

The background is a high-contrast, black and white photograph of a wooden board game, likely a variation of Nim. The board is made of dark wood with light-colored chalk or paint markings forming a grid and several circular piles. In the top-left corner, there is a solid blue abstract shape. In the bottom-right corner, there is a light blue abstract shape with several small blue dots and a triangle scattered around it.

# *Parallel MinMax for Nim*

---

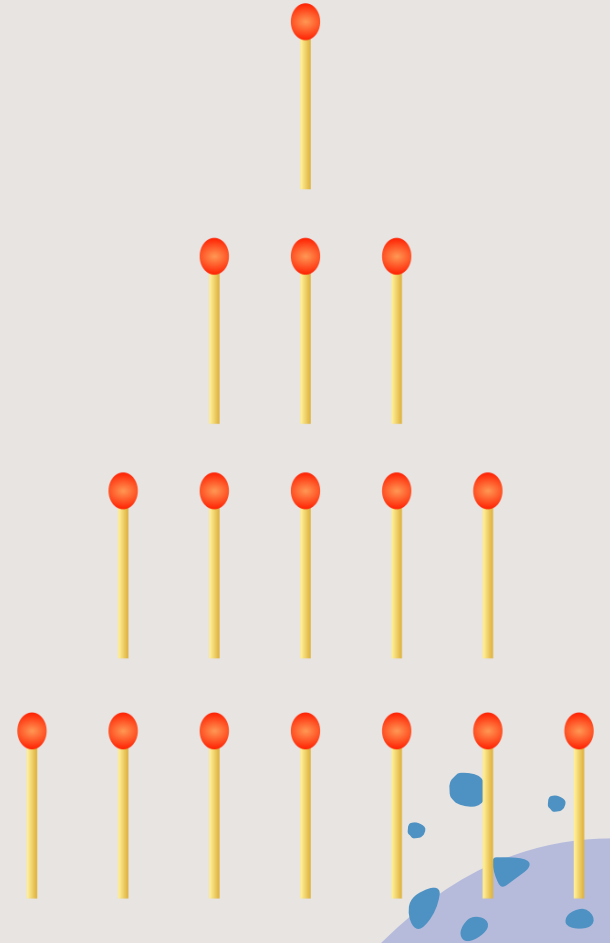
Faculty of Computer Engineering, Politecnico  
di Torino, Italy

# *The Nim game*

---

**Nim** is a two-player mathematical game of strategy in which players take turns removing objects from distinct heaps or piles of the board:

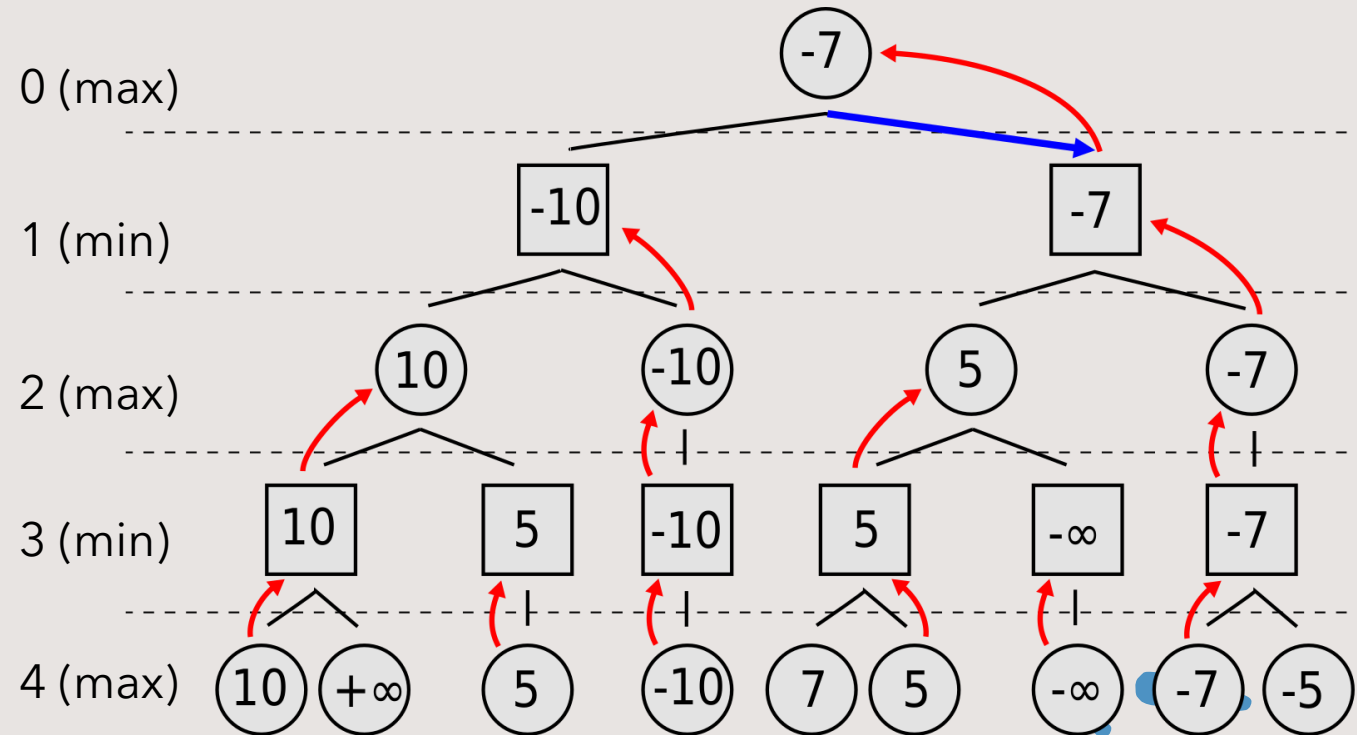
- The board typically consists of several piles of objects each pile contains an increasing odd number of sticks.
- On each turn, a player must remove one or more objects from any pile.
- The goal of the game is to be the player to take the last object.



# *The MinMax algorithm*

Minmax is an algorithm used in **game theory** to determine the best move in a two-player, zero-sum game:

- The opponent will make the move that is most detrimental to the current player, so the he will always try to *minimize the reward*.
- The current player choose the move that minimizes the worst-case outcome, so he will always try to *maximize his reward*.





# *Project aim*

---

The aim of the project is exploiting the power of GPUs to compute the optimal move for Nim by creating a **parallel** version of the minmax algorithm, by achieving:

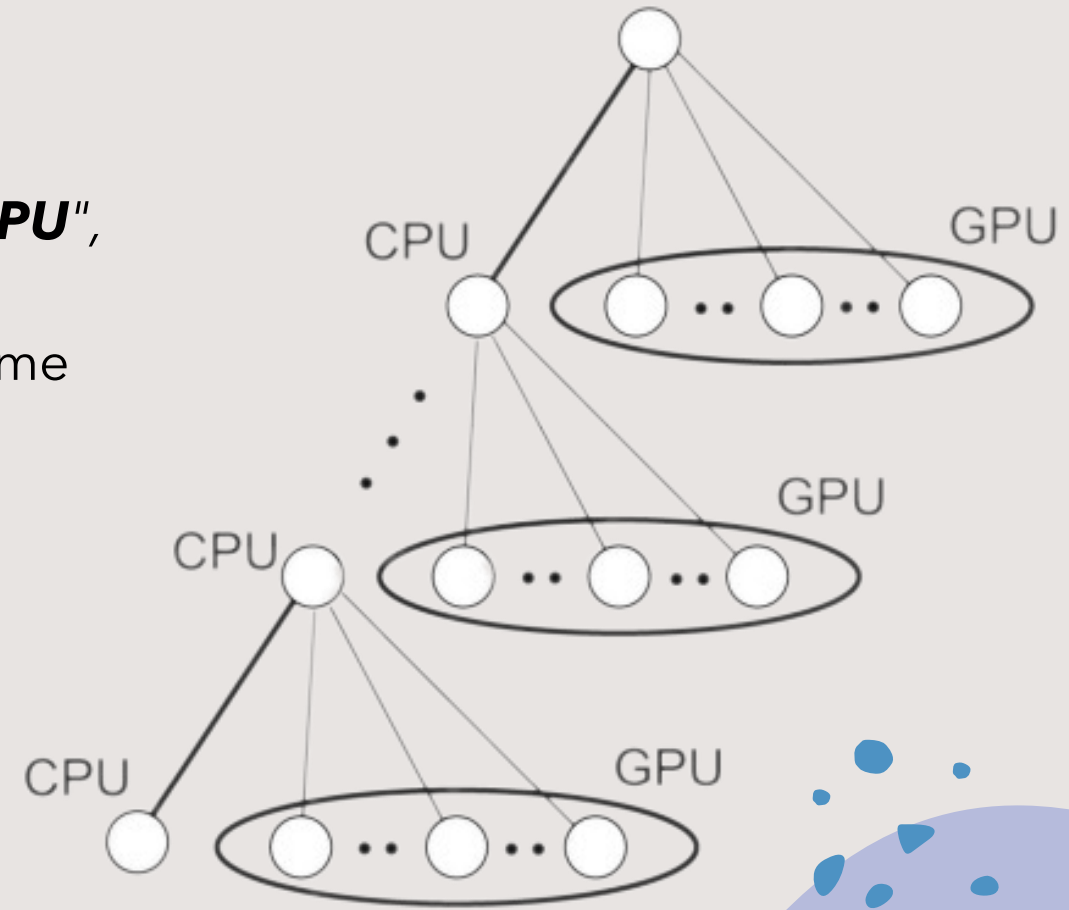
- Performance
- Scalability
- Portability
- Power efficiency



# *Related Work*

In the paper "**Parallel Alpha-Beta Algorithm on the GPU**", *Damjan Strnad* and *Nikola Guid* describe the parallel implementation of the alpha-beta algorithm for the game of Reversi by using the **PV-Split algorithm**:

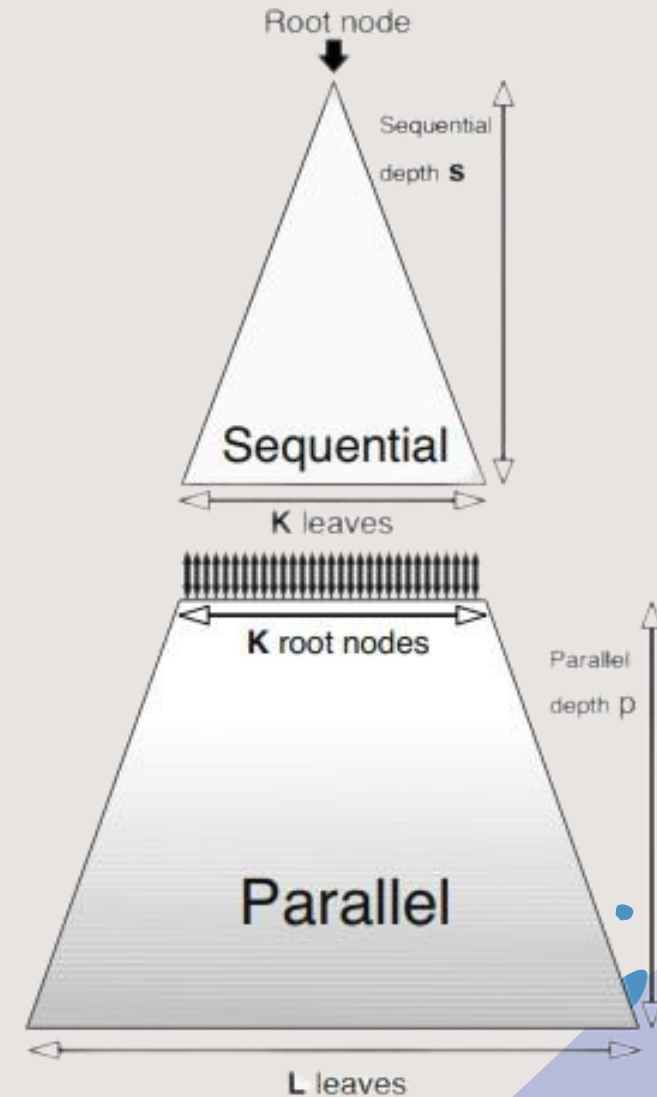
- The leftmost child of each PVnode is searched on the CPU
- The rest of PVnode's descendants are searched in parallel on the GPU.



# *Related Work*

Kamil Rocki and Reiji Suda, in their "**Parallel Minimax Tree Searching on GPU**" adapted the Minimax algorithm to the Reversi game by splitting the tree into two parts:

- The upper tree of depth is processed in a *sequential* manner.
- The lower part of depth is processed *parallelly* and sliced into subtrees, so that each of them can be searched separately.



# *Proposed Method*

During the development, four main version of the parallel algorithm were implemented, plus one version of the sequential algorithm:

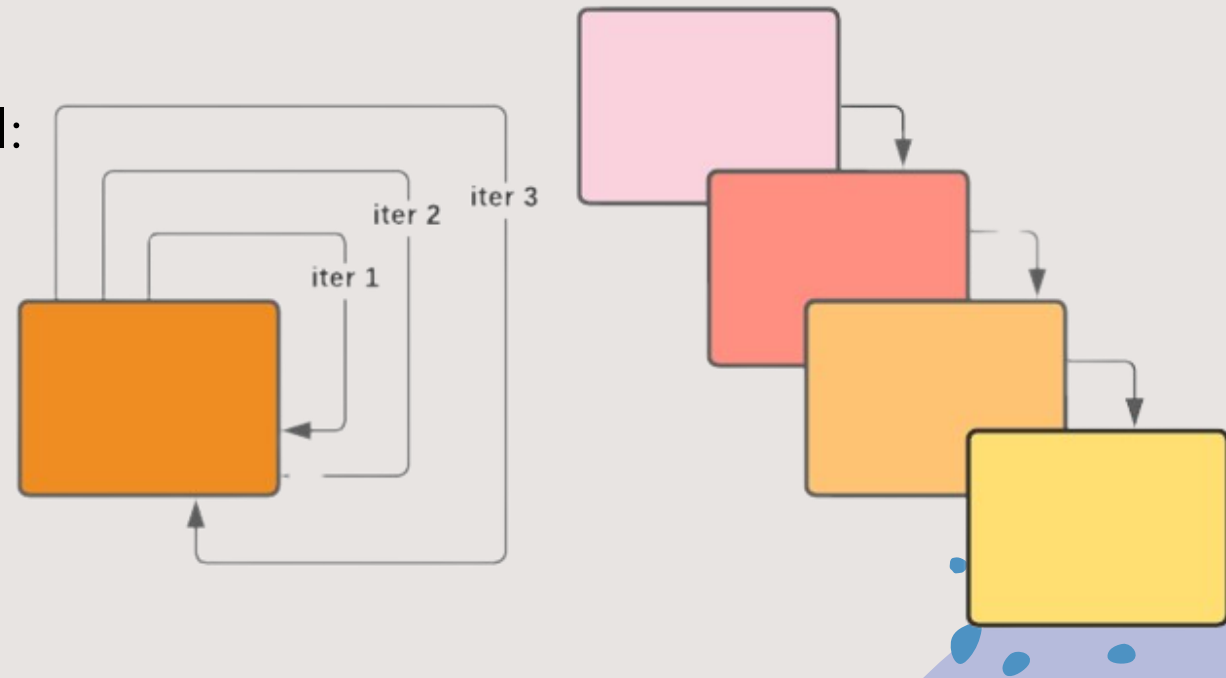
- **V0** – Iterative C Implementation
- **V1** – First CUDA version
- **V2** – Data structures optimization
- **V3** – More levels in shared memory
- **V4** – Memory transactions reduced



# *V0 – Iterative C Implementation*

The **Nim library** and the **minmax algorithm** were adapted from Python to C, before parallelizing the algorithm itself in a CUDA kernel:

- From recursive to iterative form
- Usage of a Stack
- Dynamic memory
- High complexity
- Faster than Python

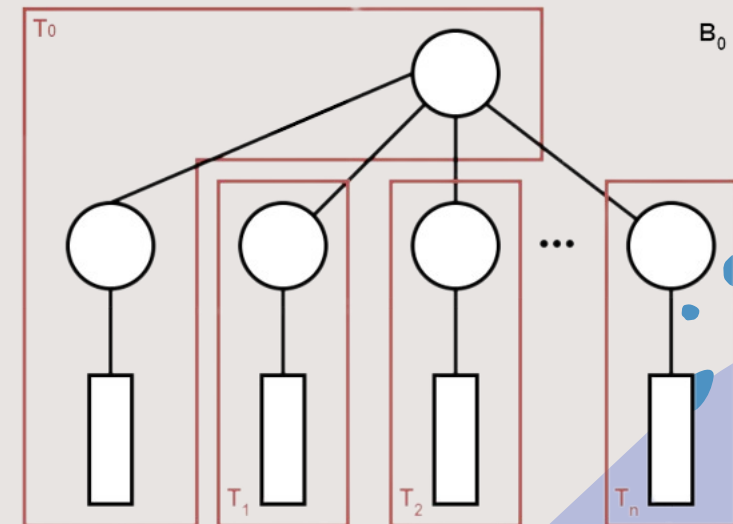
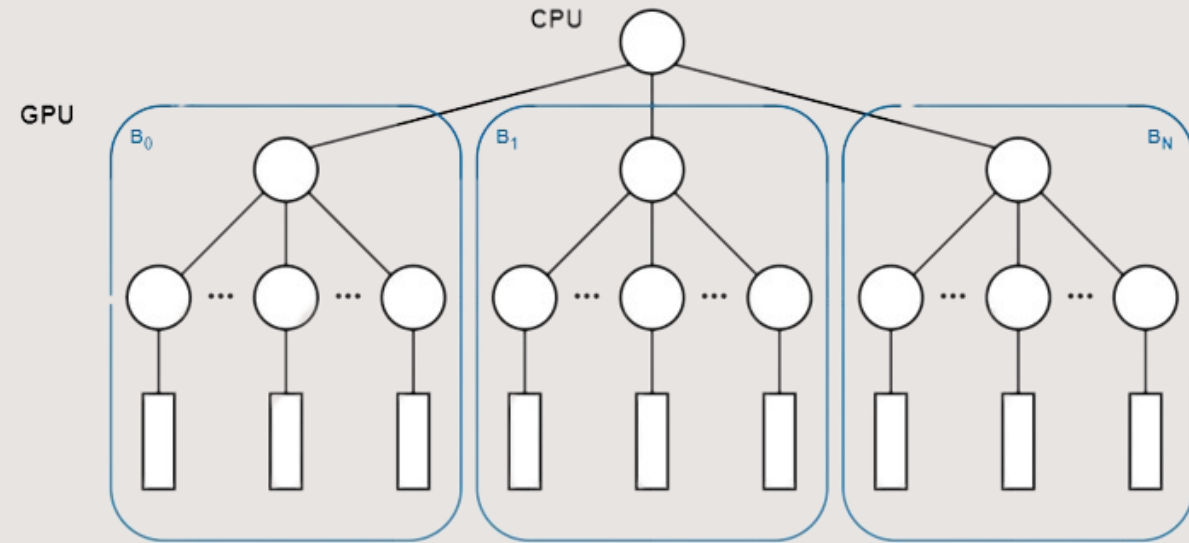




# *V1 – First CUDA version*

The GPU is used to **parallelize** the search and node-creation process:

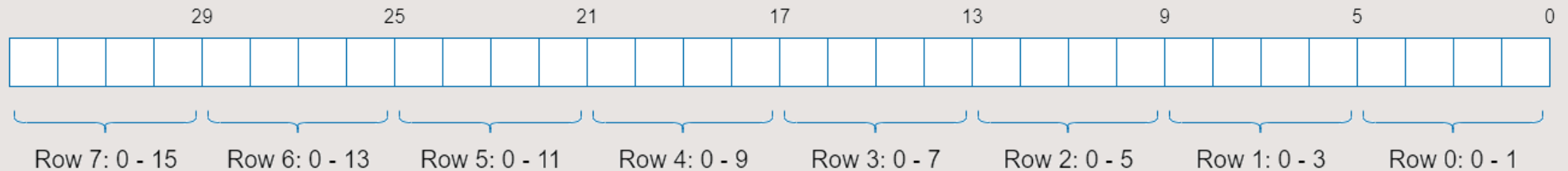
- The game tree is divided into smaller subtrees
- Each subtree is processed by one block
- Each block evaluates one child nodes for each thread
- The results are evaluated in the host



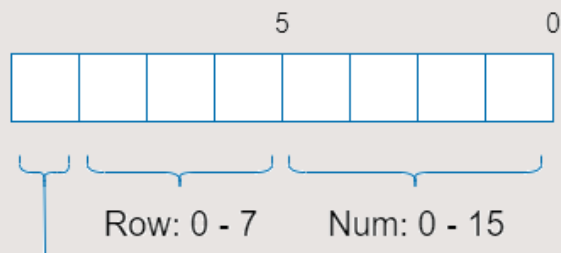
# *V2 – Data structures optimization*

The **memory read/write transactions** were reduced, and the constant memory was used.

Nim representation



Nimply representation

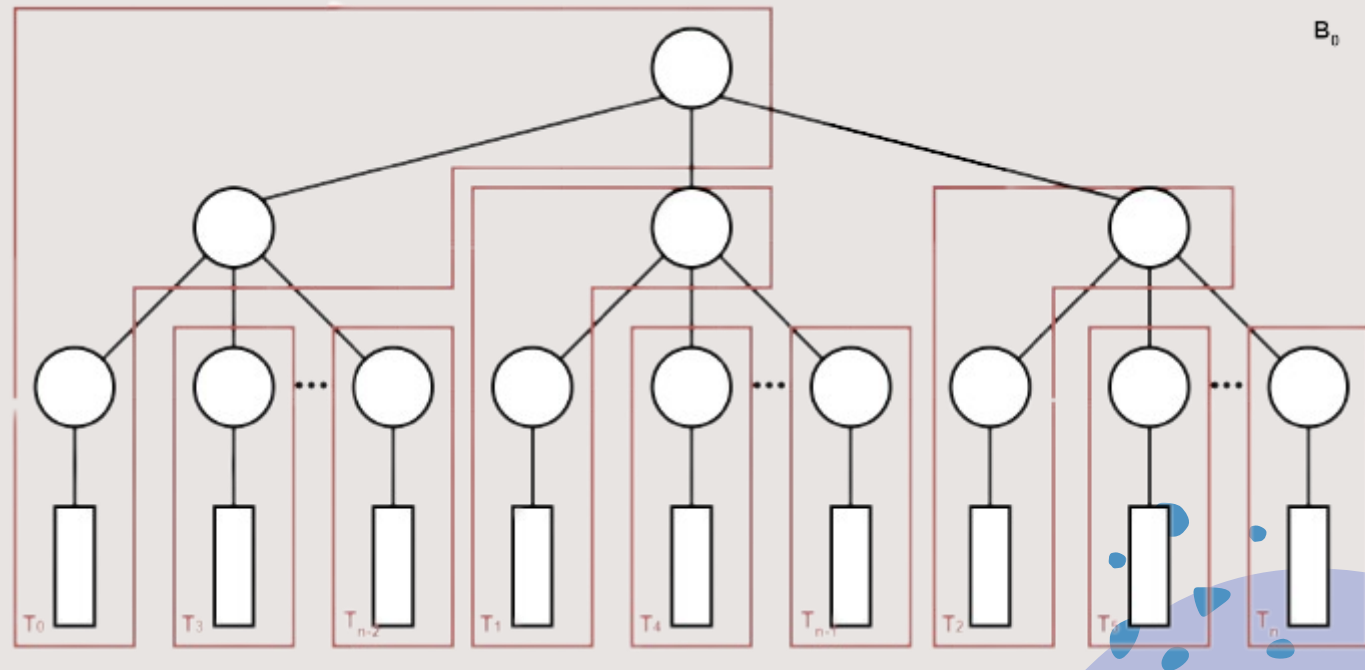


Value: -1, 1

## *V3 – More levels in shared memory*

The third version tries to achieve a **higher level of parallelism**:

- One level of tree search removed from stack.
- Square the threads.
- Several results arrays in the *shared memory*.
- Each block evaluates one child nodes for each thread.



# *V4 - Memory transactions reduced*

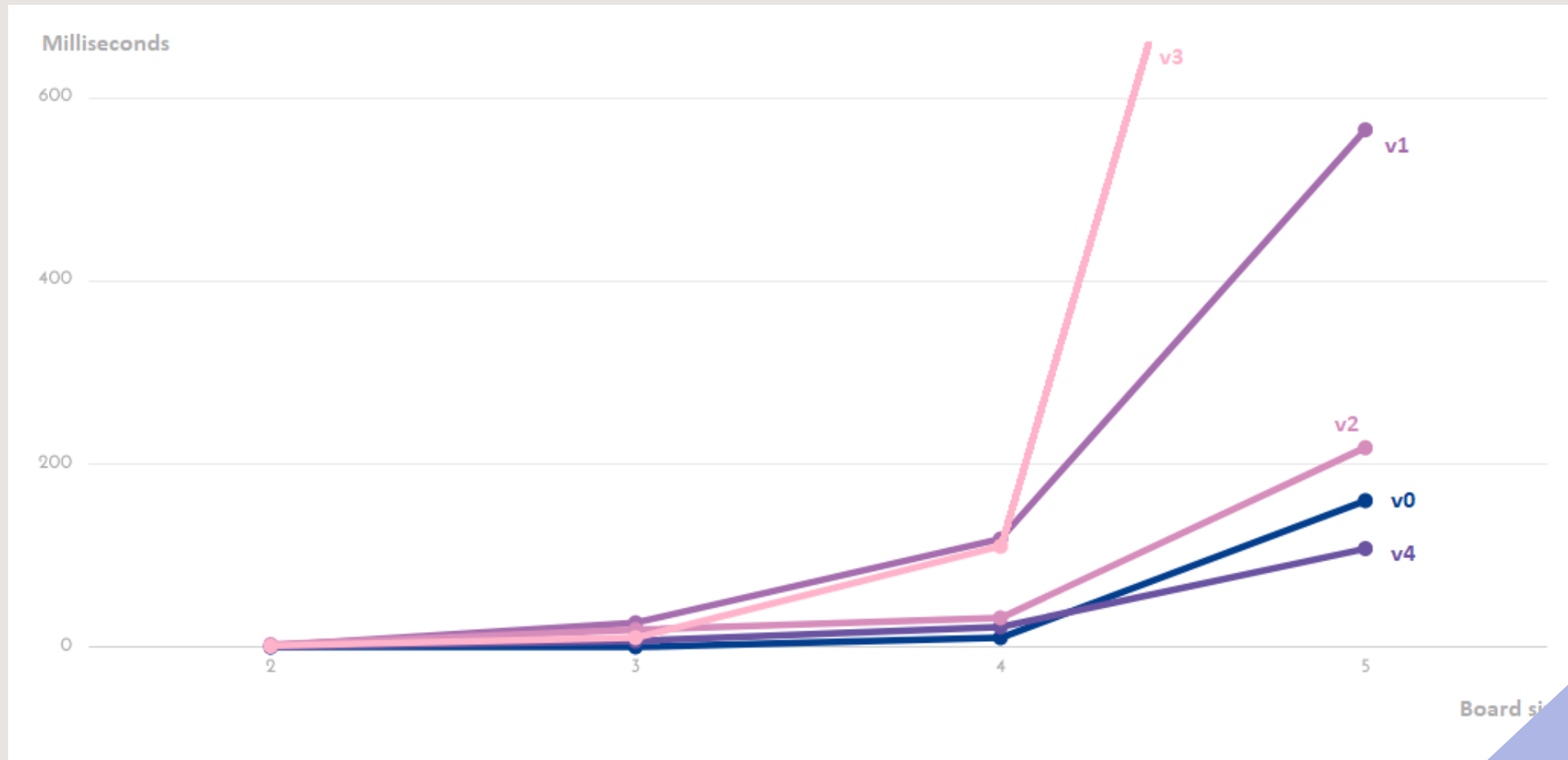
The fourth version tries to remove the overhead added by the **memory transactions between the host and the device**:

- Based on v2
- The kernel starts from the very first game state
- The optimal move is returned



# *Results and Analysis*

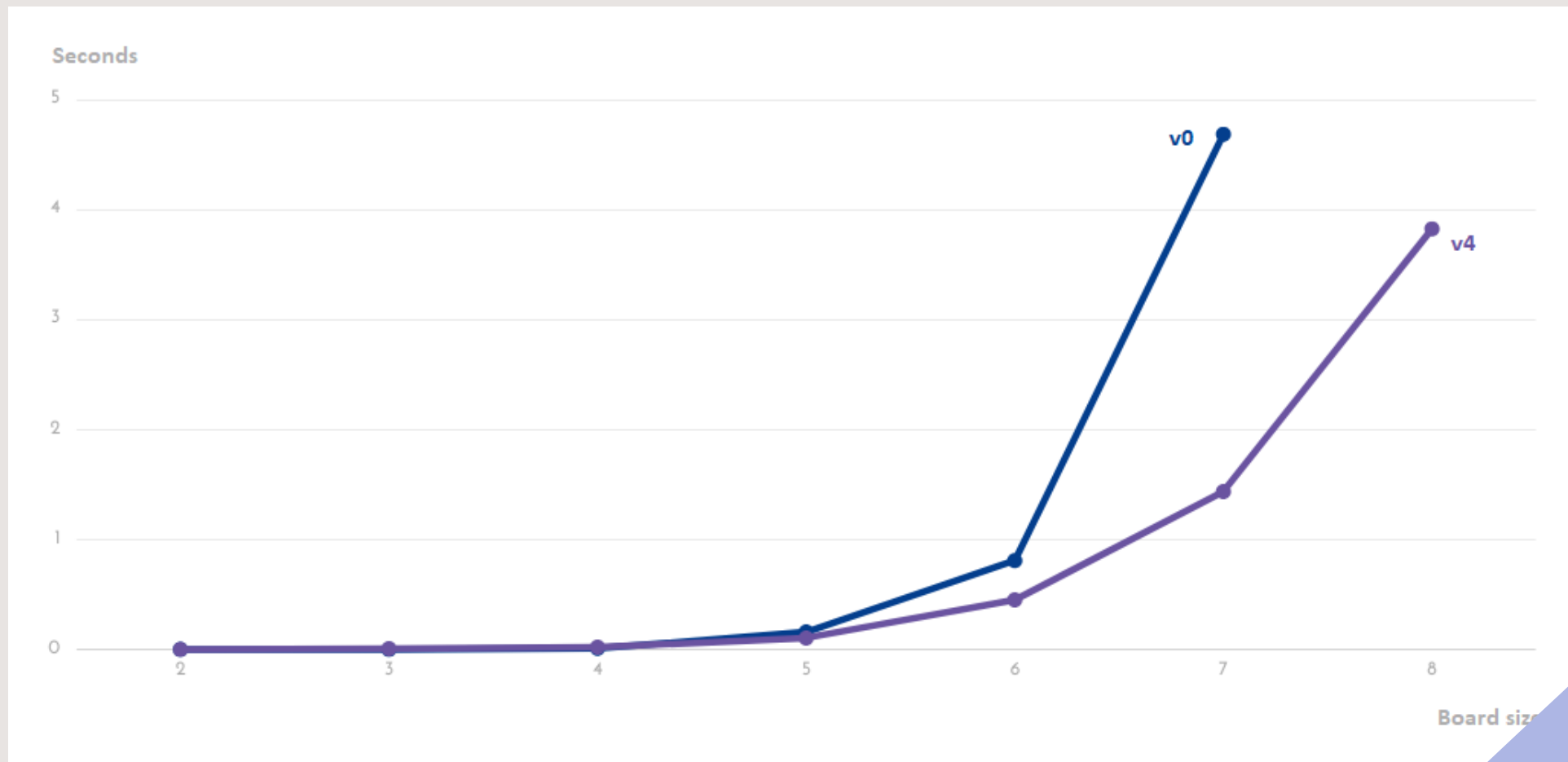
**Duration** in *milliseconds* of the minmax algorithm for different board sizes. The maximum depth was set to 7.





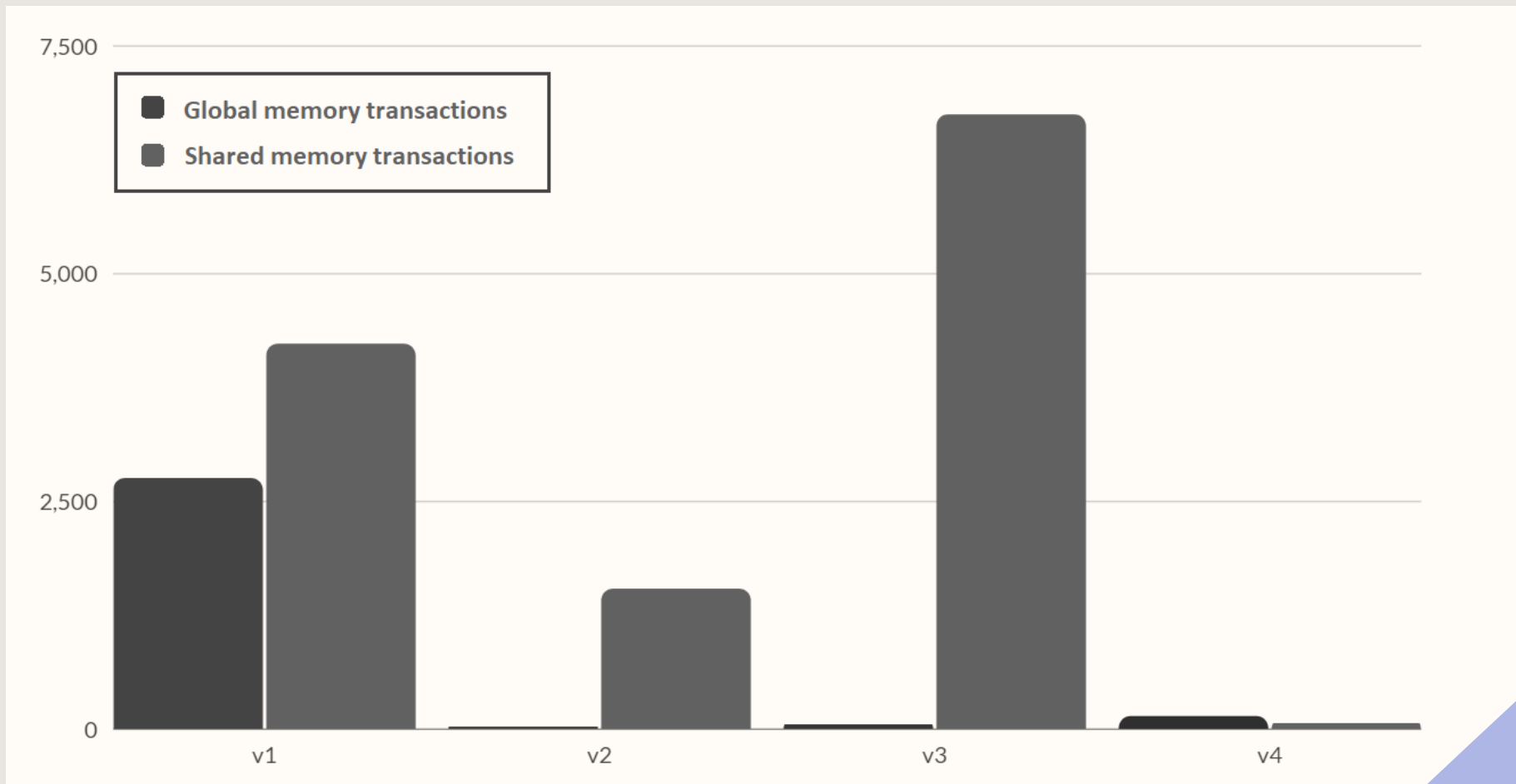
# *Results and Analysis*

**Duration** in *milliseconds* for different board sizes. The best version (v4) is compared with the base one.



# *Results and Analysis*

Comparison between the number of **global and shared transactions** (read and write) with a board of 5 rows.



# *Results and Analysis*

Some observations:

- Between v1 and v2, the **global transactions** decreased by 98.98%, while the **shared** ones decreased by 63.65%.
- Despite the **higher level of parallelization**, v3 performs too many transactions in the shared memory.
- The **global transactions** between v4 and v2 increased, but the **shared** and the **host-device** ones decreased, leading to better performances.



# *Results and Analysis*

Some observations:

- The algorithm resulted extremely efficient for bigger boards, while the **GPU resources** are underused on smaller boards.
- One of the main problems of these implementation is the **warp divergence**.
- The used **GPU technology** is not able to perform a full create-and-search tree algorithm, without setting up a maximum explorable depth.



# *Conclusion*

---

The GPU is able to calculate the optimal move **faster** than the CPU for almost all the board sizes, despite the relatively **low complexity** of the Nim game.

Some possible new implementations:

- Parallelize the **evaluation function**
- **Remove** the standard minmax from the threads
- Extend the number of **threads**
- **Split the tree** search between the host and the device







# *The end*

---

Thank you for your attention!