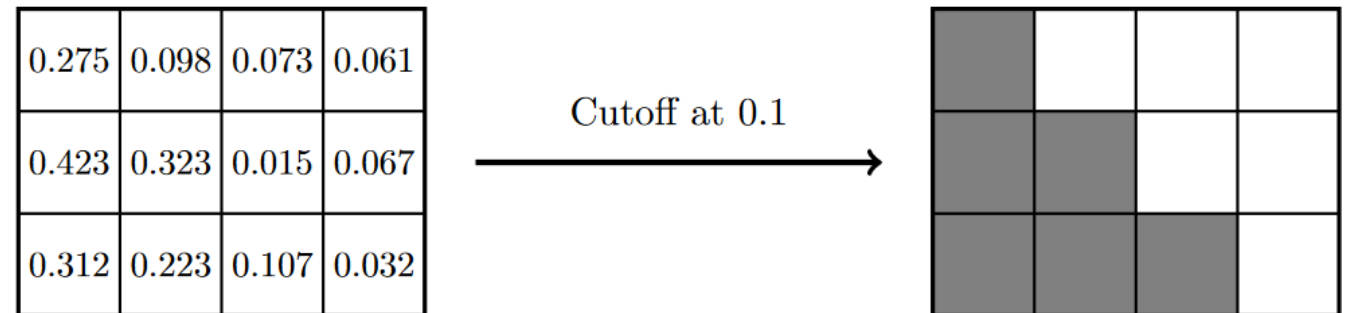
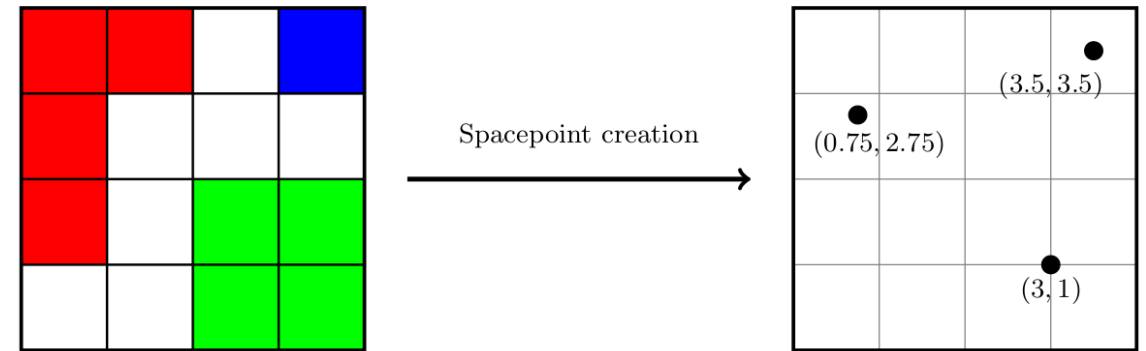
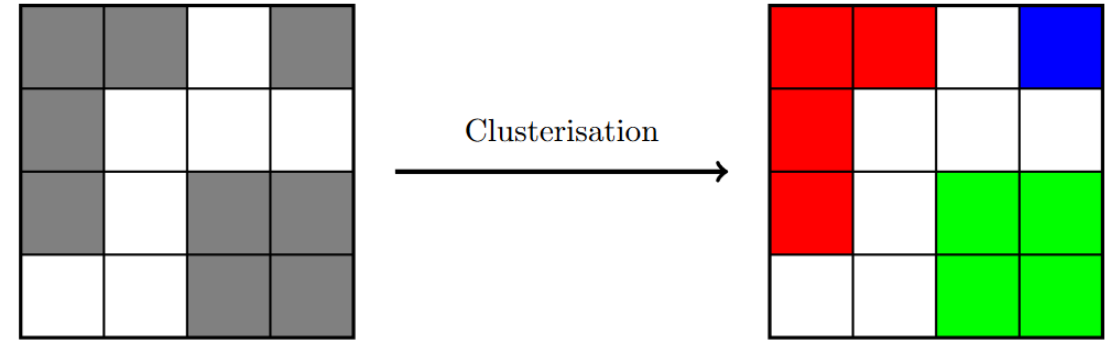


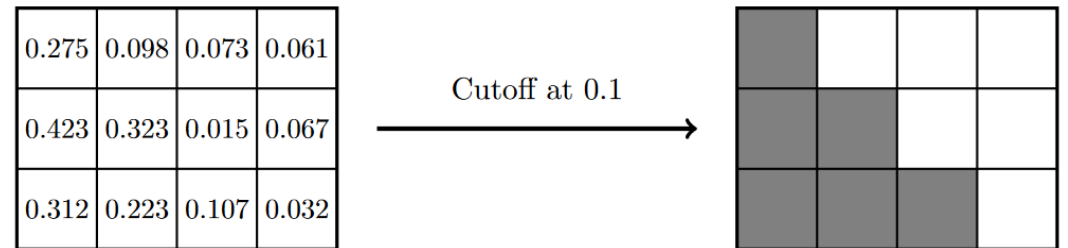
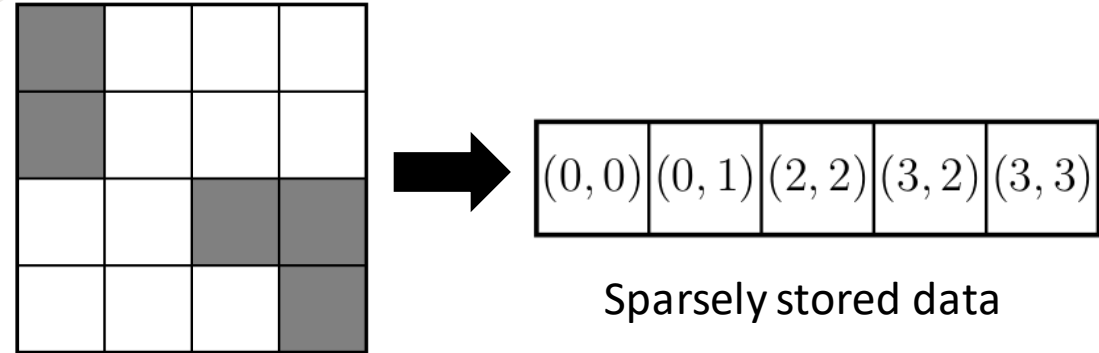
# ATLAS Phase 2 Upgrade: Cell-wise parallelisation of the clusterisation algorithm in tracc

# Clusterisation

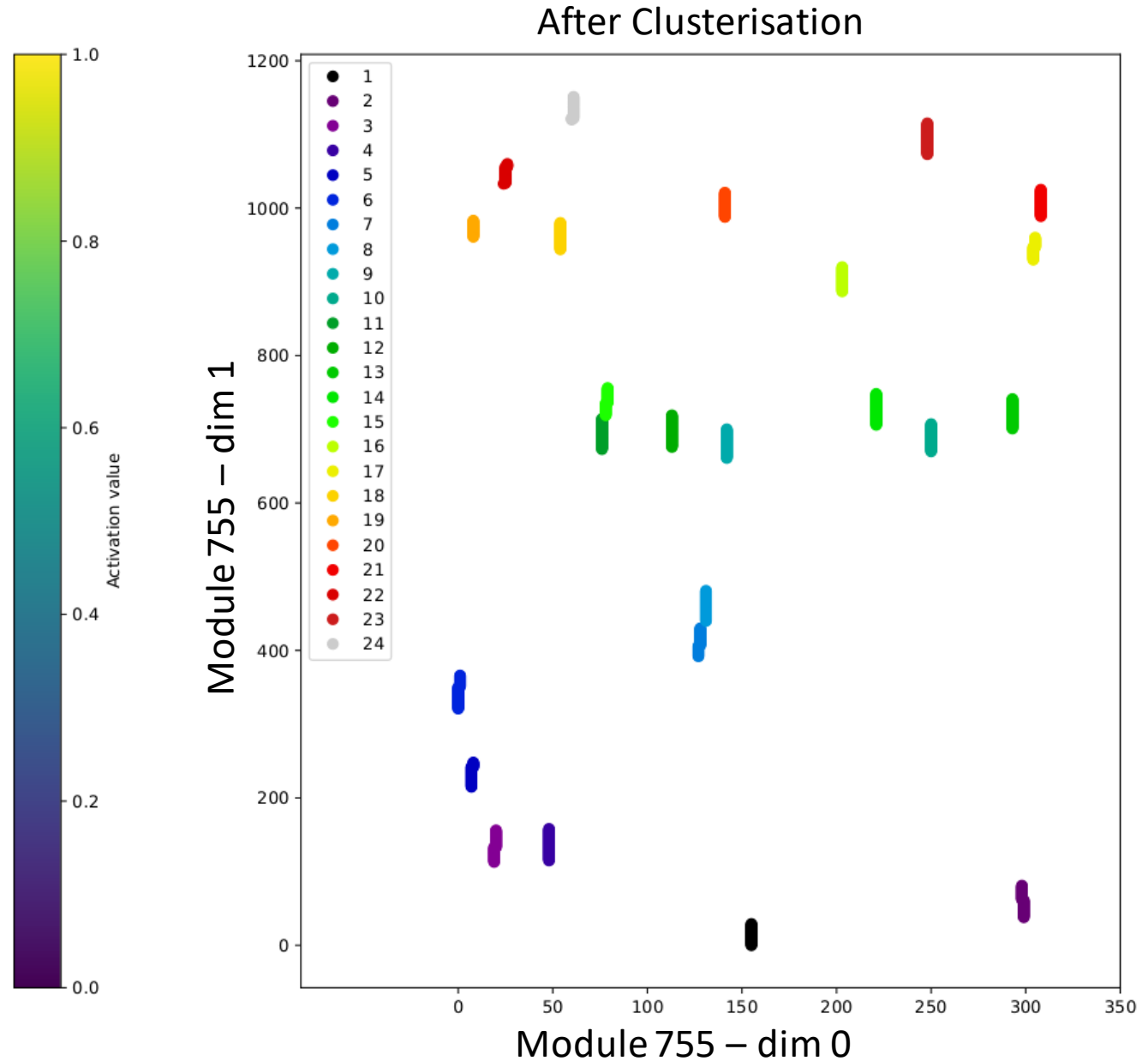
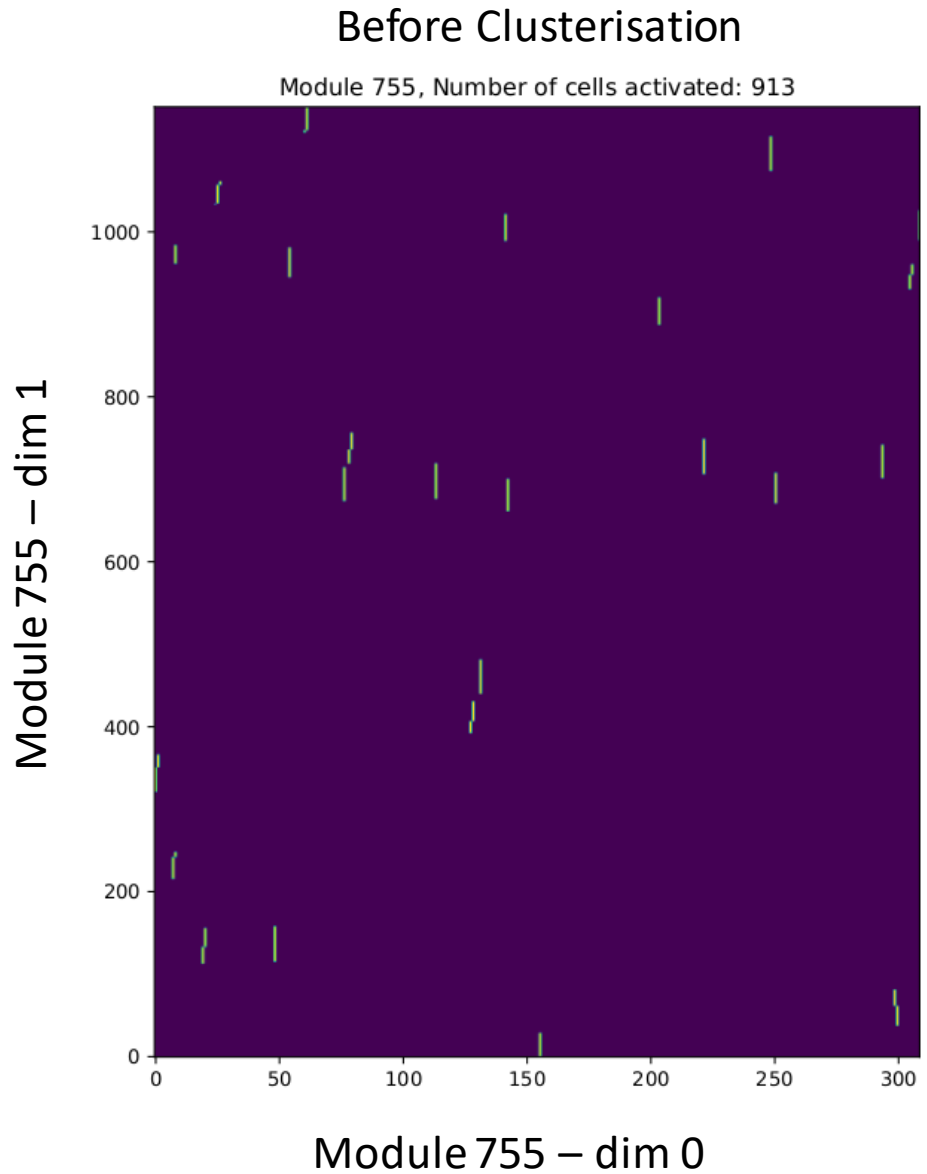


# The tracc project – Parallelising Tracking

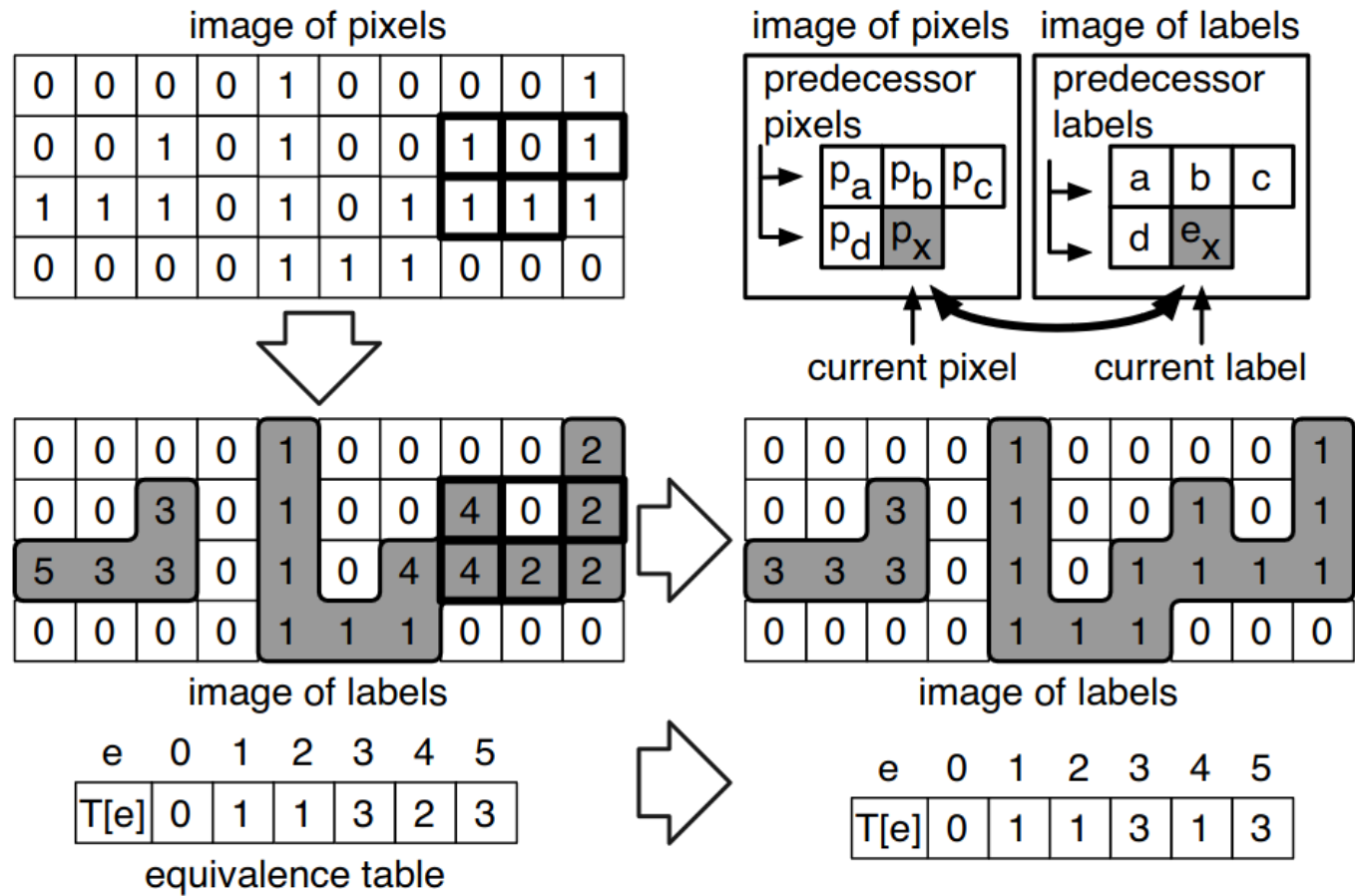
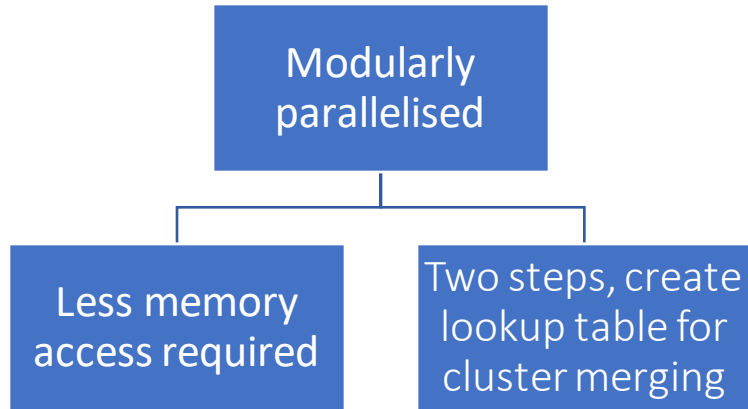
- Some GPU Terminology:
  - **Graphics Processing Unit**
  - Optimised for SIMD: Single Instruction, Multiple Data
  - The whole GPU is called a **grid**, which is made up out of **blocks**.
    - Each instance is called a **thread**, keyword: "multithreading"
    - **Blocks** contain **threads**
      - Optimised to be a multiple of 32
      - User specifiable
      - Inter-block communication is slow
      - Intra-block communication is fast
  - e.g. Change activation values to binary "Activated"/"Not activated"
  - Cell data in *tracc* is stored sparsely



# Example from Simulation in *tracc* – Figures

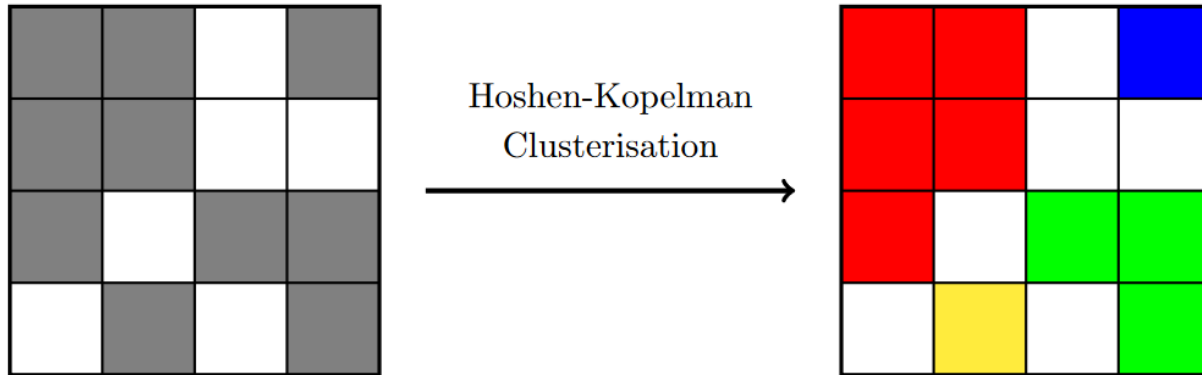


# Sparse CCL



[1]

# Hoshen-Kopelman

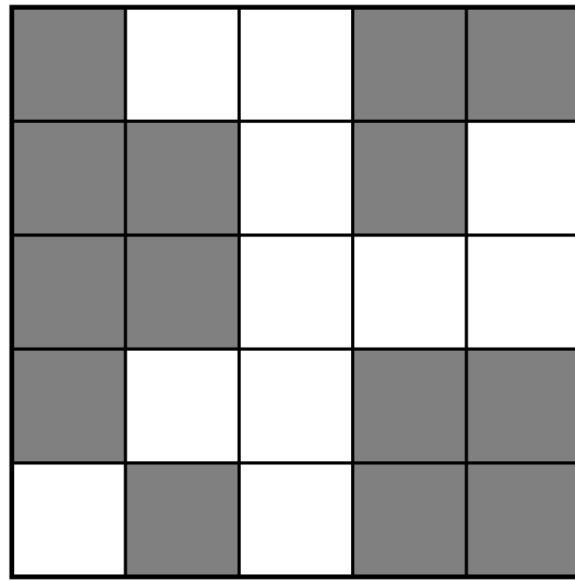


**Every cell belongs to the same cluster as all its nearest neighbours** <sup>[2]</sup>

For each cell:  
Check above and left only, no diagonals.

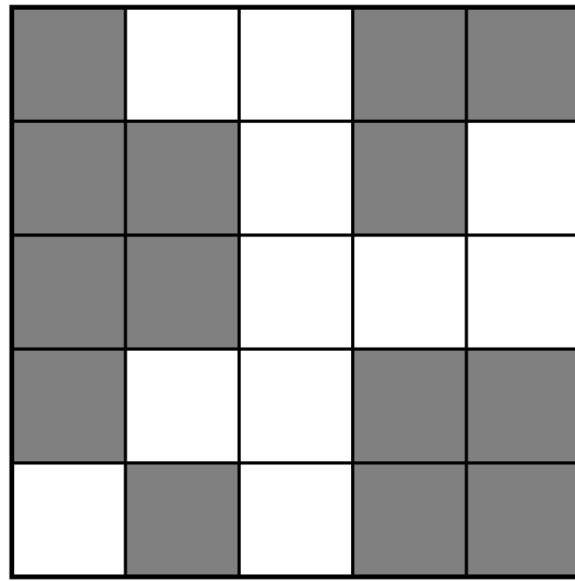
- Extended version:
- Inaccuracies with missing long stripes
  - ➔ Include diagonals
    - Clusterisation accuracy jumps from  $\approx 85$  to  $\approx 98.5\%$

FCONN:  
Parallelised  
Hoshen-  
Kopelman

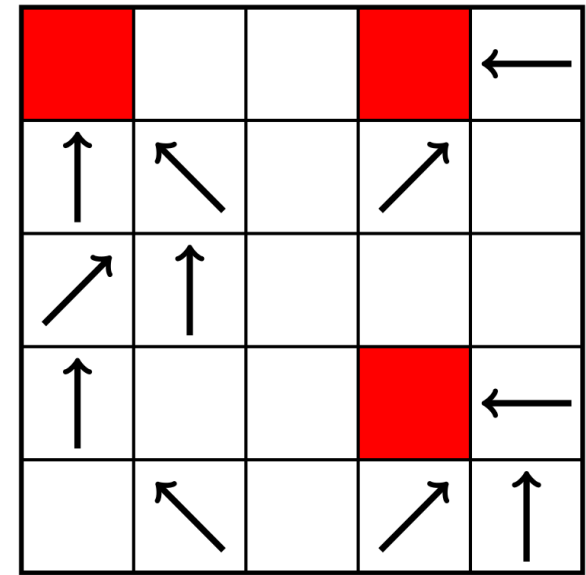


# FCONN: Parallelised Hoshen- Kopelman

## Step 1



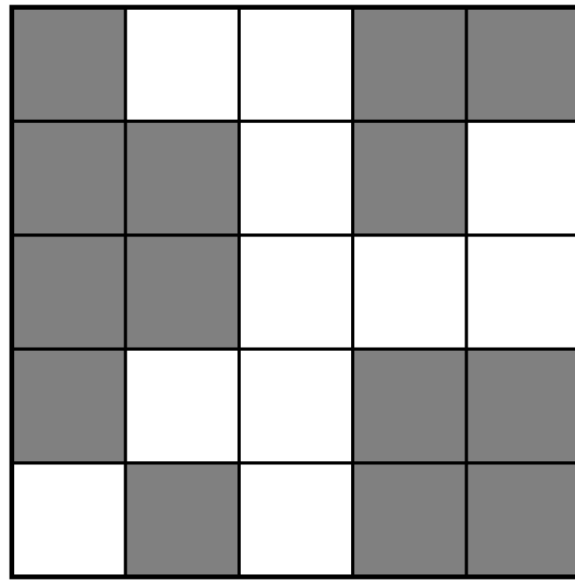
a) FCONN →



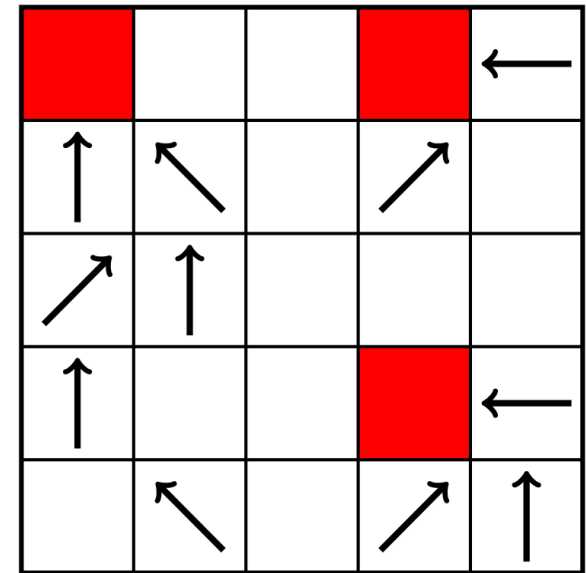


# FCONN: Parallelised Hoshen- Kopelman

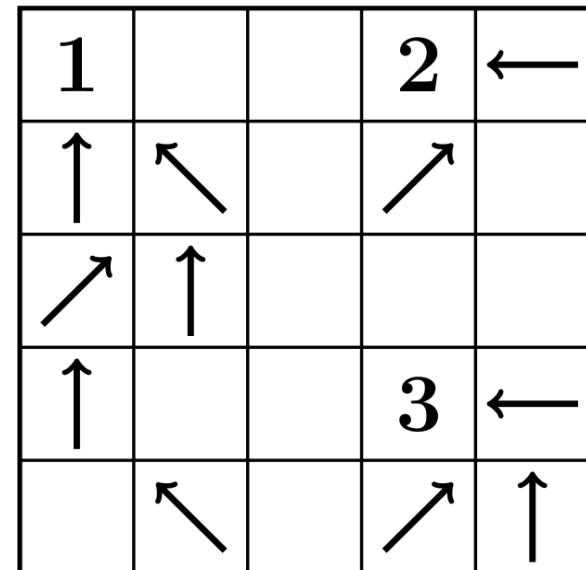
## Step 2



a) FCONN

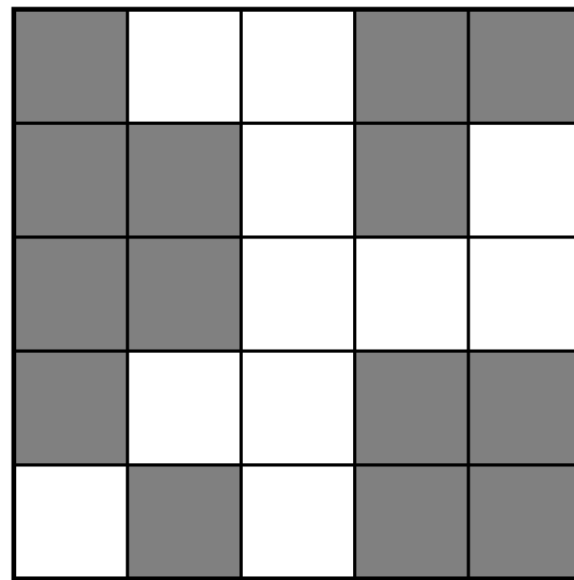


b) label origins

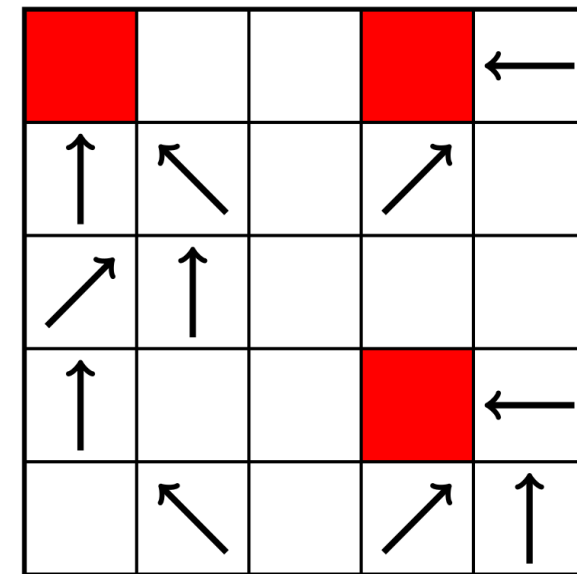


# FCONN: Parallelised Hoshen- Kopelman

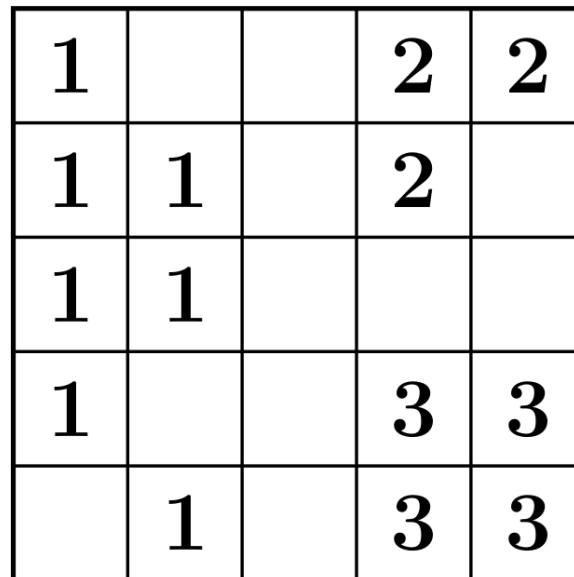
## Step 3



a) FCONN →



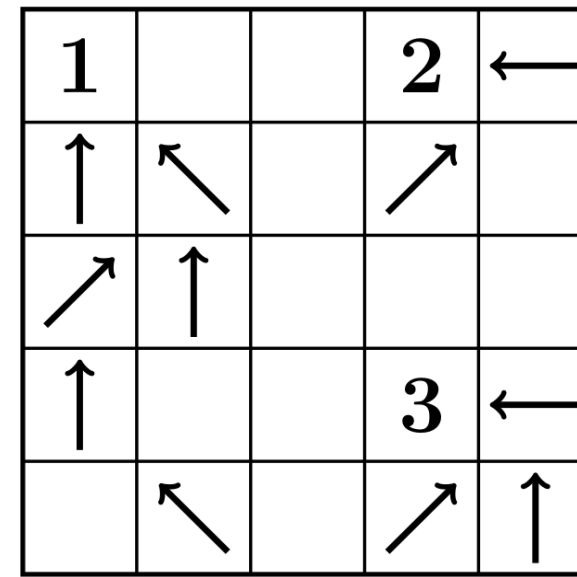
full clusterisation with  
extended FCONN



c) trace back ←

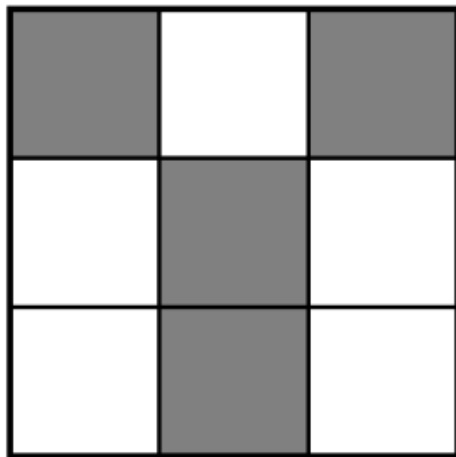


b) label origins

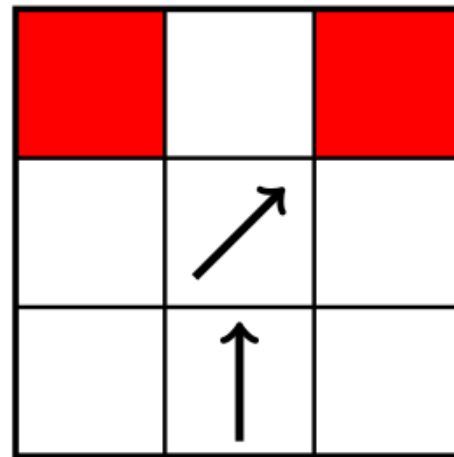


# FCONN Inaccuracy or Extra Accuracy?

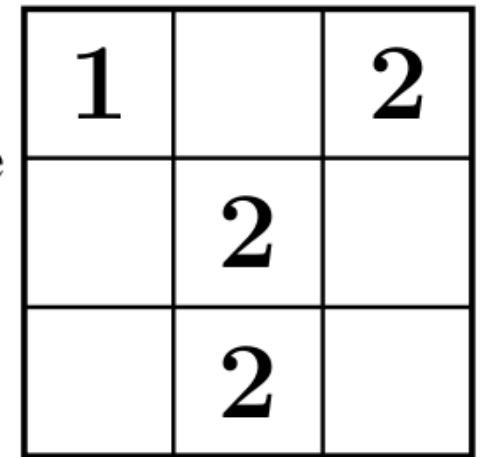
- Sparse particle hits: Worse
- Dense particle hits: Might be better?



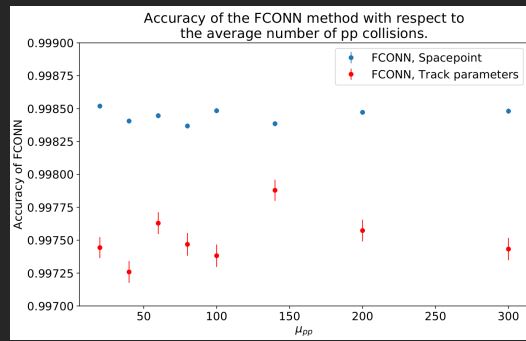
FCONN  
→



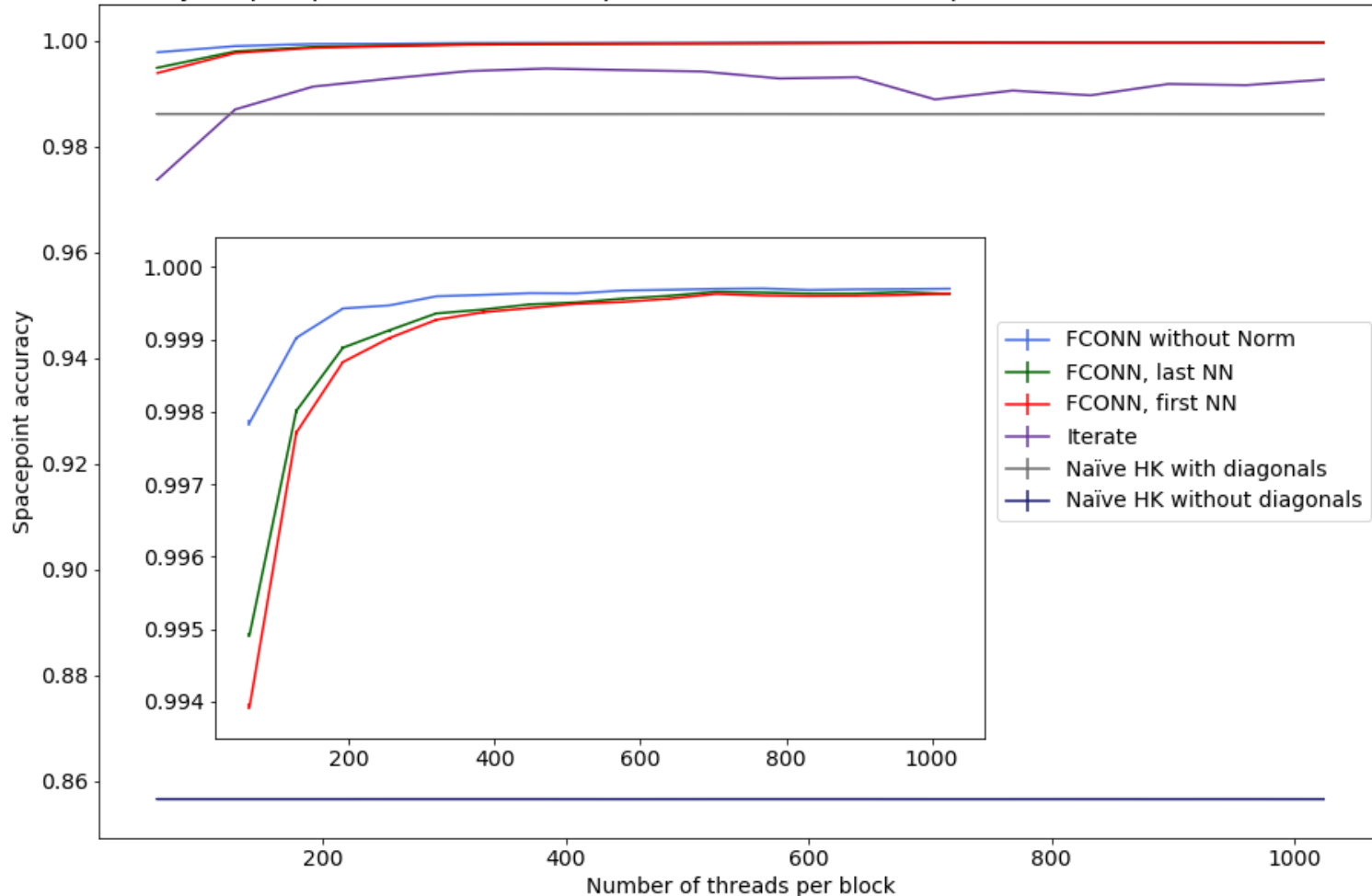
Label and Trace  
→



# Results – Accuracy

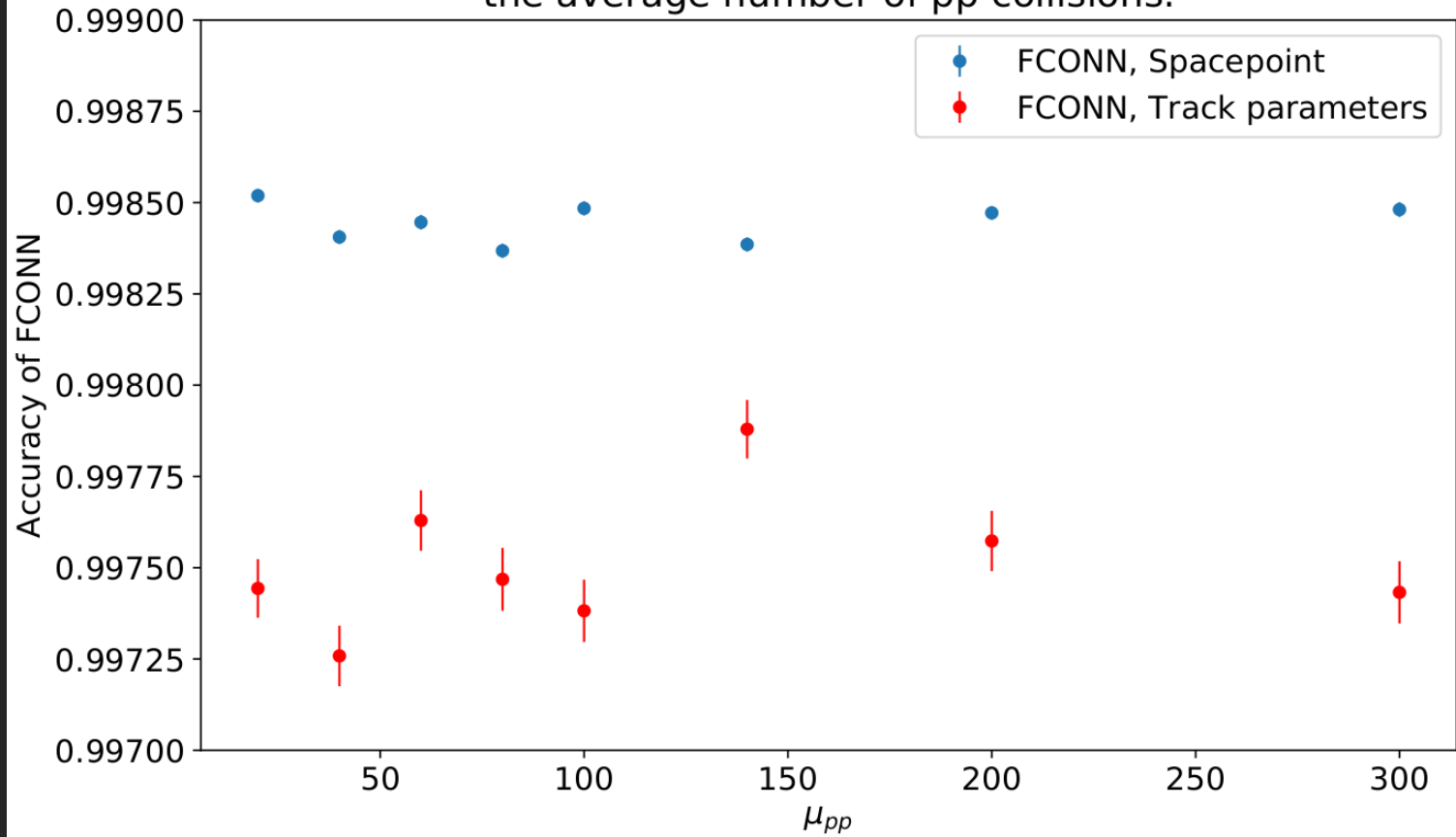


Accuracy of spacepoint creation with respect to number of threads per block for all considered models



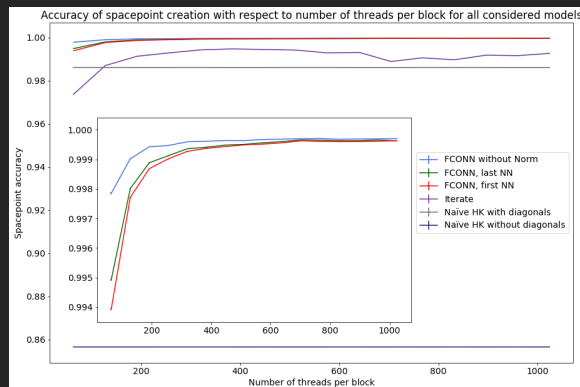
- Smaller benchmarking dataset
- Comparison of methods
- Accuracy performed against the number of threads per block

Accuracy of the FCONN method with respect to the average number of pp collisions.



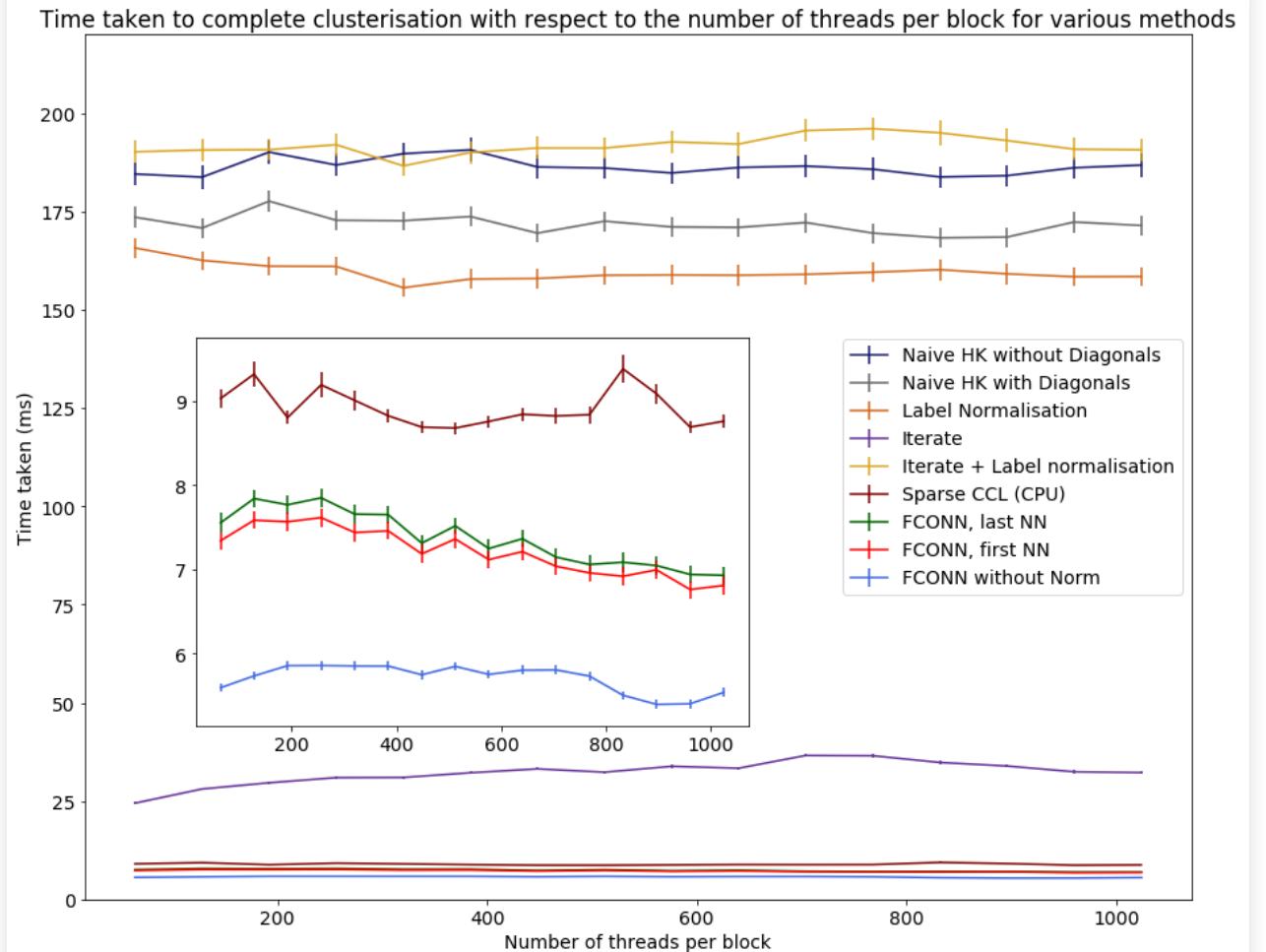
# Results – Accuracy

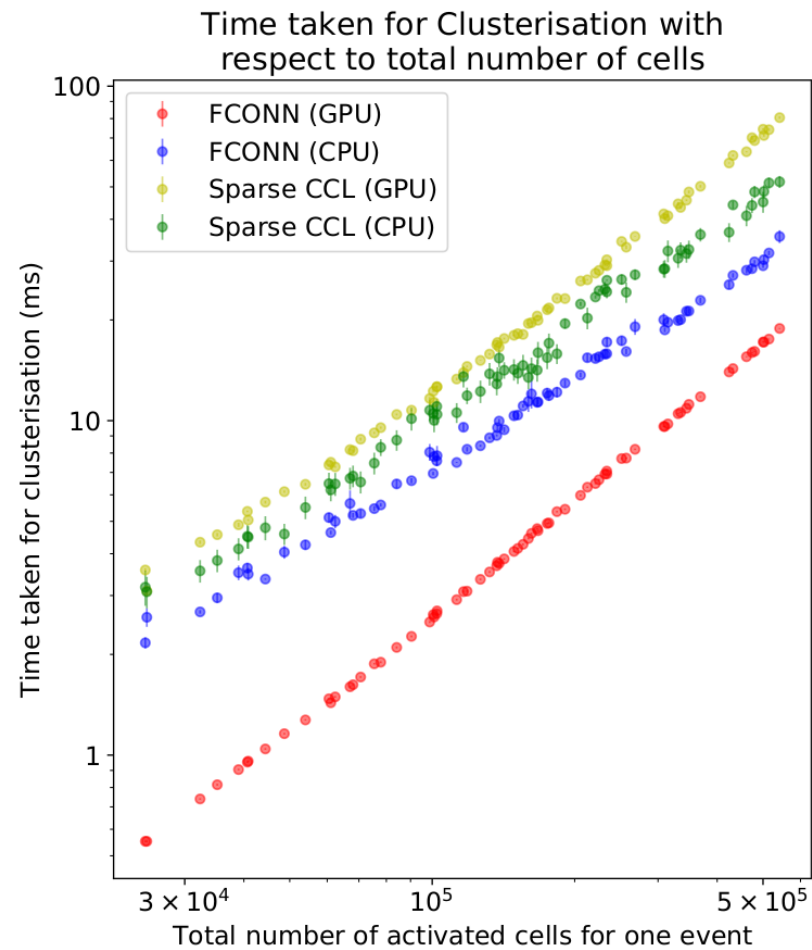
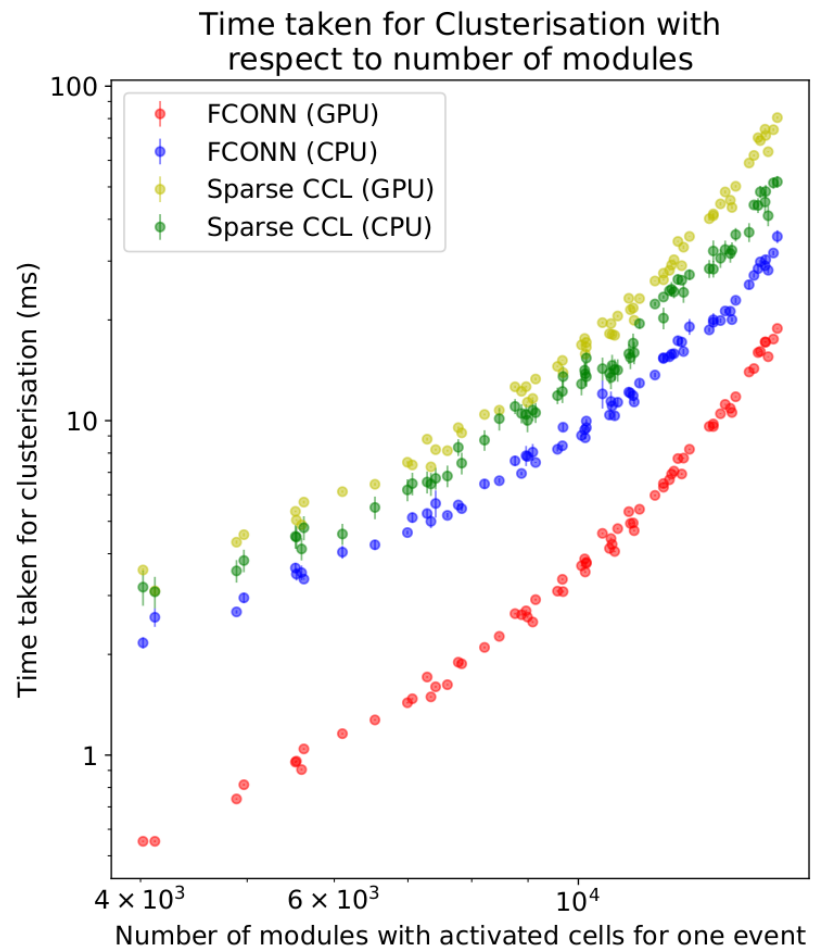
- Extended datasets with varying  $\mu$
- Comparison of Sparse CCL with FCONN only



# Results – Time performance

- Smaller benchmarking dataset
- Comparison of methods

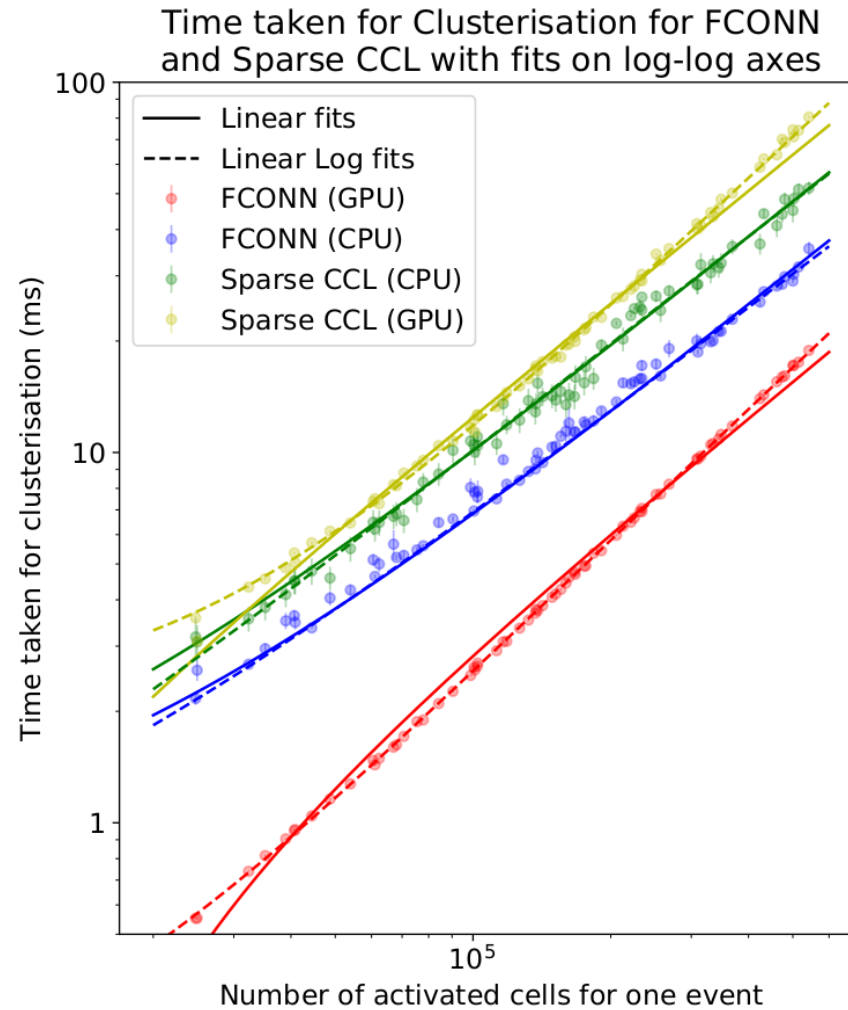
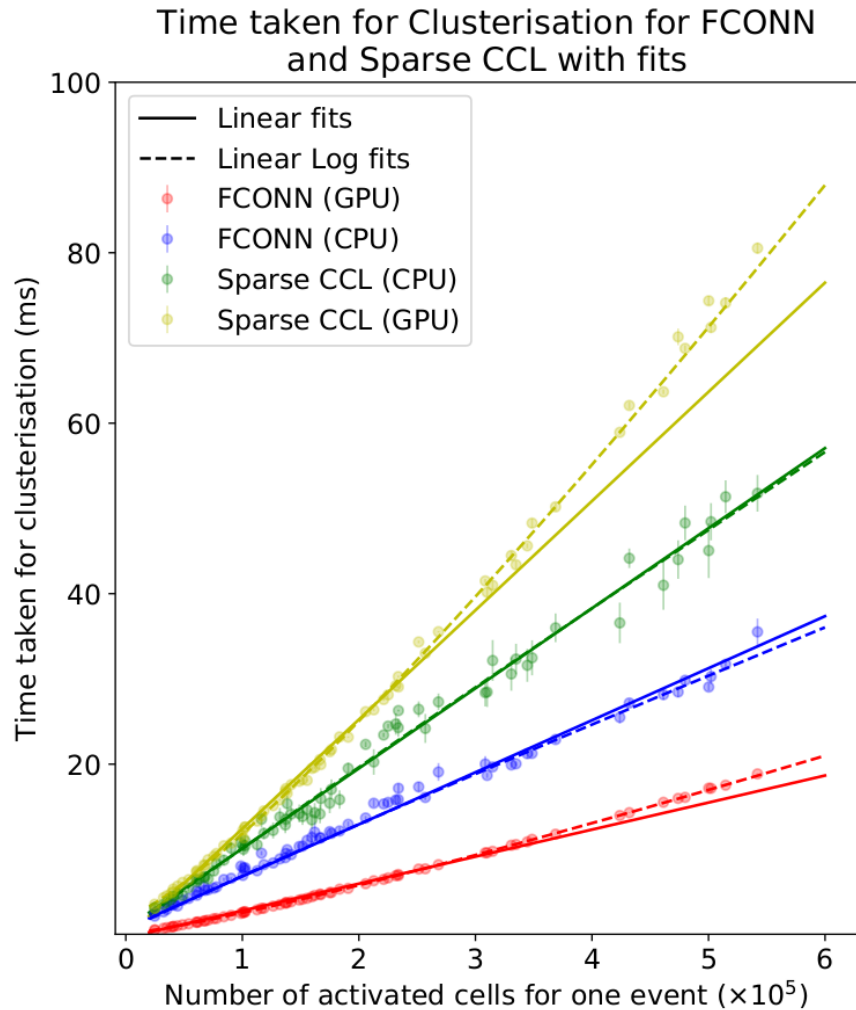




## Results – Time performance

- Extended datasets with varying  $\mu$
- Comparison of Sparse CCL with FCONN only

# Result Fitting – Cells



GPU implementation:  $O(n \log(n))$

CPU implementation:  $O(n)$

Why?  
Clusterisation an inherently iterative problem?

➔ CPU hardware (cache focused) outperforms GPU hardware (data processing focused)



# Summary and Future extensions

- Clusterisation is a GPU bottleneck
  - FCONN improves time performance compared to Sparse CCL for all probed  $\mu$ 
    - Factor  $3.22 \pm 0.29$  vs CPU for  $\mu = 200$
    - Factor  $4.37 \pm 0.44$  vs GPU for  $\mu = 200$
  - FCONN retains high accuracy throughout
    - Stays constant as a function of  $\mu$
  - However: GPU concedes a factor of  $\log(n)$  in runtime with respect to number of cells. Is it possible to reduce the asymptotic time performance on GPU?
- Possible improvements
- Takeaways

# Summary and Future extensions

- Clusterisation is a GPU bottleneck
- Possible improvements
  - FCONN
    - Reduce the number of lookups in global memory
      - GPU: Fast processing, slow lookup: Focus on processing
      - CPU: Slow processing, fast lookup: Focus on caches
    - More in depth analysis with NVIDIA profiling tool to see where time inefficiencies arise
  - General
    - Study the theoretical limit: Why are the GPU implementations asymptotically slower than the same implementations on CPU? Is it because of the memory management or is it more inherent and will exist in other methods too?
    - Study a potential interplay of CPU and GPU:
      - Modules with smaller number of activated cells: GPU
      - Modules with larger number of activated cells: CPU
- Takeaways

# Summary and Future extensions

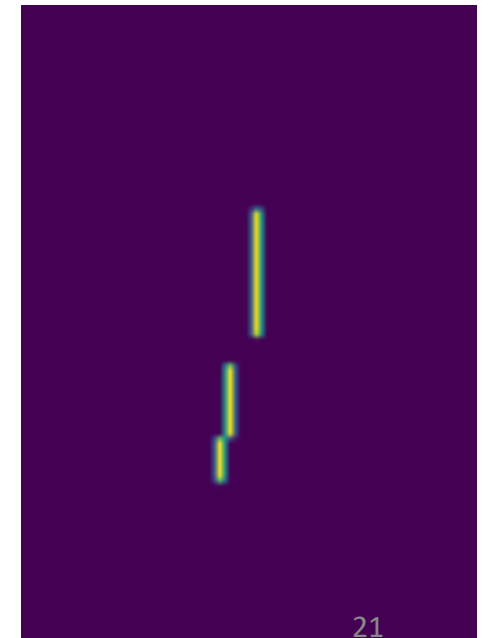
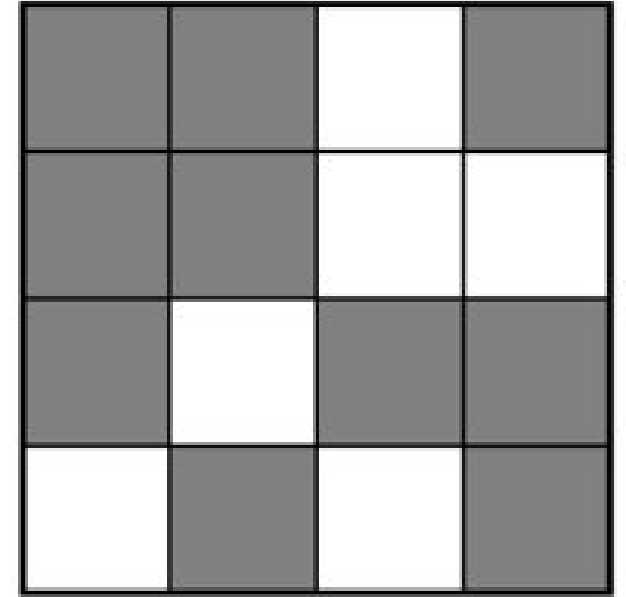
- Clusterisation is a GPU bottleneck
- Possible improvements
- Takeaways
  - GPU methods valuable for track reconstruction
  - FCONN is an improvement in the  $\mu$  ranges that are experimentally relevant
  - Viability of GPU programming methods proven: Future development essential

# References

- [1] *Arthur Hennequin, Ben Couturier, Vladimir V. Gligorov, and Lionel Lacassagne*. Sparse-CCL: Connected components labeling and analysis for sparse images. In 2019 Conference on Design and Architectures for Signal and Image Processing (DASIP), pages 65–70, 2019.
- [2] *Hoshen, J.; Kopelman, R.* (15 October 1976). "[Percolation and cluster distribution. I. Cluster multiple labeling technique and critical concentration algorithm](#)". *Phys. Rev. B*. **14** (8): 3438–3445. [Bibcode:1976PhRvB..14.3438H](#). [doi:10.1103/PhysRevB.14.3438](#) – via APS.

# Troubles with parallelisation

- Inconsistent number of cells per module
  - Cannot effectively launch 2D threads
  - Need lookup table for module by cell
    - Global Memory access -> Spatial and time inefficiency
- Cells cannot interact efficiently
  - Purpose of effective parallelism is SIMD
    - "Single Instruction, Multiple Data"
  - Checking for neighbours for every cell is inconsistent
  - Overwriting neighbours is dangerous
- Solve by just checking half the neighbours and iterating
  - Only overwrite "yourself" -> No cross-writing issues
  - Slow, many threads idling



# Iterative Hoshen-Kopelman

- Choose neighbour above/left with diagonals
  - Consistent neighbour selection rule, e.g. first, last, lowest label etc.
    - Example below is with lowest neighbour label selection rule
  - Always write from that neighbour
  - Iterate until no more changes between states

<b>6</b>	<b>7</b>		<b>8</b>
<b>4</b>			
<b>1</b>		<b>5</b>	<b>9</b>
		<b>4</b>	<b>2</b>

Iter 1  
→

<b>6</b>	<b>6</b>		<b>8</b>
<b>6</b>			
<b>4</b>		<b>5</b>	<b>5</b>
		<b>5</b>	<b>4</b>

Iter 2  
→

<b>6</b>	<b>6</b>		<b>8</b>
<b>6</b>			
<b>6</b>		<b>5</b>	<b>5</b>
		<b>5</b>	<b>5</b>

# Fitting – Modules

