

OCELOT: LARGE TRACE OVERVIEWS BASED ON MULTIDIMENSIONAL DATA AGGREGATION

OCELOT: CLOSE ENCOUNTERS OF THE THIRD KIND

8th International Parallel Tools Workshop
1st October 2014

Damien Dosimont^{1 2}, Youenn Corre^{1 2}, Lucas M. Schnorr³,
Guillaume Huard^{2 1}, Jean-Marc Vincent^{2 1}

¹ Inria,
first.last@inria.fr,
² Univ. Grenoble Alpes, LIG, CNRS, F-38000 Grenoble, France
first.last@imag.fr
³ Informatics Institute, UFRGS, Porto Alegre
schnorr@inf.ufrgs.br



INTRODUCTION

TRACE VISUALIZATION PROBLEMATIC

► Trace contents:

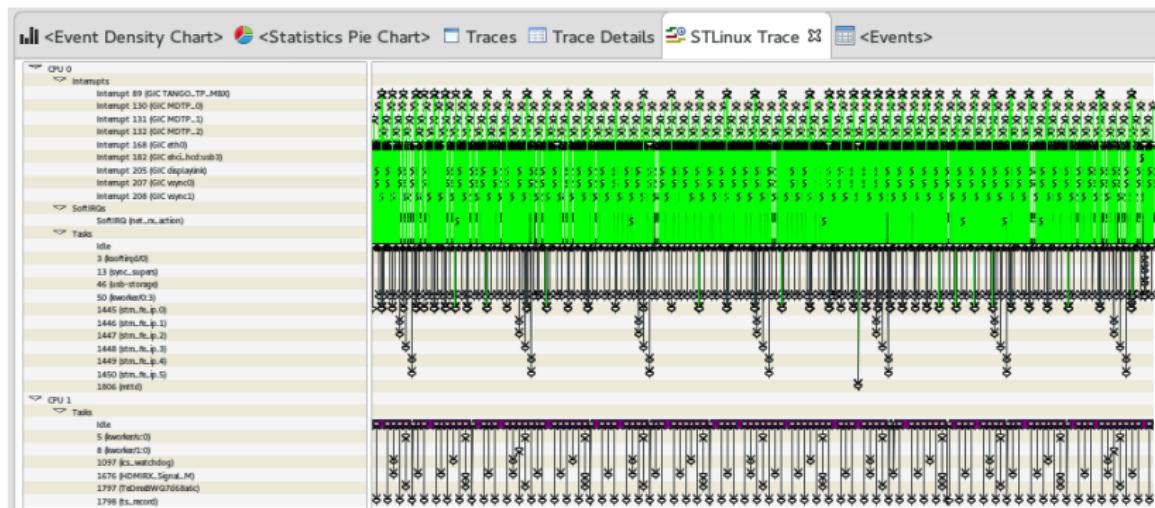
- **SPACE** = application structure:
 - ▶ **hardware** components: *clusters, machines, cores, etc.*
 - ▶ **software** components: *processes, threads, etc.*
- **TIME** = timestamped events:
 - ▶ *function calls, communications, CPU load, malloc, etc.*

► Traces can be **HUGE**

→ **scalability issues** of space-time representations



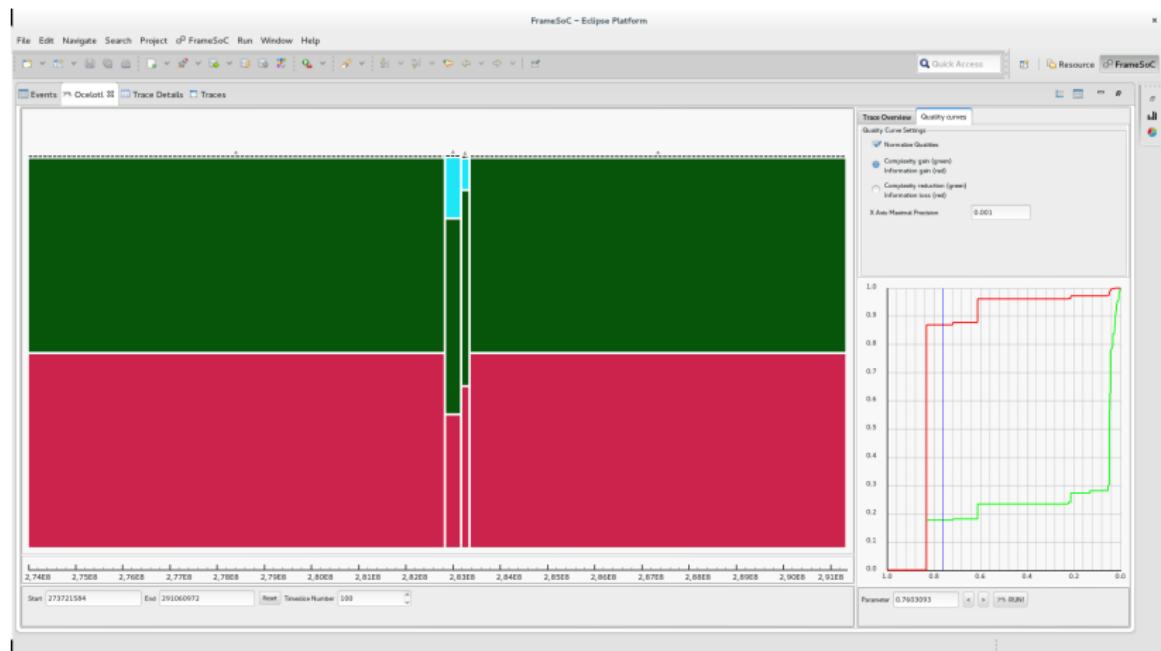
PROBLEMATIC VISUALIZATION



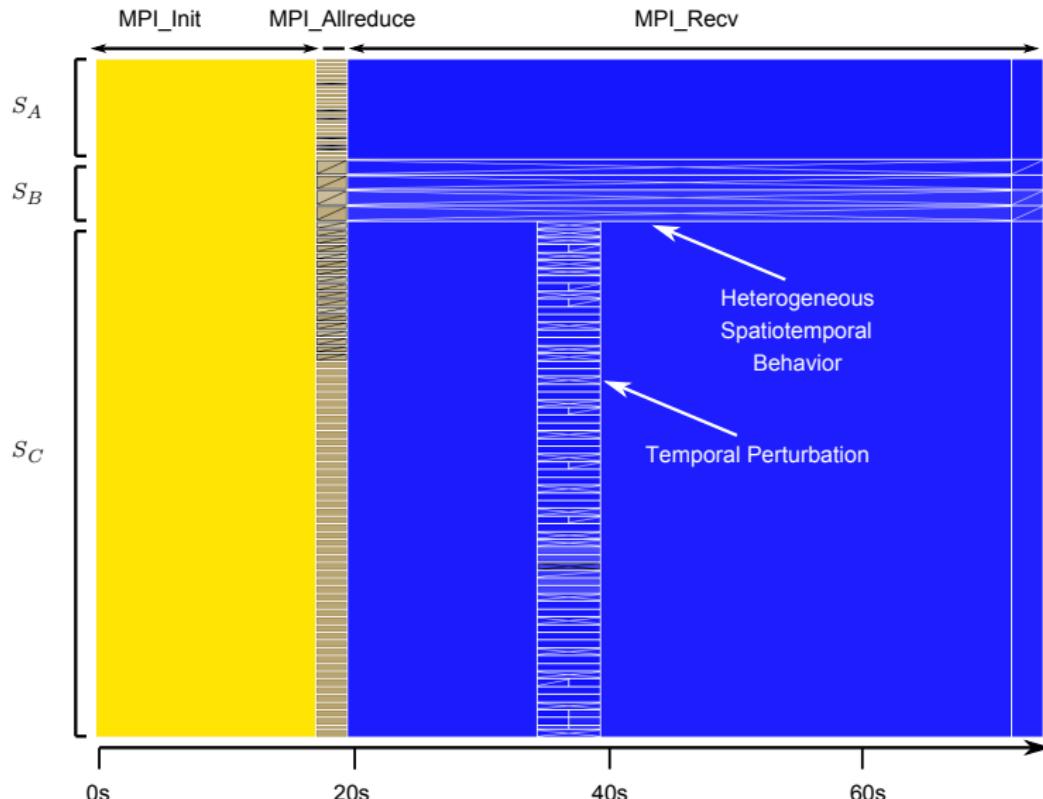
OUR PROPOSAL MULTIDIMENSIONAL OVERVIEWS

- ▶ Several overviews generated thanks to **data aggregation**
 - Temporal
 - Spatiotemporal
- ▶ Showing **meaningful information** (phases, perturbations)
- ▶ Possibility to adjust dynamically the **level of details**

EXAMPLE : TEMPORAL OVERVIEW

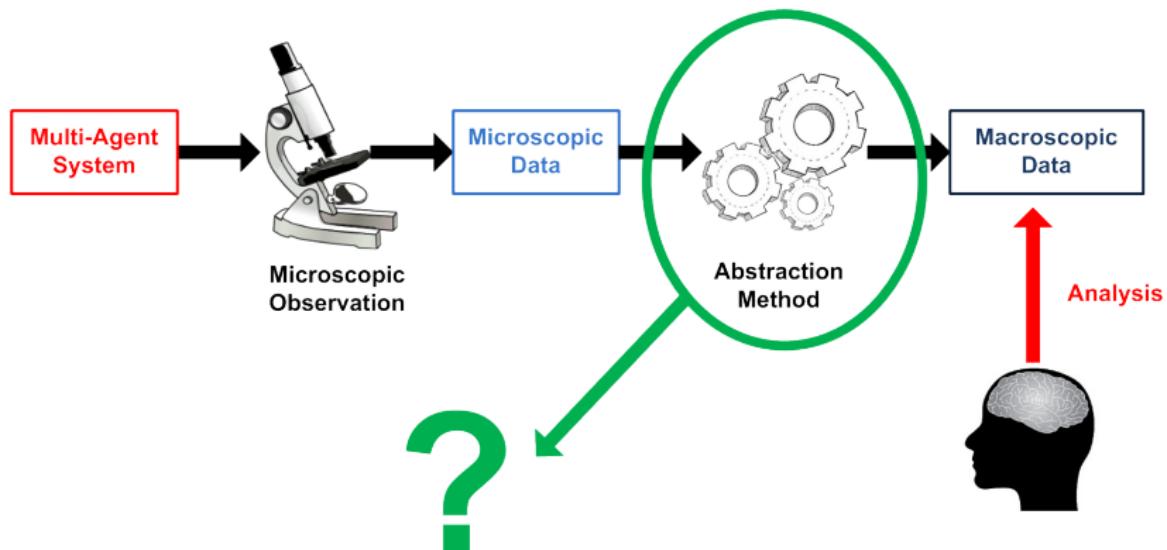


EXAMPLE : SPATIOTEMPORAL OVERVIEW

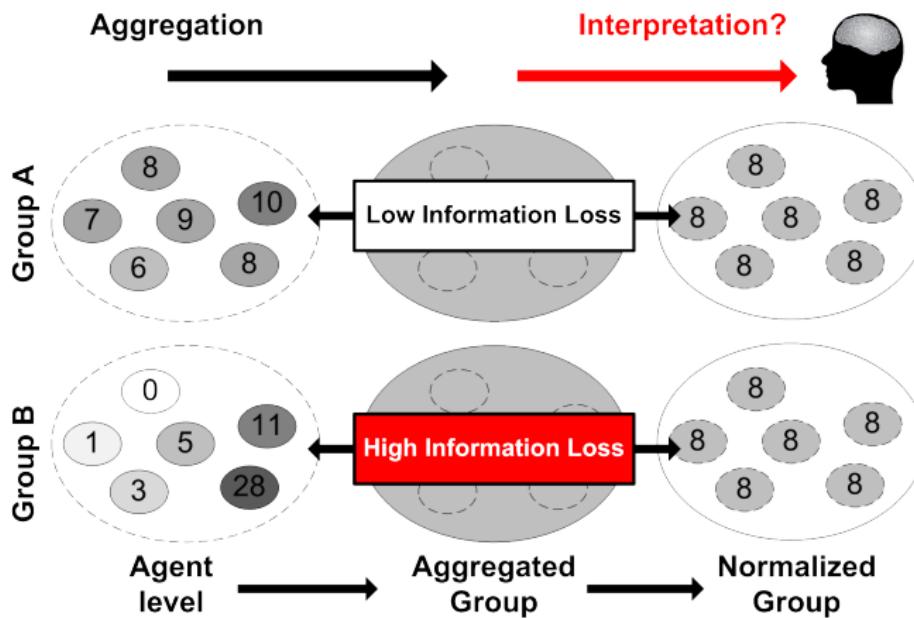


THEORETICAL BACKGROUND : LAMARCHE-PERRIN METHODOLOGY

ADAPTING AN AGGREGATION METHODOLOGY

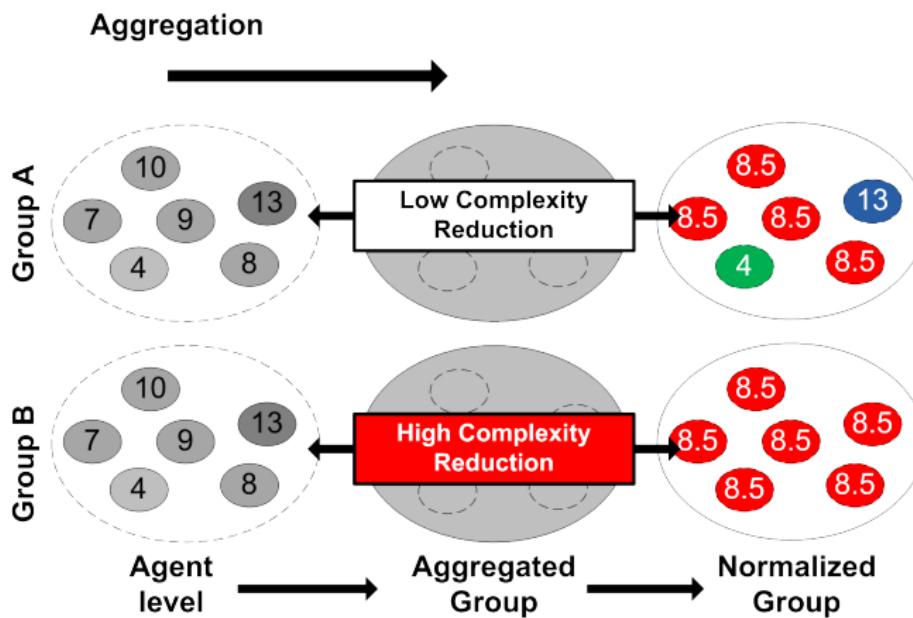


INFORMATION LOSS: KL DIVERGENCE



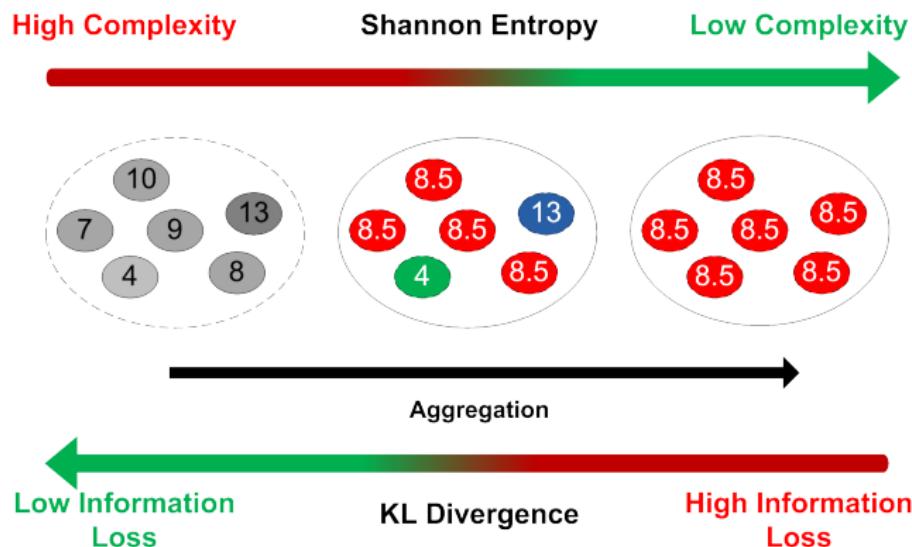
$$\text{loss}_E = \sum_{e \in E} \rho_e \log_2 \left(\frac{\rho_e}{\rho_E} \right)$$

COMPLEXITY REDUCTION: SHANNON ENTROPY



$$\text{gain}_E = \rho_E \log_2 \rho_E - \sum_{e \in E} \rho_e \log_2 \rho_e$$

TRADE-OFF: PIC



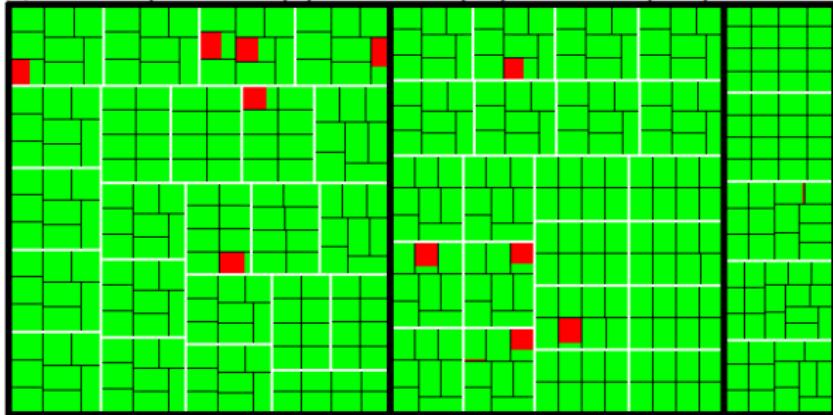
$$\text{pIC}_E = p \text{gain}_E - (1-p) \text{loss}_E$$

$$\text{pIC}_{\mathcal{P}} = \sum_{E \in \mathcal{P}} \text{pIC}_E$$

- ▶ For a given p : choose \mathcal{P} with the highest pIC
- ▶ Aggregate in priority most homogeneous values

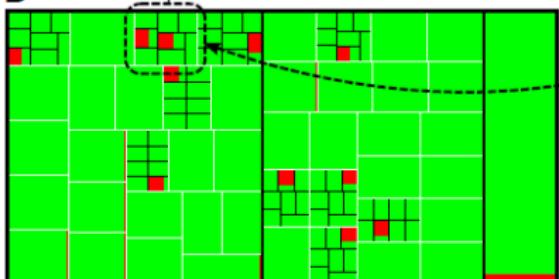
VIVA: SPATIAL AGGREGATION (SCHNORR & LP)

A Hierarchy: Cluster (3) - Machine (50) - Process (433)

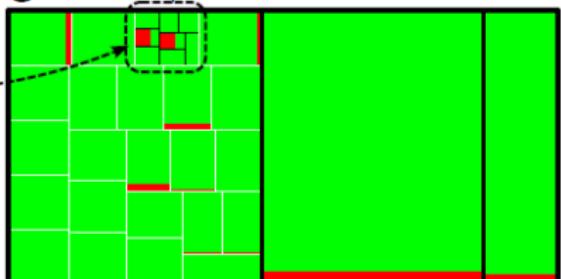


A.1 Machine level
A.2 Cluster level
A.3 Full aggregation

B Ratio Gain/Loss with P = 10%

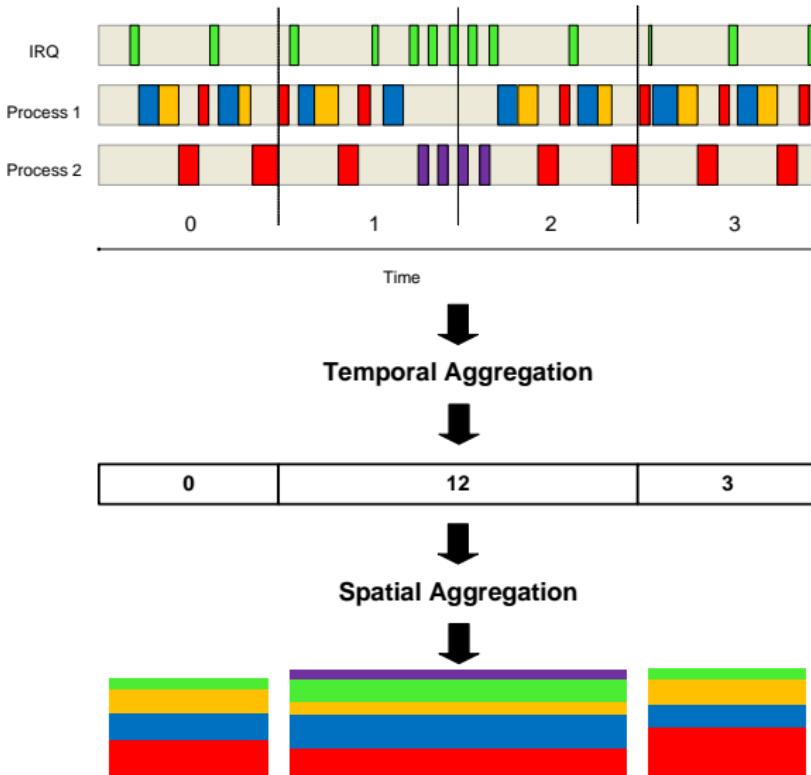


C Ratio Gain/Loss with P = 30%

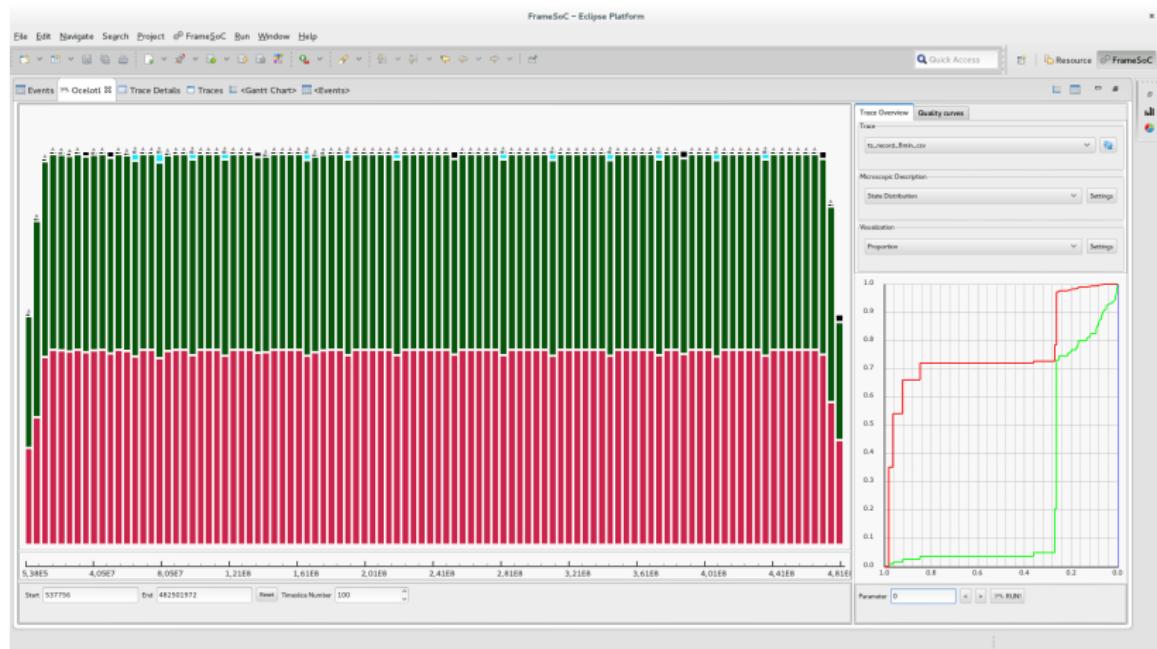


TEMPORAL OVERVIEW

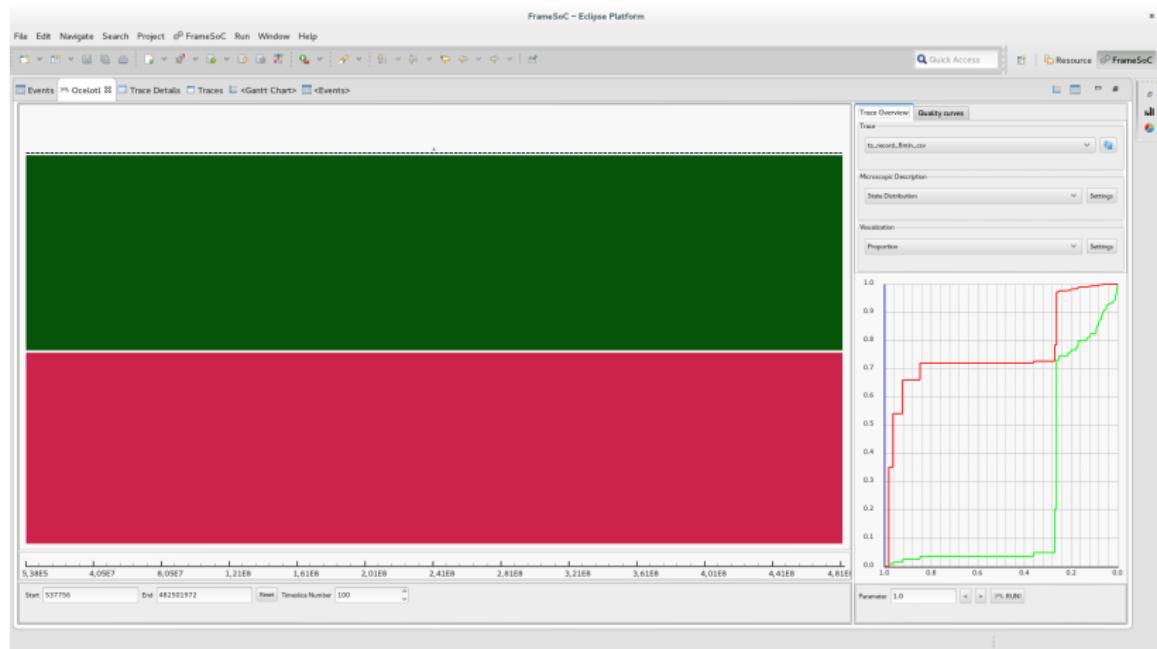
TEMPORAL AGGREGATION AND VISUALIZATION



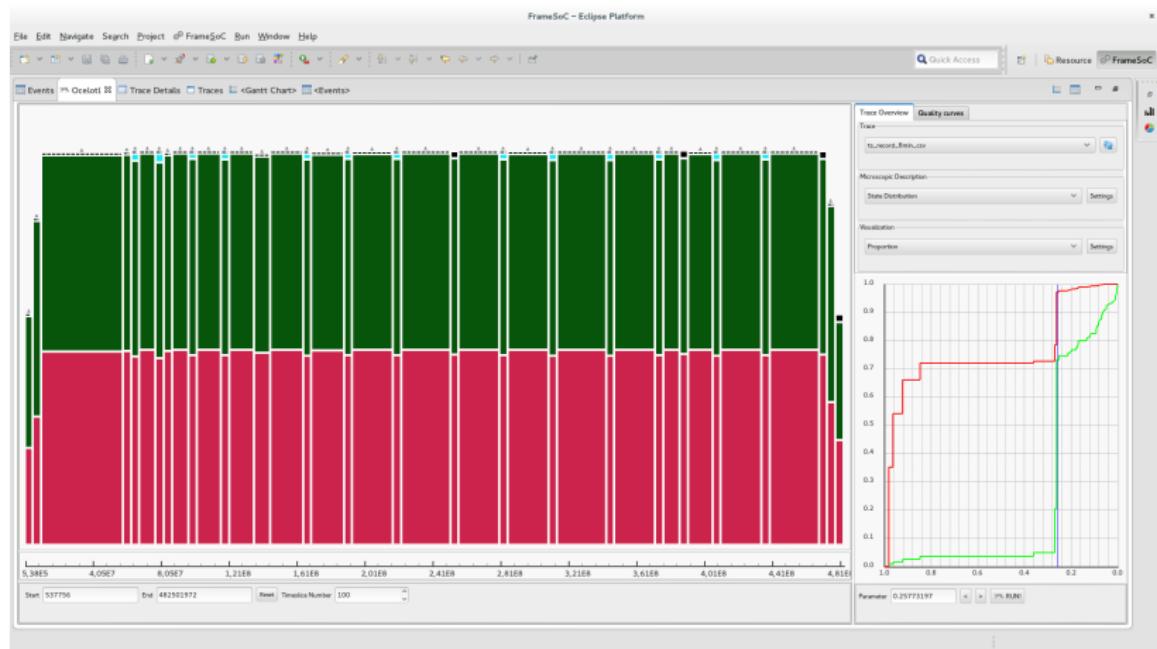
MINIMUM INFORMATION LOSS: P=0



MAXIMUM COMPLEXITY REDUCTION: P=1

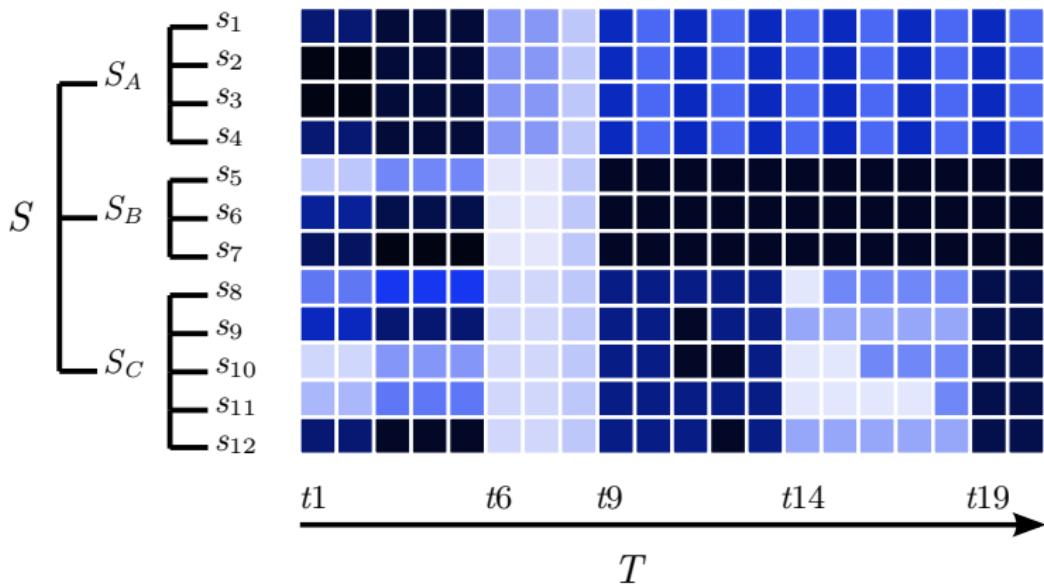


INTERESTING TRADE-OFF



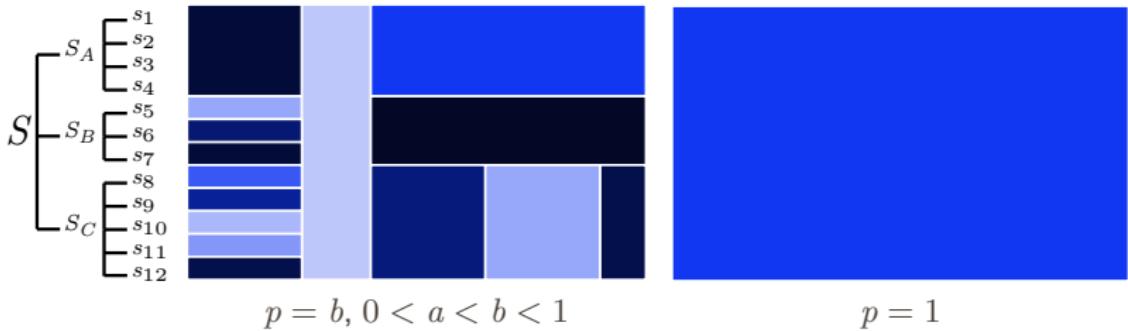
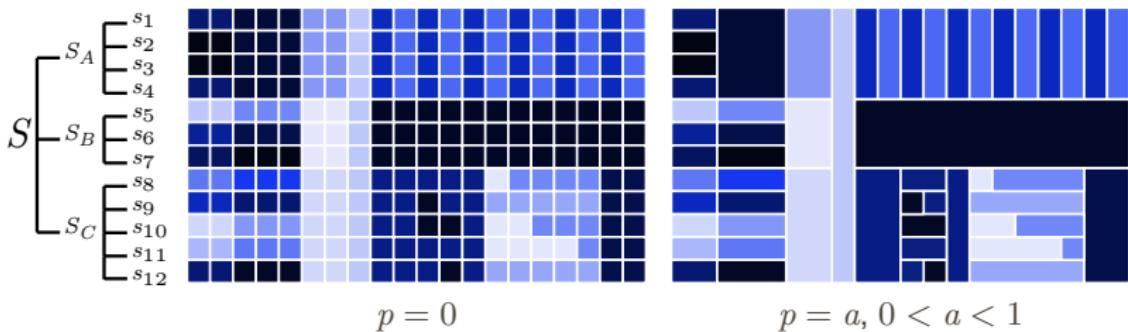
SPATIOTEMPORAL OVERVIEW

GENERATE A TRACE MICROSCOPIC MODEL



$$|X| = 2, \rho_x(s, t) = d_x(s, t)/d(t) \in [0, 1], \rho_1(s, t) = 1 - \rho_2(s, t)$$

AGGREGATE THE MICROSCOPIC MODEL

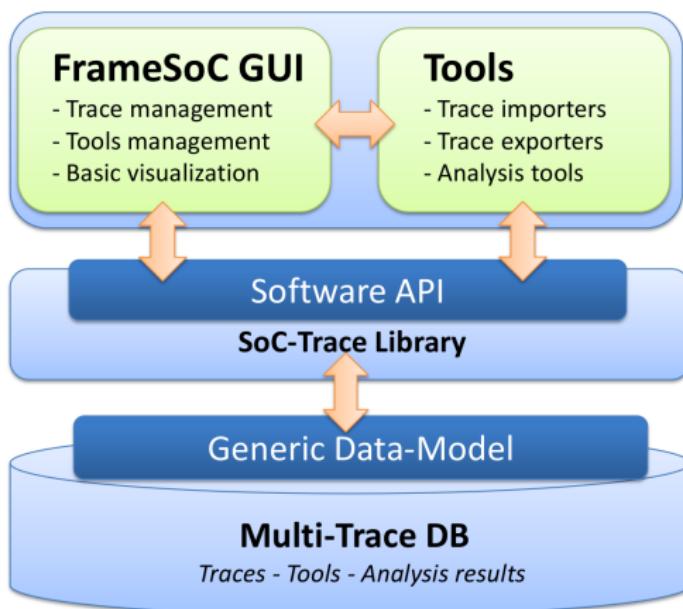


IMPLEMENTATION AND FEATURES

OCELOT TOOL

- ▶ Implementation of the overview techniques
- ▶ Generic architecture. Add:
 - Your own **aggregation operator** (dimensions, metric)
 - Your own **visualization**
- ▶ Persistent caches to avoid long recomputations
- ▶ Integrated in **Framesoc**:
 - Trace and tools management
 - **Fast** trace reading (DB queries)
 - **Interaction** with other analysis tools
 - Also enable to **add your own tools**

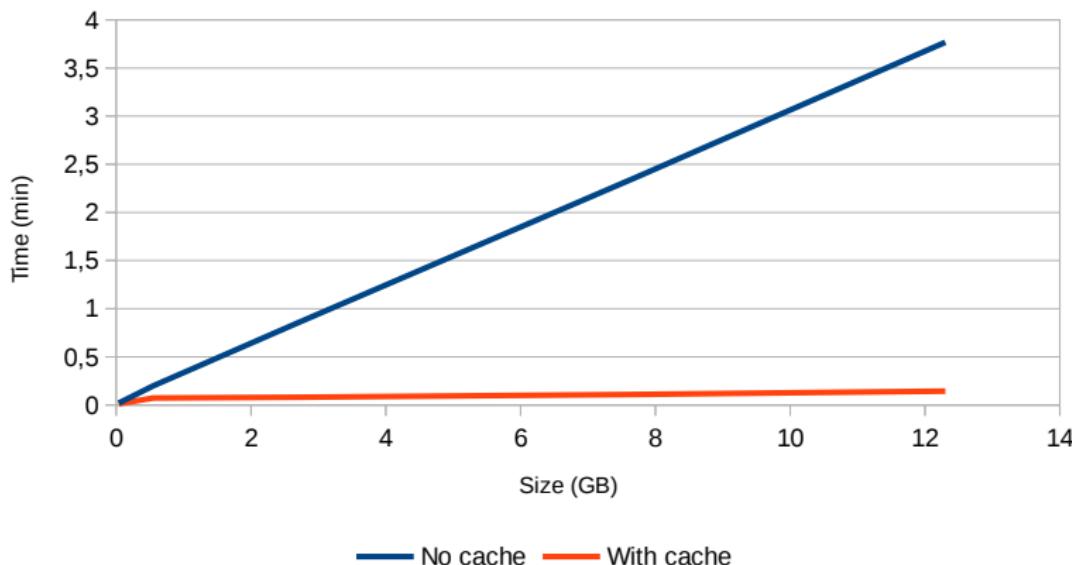
FRAMESOC



- Trace format compatibility : Pajé (Akypuera: tool to convert from OTF2, Tau), LTTng, KPTrace

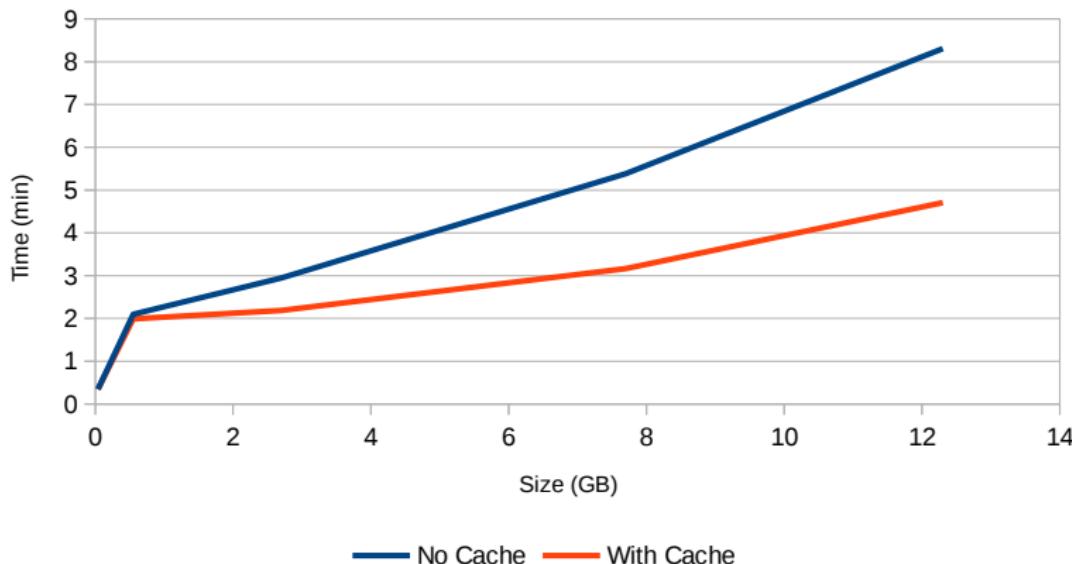
PERFORMANCE: TEMPORAL ANALYSIS

Total analysis time as a function of trace size (100 time slices)



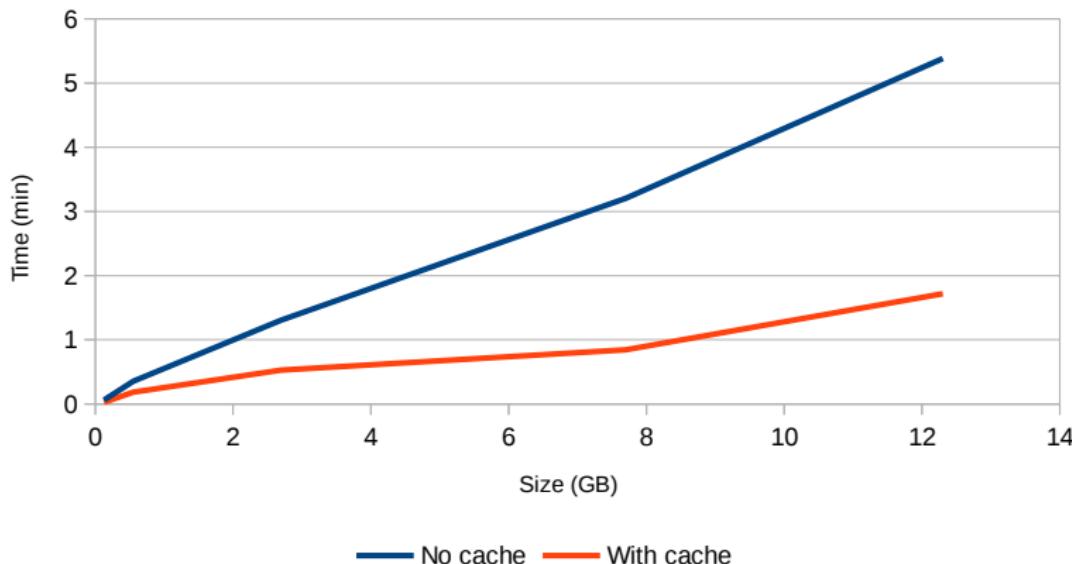
PERFORMANCE: TEMPORAL ANALYSIS

Total analysis time as a function of trace size (1000 time slices)



PERFORMANCE: SPATIOTEMPORAL ANALYSIS

Total analysis time as a function of trace size (30 time slices)



DEMONSTRATION

CONCLUSION

CONCLUSION

- ▶ **Visualizations** based on spatiotemporal **data aggregation**
 - Solves screen, computing and analyst capability **limitations**
 - Gives **meaningful information** about homogeneity (phases, perturbations)
- ▶ **Implementation:**
 - **Interaction** (zoom, switch to other tools)
 - Helps to drastically **reduce computation times** (caches)
 - **Generic architecture:** add your own aggregation and visualization
- ▶ **Future work:**
 - **Extend methodology** and design new algorithms ($\mathcal{H}(S) \times \mathcal{H}(S) \times \mathcal{I}(T)$, surface, etc.)
 - **Improve visualization** and **interaction** to get more details
 - Framesoc: native compatibility with **OTF2** (soon)

LINKS

Ocelotl:

<http://github.com/dosimont/ocelotl>

Framesoc:

<http://github.com/generoso/framesoc>

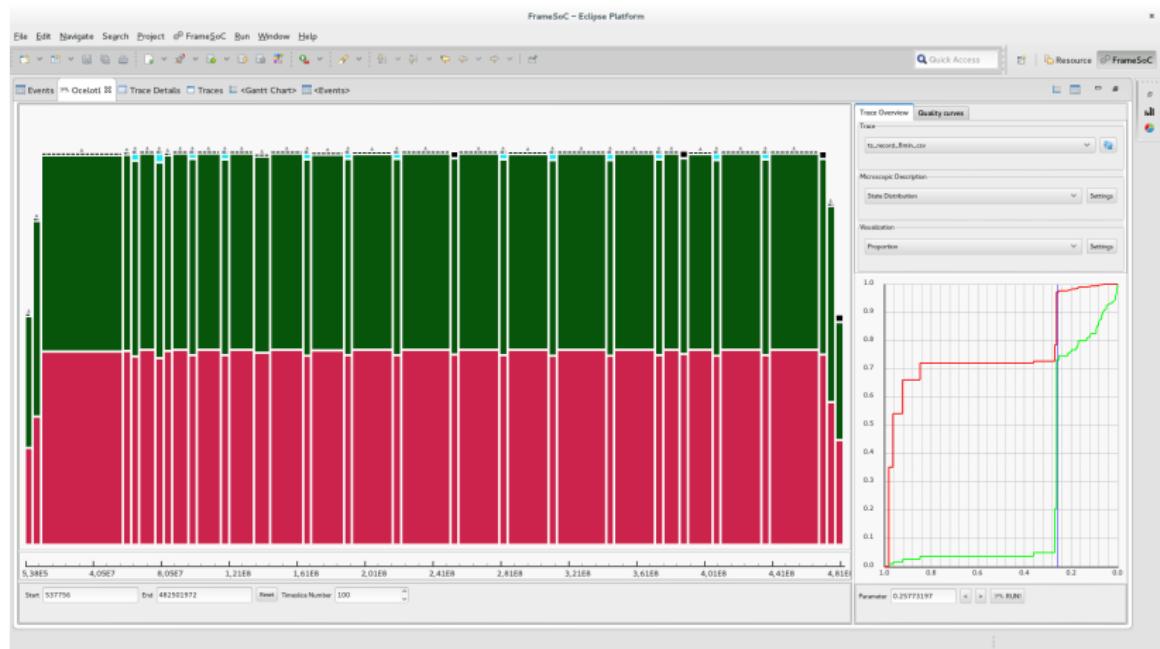
Viva:

<http://github.com/schnorr/viva>

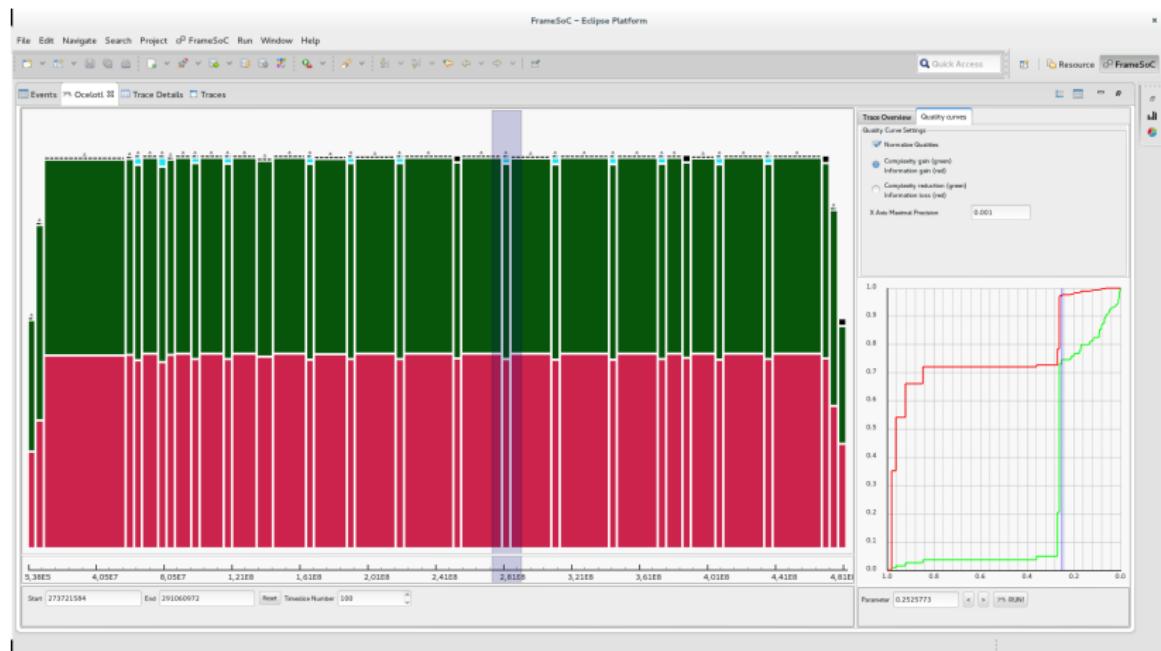
THANK YOU FOR YOUR ATTENTION



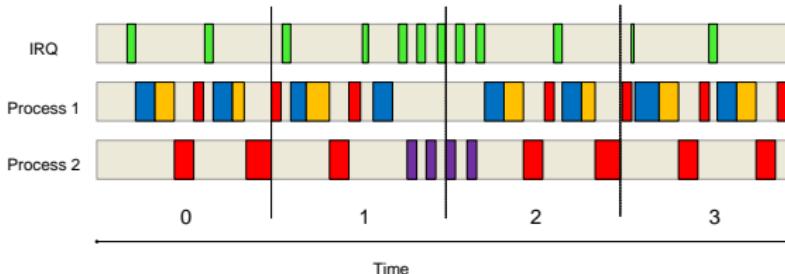
OCELOT: TEMPORAL AGGREGATION (1)



OCELOT: TEMPORAL AGGREGATION (2)



GENERATE A TRACE MICROSCOPIC MODEL



IRQ	0	0	0	0
Process 1	1	2.1	1	3
Process 2	4.1	2	4.1	4

IRQ	2	4.9	3	2.4
Process 1	0	0	0	0
Process 2	0	0	0	0

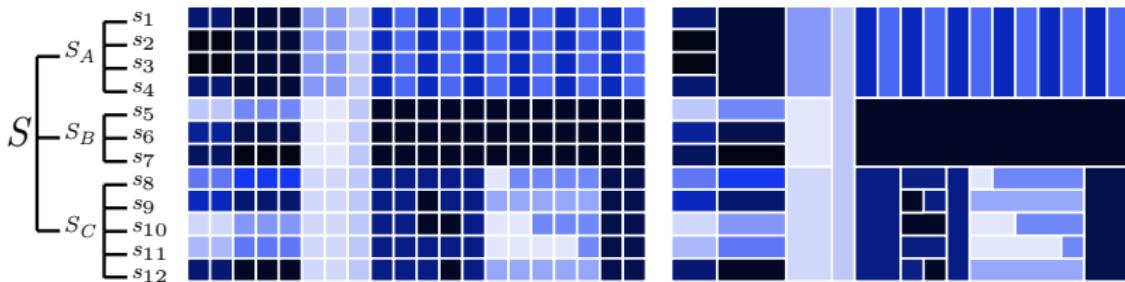
And so on...

DATA AGGREGATION METHODOLOGY

- ▶ A1. Choose a **model** and a **metric**
- ▶ A2. Choose on **which dimension(s)** aggregate
- ▶ A3. Define the **operands**
- ▶ A4. **Constrain** the aggregation : → partitions \mathcal{P} allowed
- ▶ A5. Define the **operator**
- ▶ A6. Define the **trigger** - the aggregation condition
- ▶ A7. Build the **algorithm** satisfying A1-A6

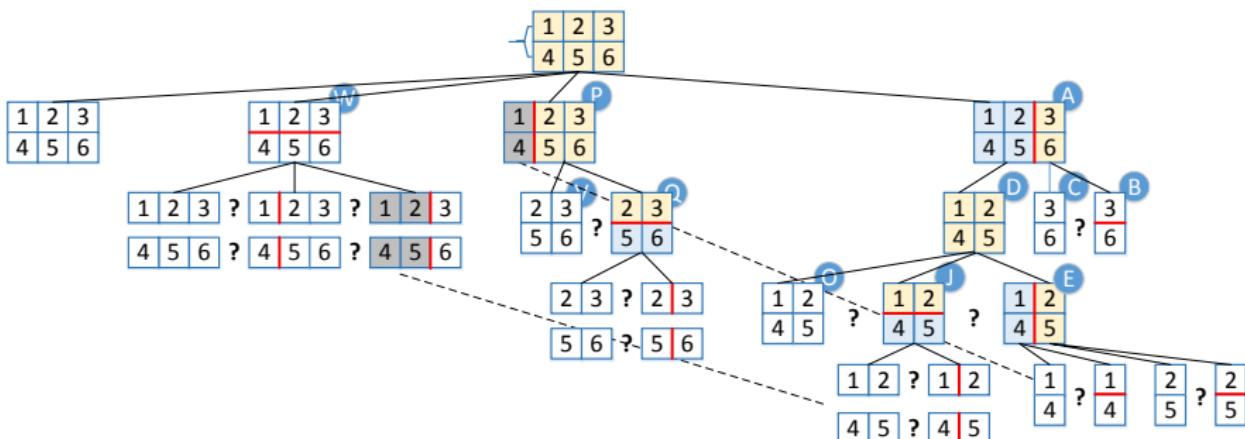
A2-A5

- ▶ A2. We aggregate simultaneously on T and S
- ▶ A3. Operands: $(s, t) \in S \times T$
- ▶ A4. Constraint: $\mathcal{A}(S \times T) = \mathcal{H}(S) \times \mathcal{I}(T)$
Aggregation result is a partition $\mathcal{P}(S \times T) \in \mathcal{A}(S \times T)$
- ▶ A5. Operator: $+$
- ▶ A6. Trigger: maximize pIC of the partition $\mathcal{P}(S \times T)$



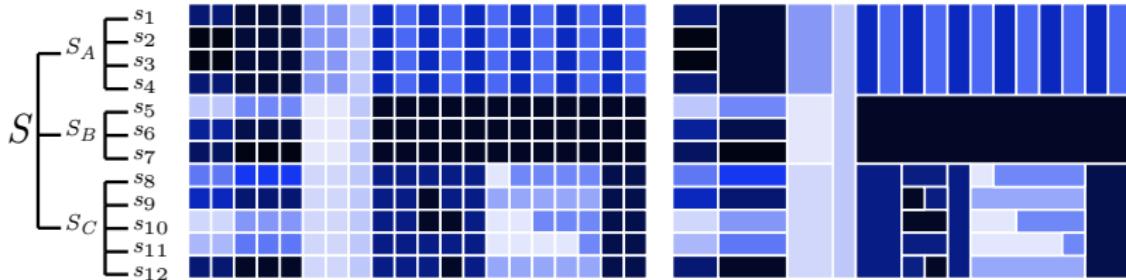
BEST CUT ALGORITHM

- ▶ Compute the partition with the highest pIC :
 - Cut an area : time, space (or no cut)
 - Best cut: the partition \mathcal{P} where $\sum_{E \in \mathcal{P}} \text{pIC}_E$ is max
 - Recursively cut and evaluate the partitions of $E_1, E_2 \in \mathcal{P}$
 - Useless recomputation is avoided



A6. TRIGGER THE AGGREGATION

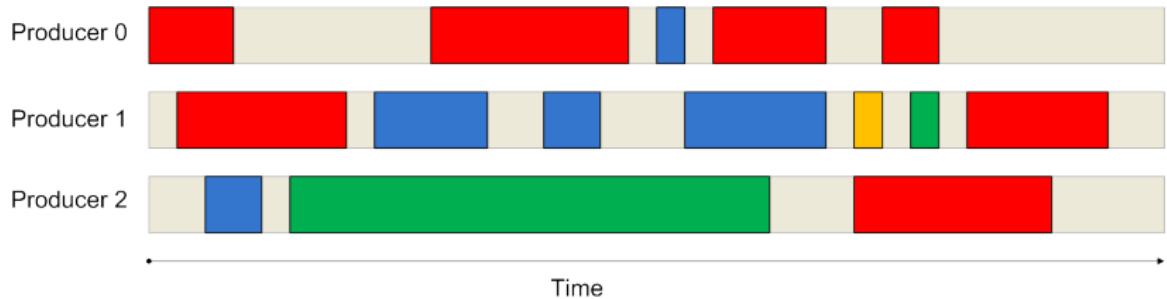
- ▶ Quantification of data reduction and information loss
 - aggregate the homogeneous areas
 - preserve the microscopic information of the heterogeneous areas
- ▶ Each $(S_k, T_{(i,j)}) \in \mathcal{A}(S \times T)$ has an associated gain and loss
- ▶ gain and loss of a partition $\mathcal{P}(S \times T)$ is the sum of gain and loss of its content $(S_k, T_{(i,j)}) \in \mathcal{P}(S \times T)$



ELMQVIST-FEKETE CRITERIA

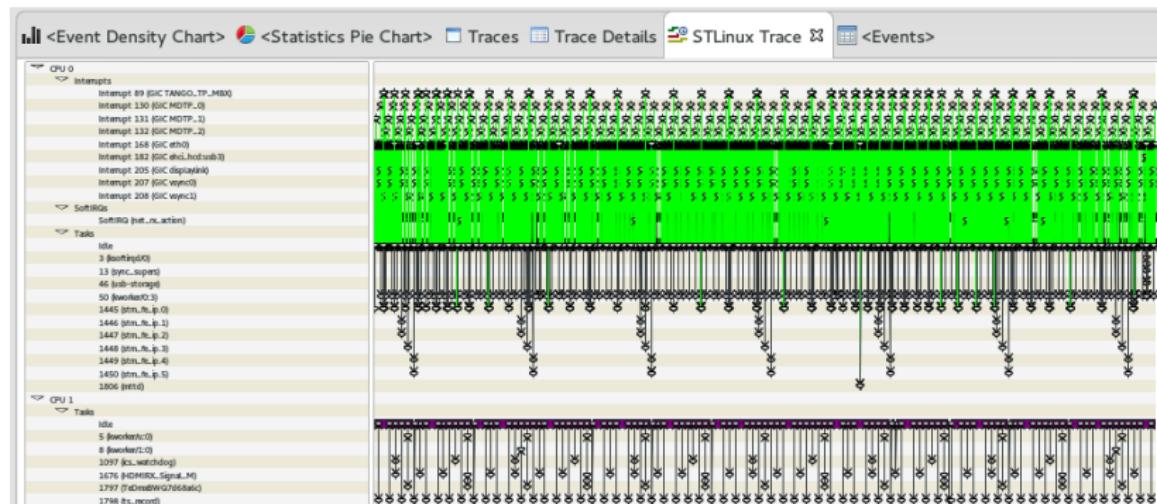
- ▶ **Shneiderman** : **overview**, zoom and filter, then get details on demand
- ▶ **Elmqvist & Fekete**: guidelines to design an **overview** visualization based on hierarchical aggregation
 - G1. Entity Budget
 - G2. Visual Summary
 - G3. Visual Simplicity
 - G4. *Discriminability*
 - G5. Fidelity
 - G6. *Interpretability*

VISUALIZATIONS NOT FULFILLING THESE CRITERIA (1)



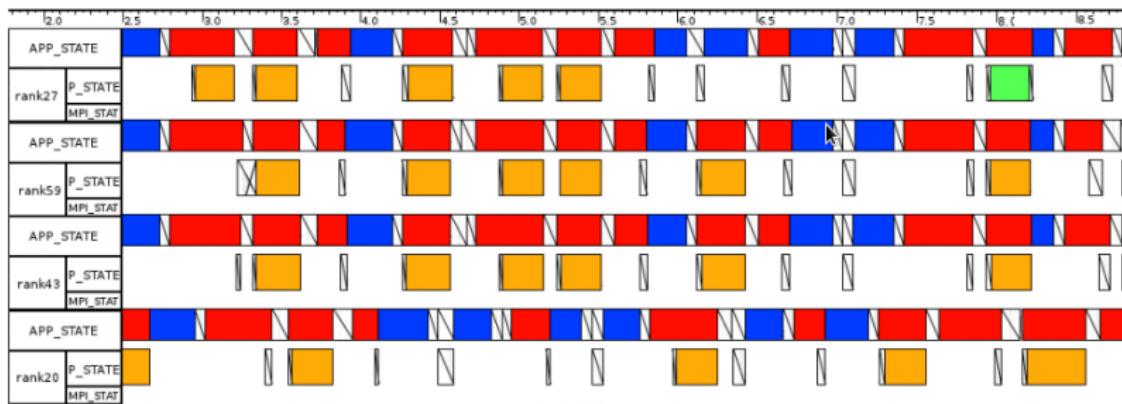
Example of Gantt chart - space-time diagram

VISUALIZATIONS NOT FULFILLING THESE CRITERIA (2)



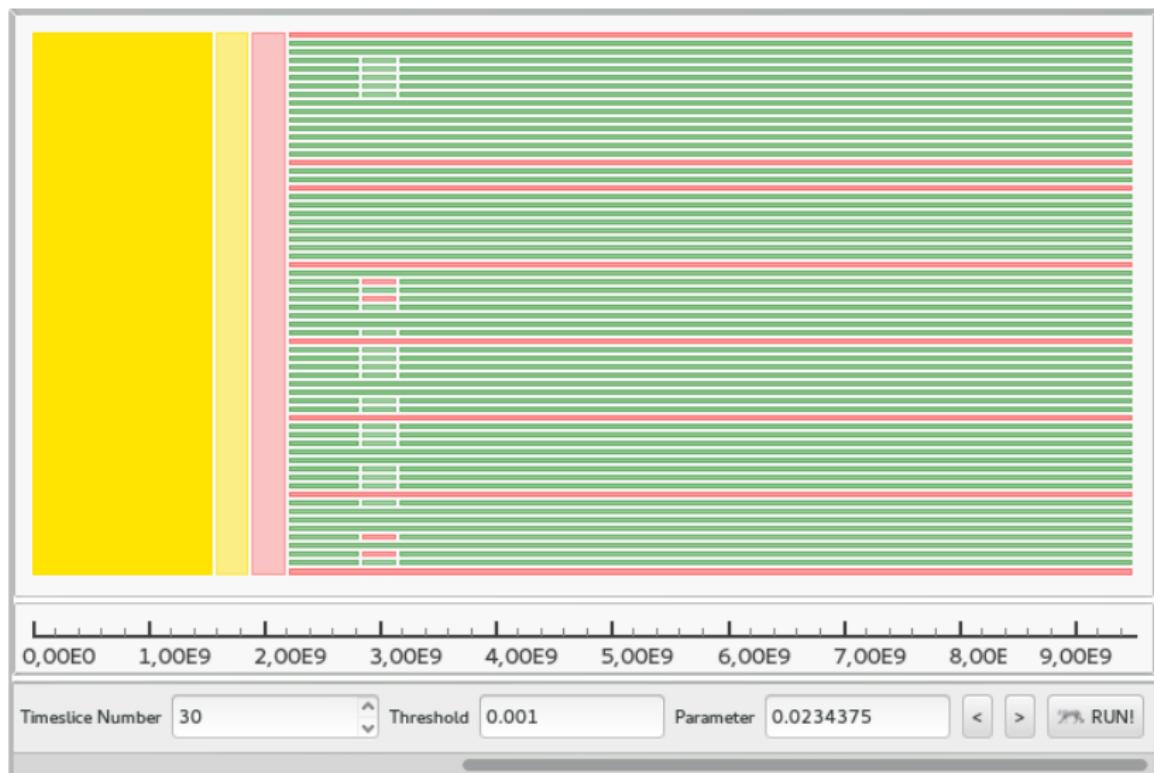
KPTTrace: $\overline{G_1}$ (time), $\overline{G_2}$, $\overline{G_4}$, $\overline{G_5}$

VISUALIZATIONS NOT FULFILLING THESE CRITERIA (2)

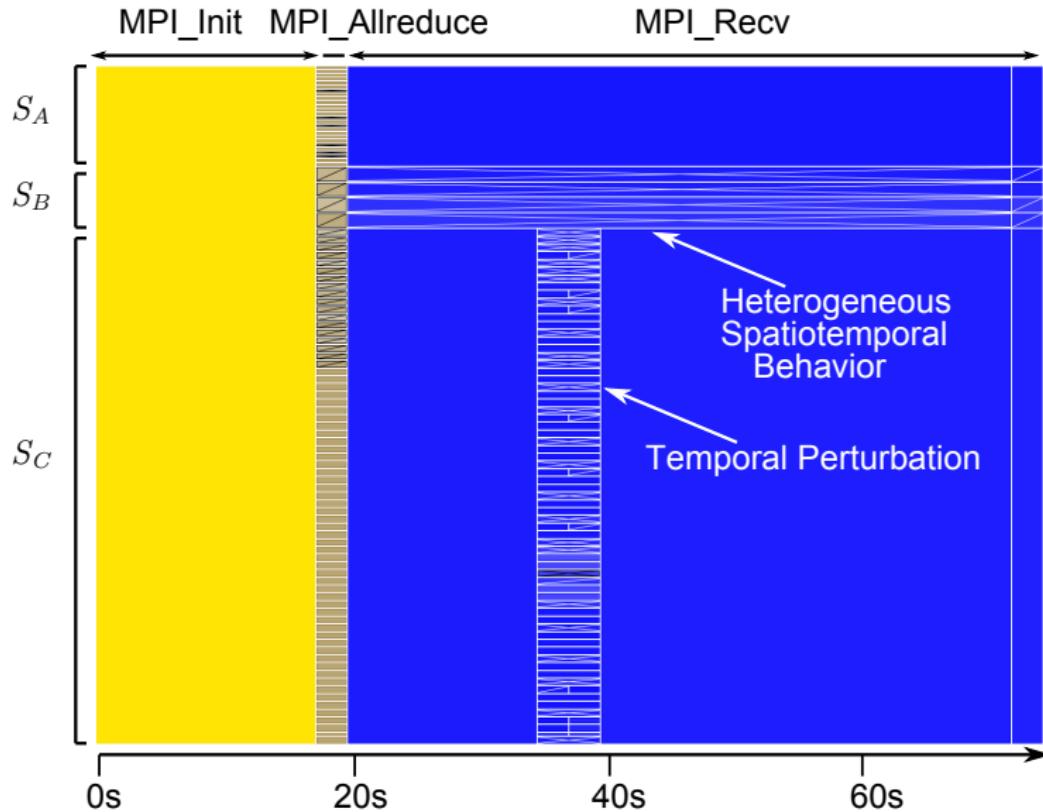


Pajé: $\overline{G_1}$ (space), $\overline{G_2}$

CG CLASS C, 64 PROCESSES ON G5K RENNES



LU CLASS C, 700 PROCESSES ON G5K NANCY



PERFORMANCES (SPATIOTEMPORAL)

	Case A	Case B	Case C	Case D
Application	CG, class C	CG, class C	LU, class C	LU, class B
Processes	64	512	700	900
Site	Rennes	Grenoble	Nancy	Rennes
Clusters (nodes)	parapide(8)	adonis(9), edel(24), genepi(31)	graphene(26), graphite(4), griffon(67)	paradent(38), parapide(21), parapluie(18)
Event number	3,838,144	49,149,440	218,457,456	177,376,729
Trace size	136.9 MB	1.8 GB	8.3 GB	6.7 GB
<hr/>				
Ocelotl computation times (30 time slices)				
Trace reading + Microscopic description	5 s	31 s	222 s	174 s
Aggregation	<1s	<1s	2s	2s