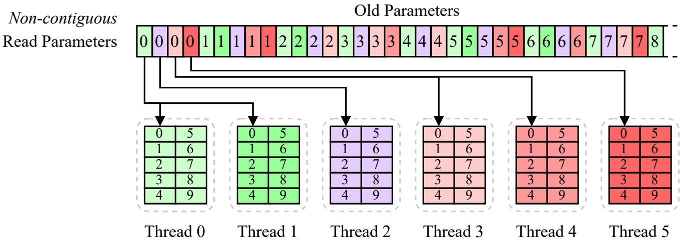
Allocation in Memory

Dataset placement in global GPU memory.



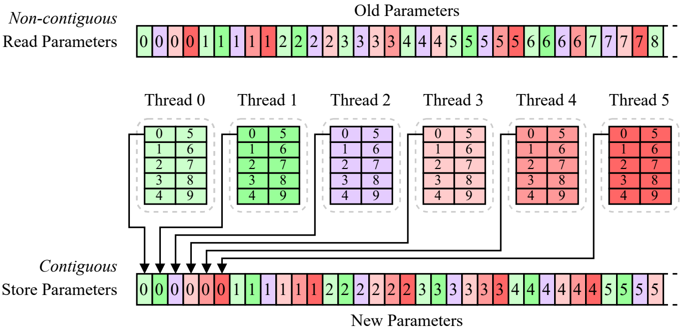
Memory Access Pattern

Compute — Threads *read* parameters from *previous* iteration.



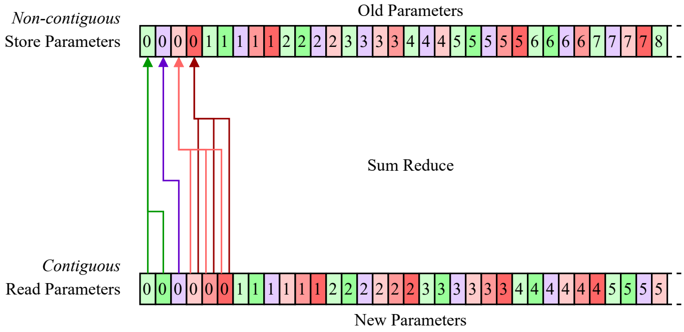
Memory Access Pattern

Compute — Threads *write* parameters from *current* iteration.



Memory Access Pattern

Update — Threads *write* parameters to *previous* iteration.



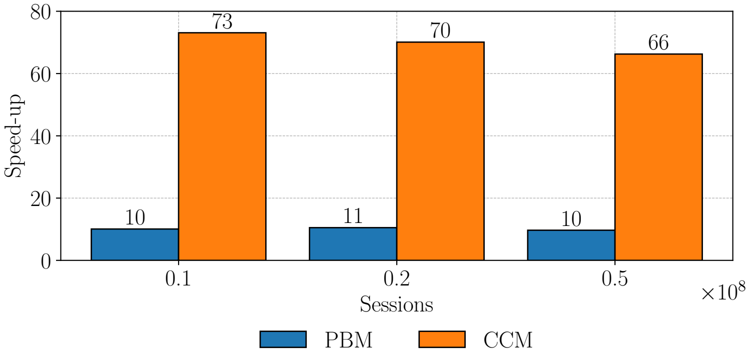
Experimental Setup

Measure performance for (up to 14) multi-GPU/multi-node configurations using **NVIDIA RTX A4000 GPUs** and 24-core **AMD EPYC 7402P CPUs** and subsets of the Yandex dataset of varying sizes (D$n = n$ million sessions dataset).

Report:

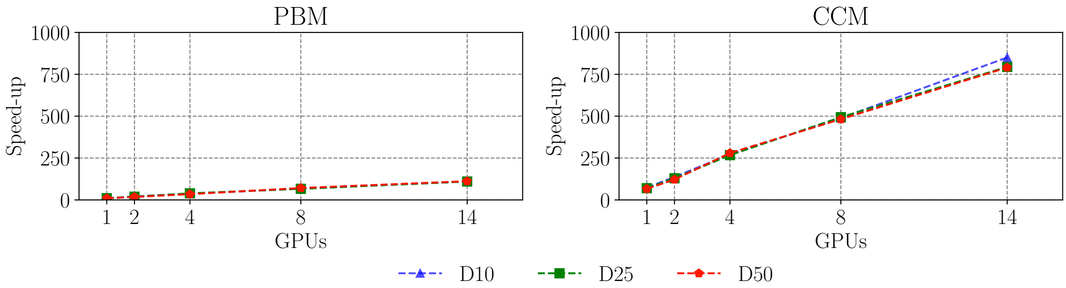
- **Speed-up** vs. ParClick, the **only alternative** for parallel click model training.
- **Scalability** for multi-GPU/multi-node setups and click logs.
- **Usability** for real-world problems.
- **Kernel performance** using a **roofline model**.

Single GPU Speed-up



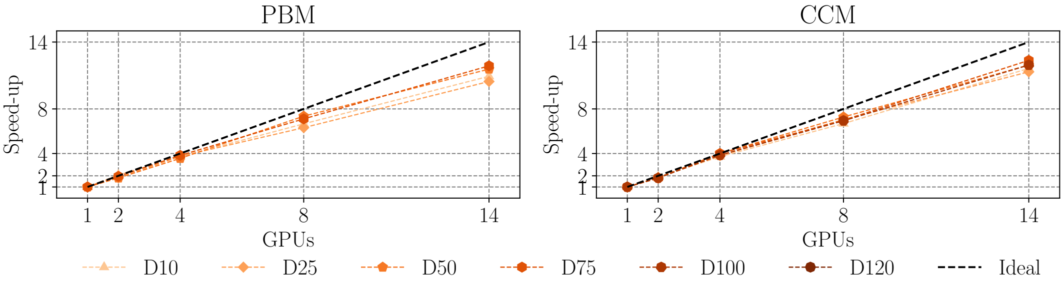
Speed-up of MassiveClicks for **PBM** and **CCM** on a single **NVIDIA RTX A4000** GPU.

Multi-GPU Speed-up



Speed-up for **PBM** (left) and **CCM** (right) for different datasets and **NVIDIA RTX A4000 GPUs** compared to ParClick on an **AMD EPYC 7402P CPU** with **48 threads**.

Scalability



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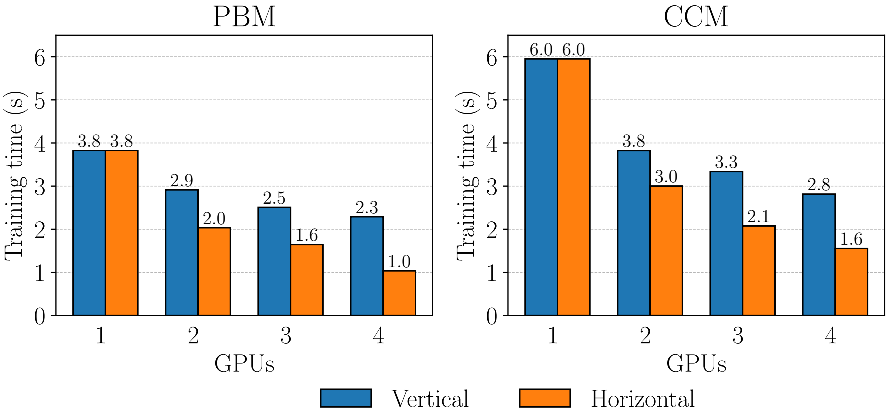


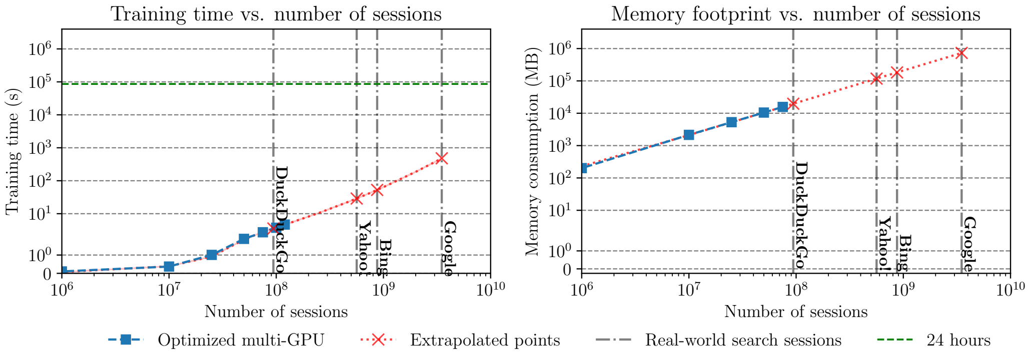
Training time of MassiveClicks for **PBM** (left) and **CCM** (right) for **D10** with different number of **NVIDIA RTX A4000** GPUs per node.

Usability

Real-world applications:

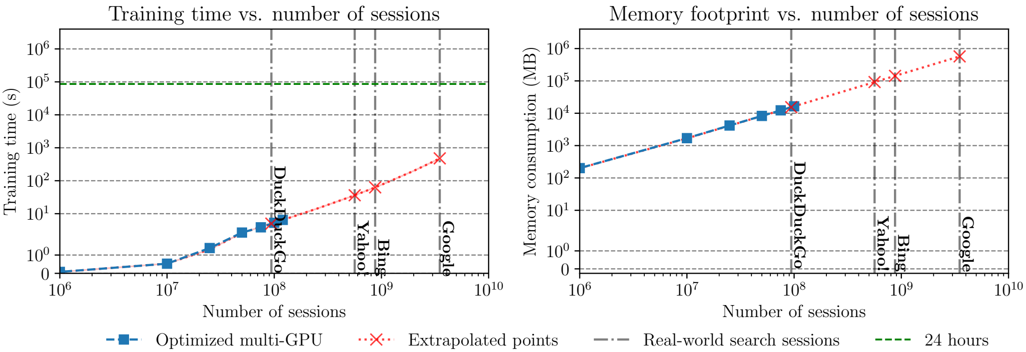
- 'Search engine'-size click logs.
- Energy consumption.

Projection



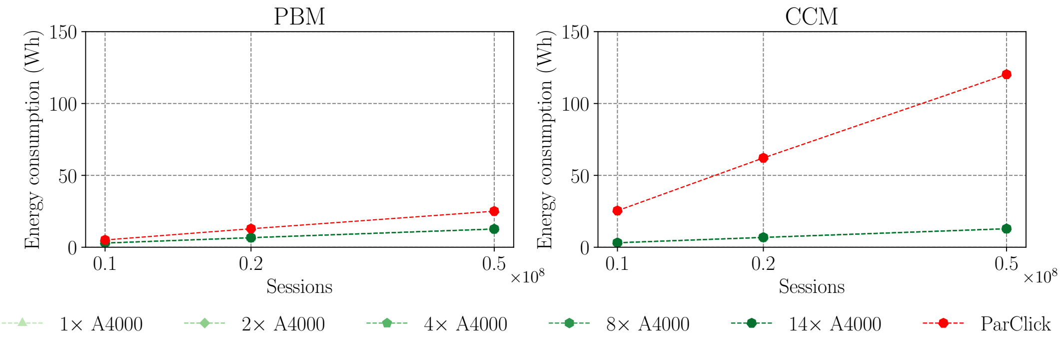
Training time (left) and **memory footprint** (right) of MassiveClicks of **PBM** for real-world datasets using 14 **NVIDIA RTX A4000** GPUs.

Projection



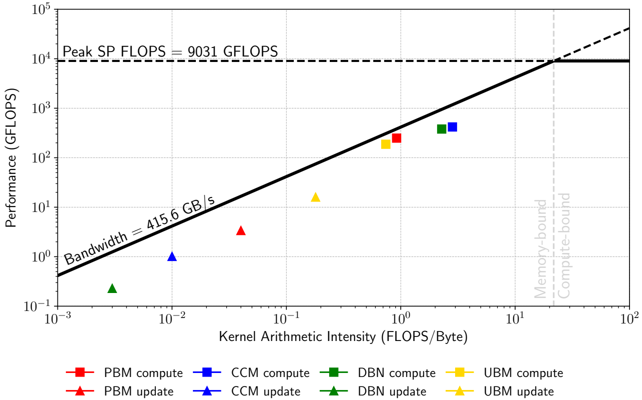
Training time (left) and **memory footprint** (right) of MassiveClicks of **CCM** for real-world datasets using 14 **NVIDIA RTX A4000** GPUs.

Energy Consumption



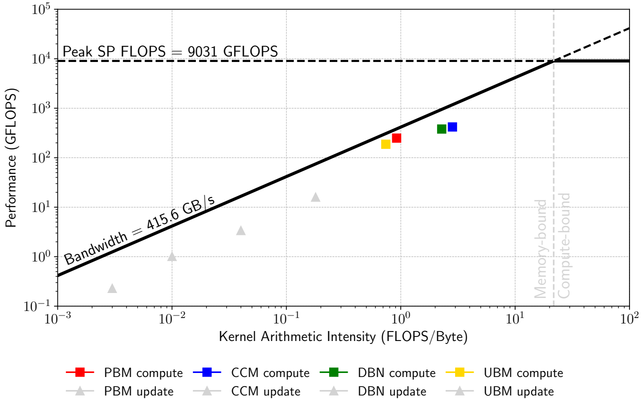
Expected **energy consumption** of MassiveClicks for **PBM** and **CCM** compared to ParClick.

Kernel Performance



Roofline model of MassiveClicks for **PBM**, **CCM**, **DBN**, and **UBM** on a single **NVIDIA RTX A4000** GPU.

Kernel Performance



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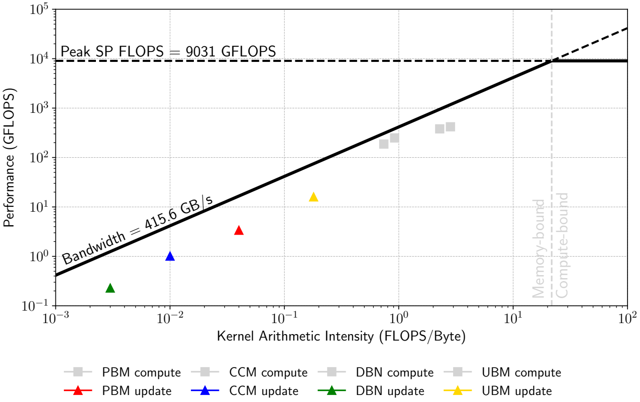

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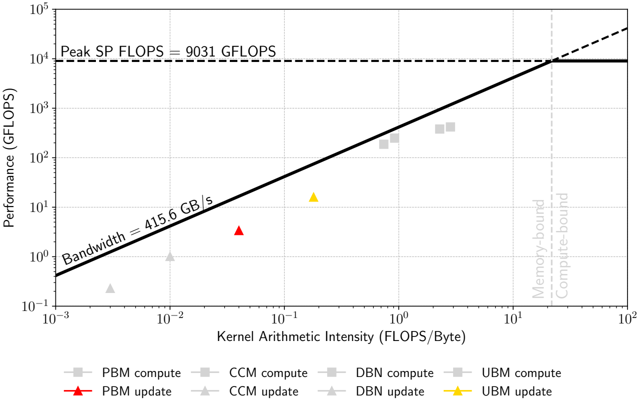

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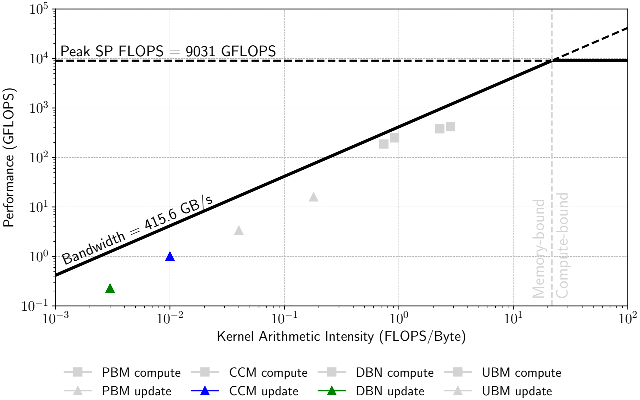


Roofline model of MassiveClicks for **PBM**, **CCM**, **DBN**, and **UBM** on a single **NVIDIA RTX A4000** GPU.

Conclusion and Future Directions

- **In Summary:** We introduced MassiveClicks, a tool for training EM-based click models on heterogeneous multi-GPU/multi-node setups, offering a significant performance improvement over existing solutions.
- **Future Work:**
  - Exploring hybrid training methods.
  - Transition to HIP for broader compatibility.
- **Repository:** Find the code and documentation for MassiveClicks at *github.com/skip-th/MassiveClicks* or the QR-code.

Hybrid training

Automatic

– Compute optimal data distribution.

Manual

– User chooses desired distribution.

Compatibility

The heterogeneity only extends to CUDA GPUs.

- AMD GPUs are not supported.
- Currently converting codebase to HIP using HIPify[1].

[1] https://github.com/ROCm-Developer-Tools/HIPIFY

Position-based Model (PBM)

$$P(C_d = 1) = P(E_d = 1) \cdot P(A_d = 1)$$

A user **clicks** a search result if, and only if, they **examined** the result and were **attracted** to it.

γ_r – rank-dependent *examination* parameters.
α_{qd} – query-dependent *attractiveness* parameter.

Click Chain Model (CCM)

$$P(C_d = 1) = P(E_d = 1) \cdot P(A_d = 1)$$

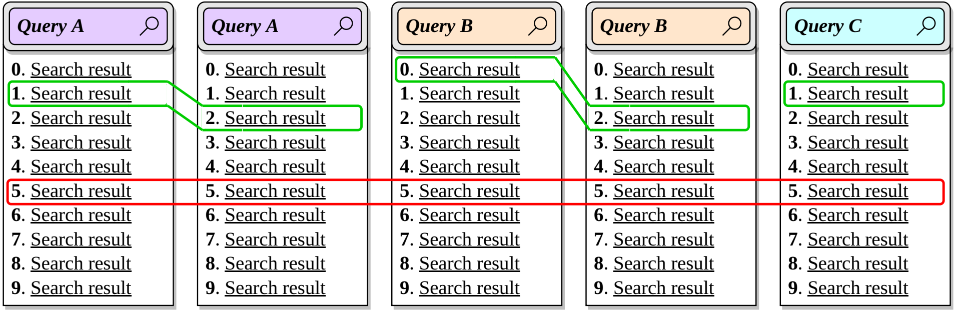
A user **clicks** a search result if, and only if, they **examined** the result and were **attracted** to it.

τ_1, τ_2, τ_3 – document-dependent *continuation* parameters.

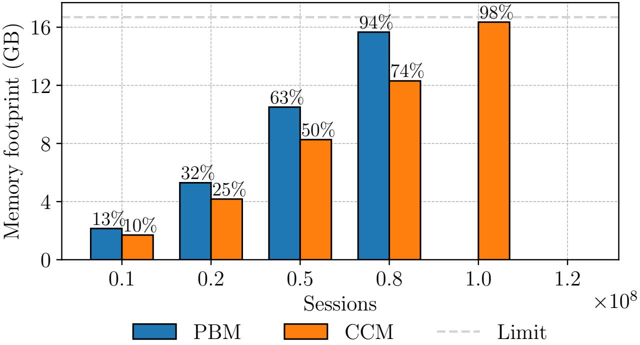
$\alpha_{q_r d}$ – query-dependent *relevance* parameter.

Parameter Types

Shared by Few	***Shared by All***
30> **Query-dependent parameters**	**10** **Rank-dependent parameters**



Memory Footprint



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New Memory Access Pattern

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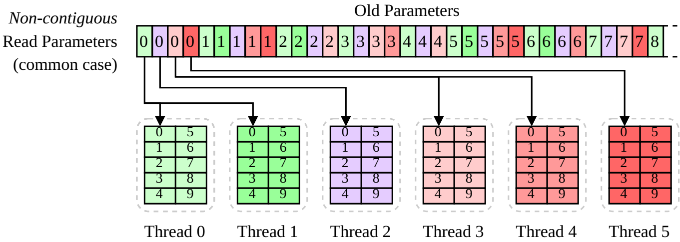
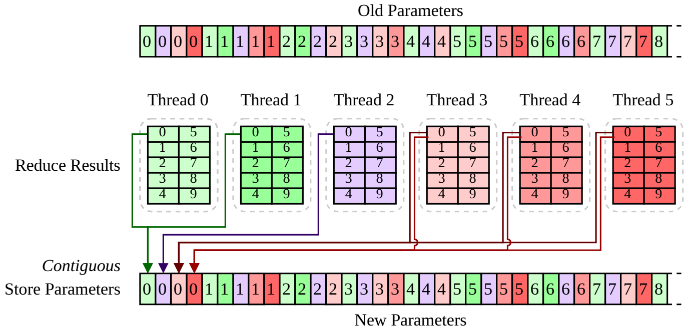


New Memory Access Pattern

Update — Threads *reduce* parameters to *current* iteration.



New Memory Access Pattern

Update — Threads *swap* old and new parameters.