

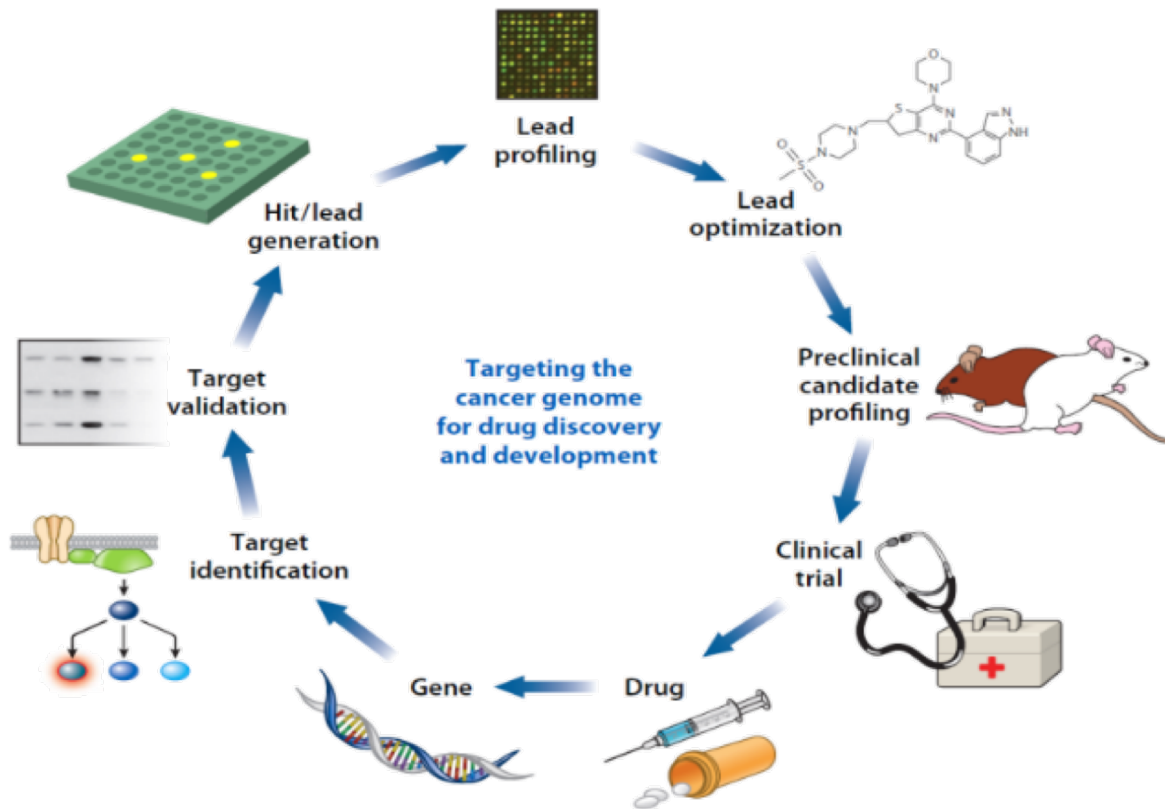


mec

EXASCALE MATRIX FACTORIZATION: MACHINE LEARNING ON SUPERCOMPUTERS TO FIND NEW DRUGS

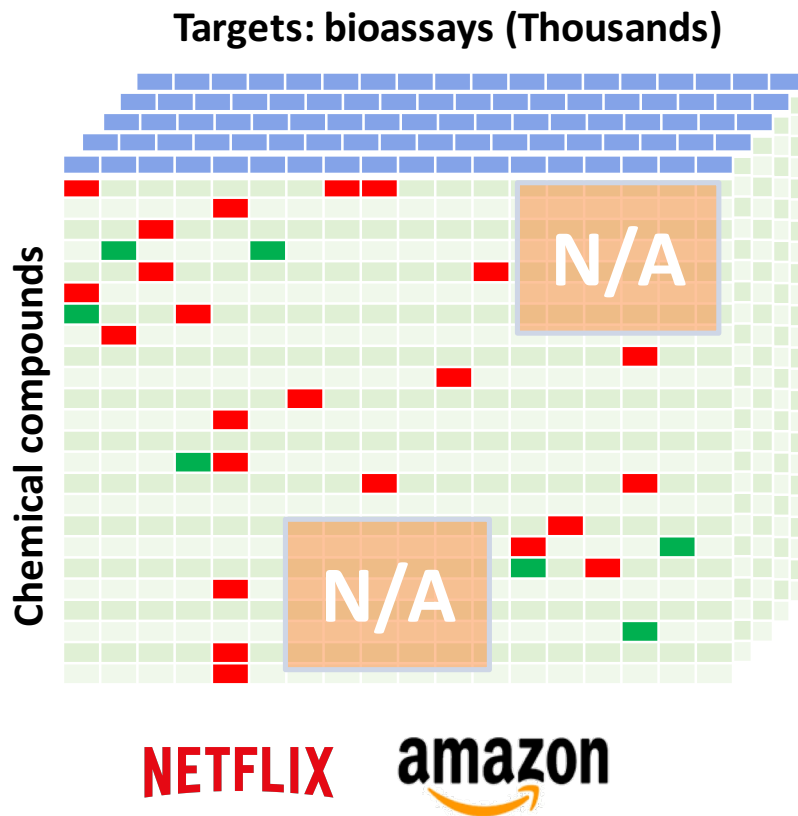
TOM VANDER AA
EXASCIENCE LIFE LAB

DRUG DEVELOPMENT IS TOO EXPENSIVE



COMPOUND ACTIVITY PREDICTION

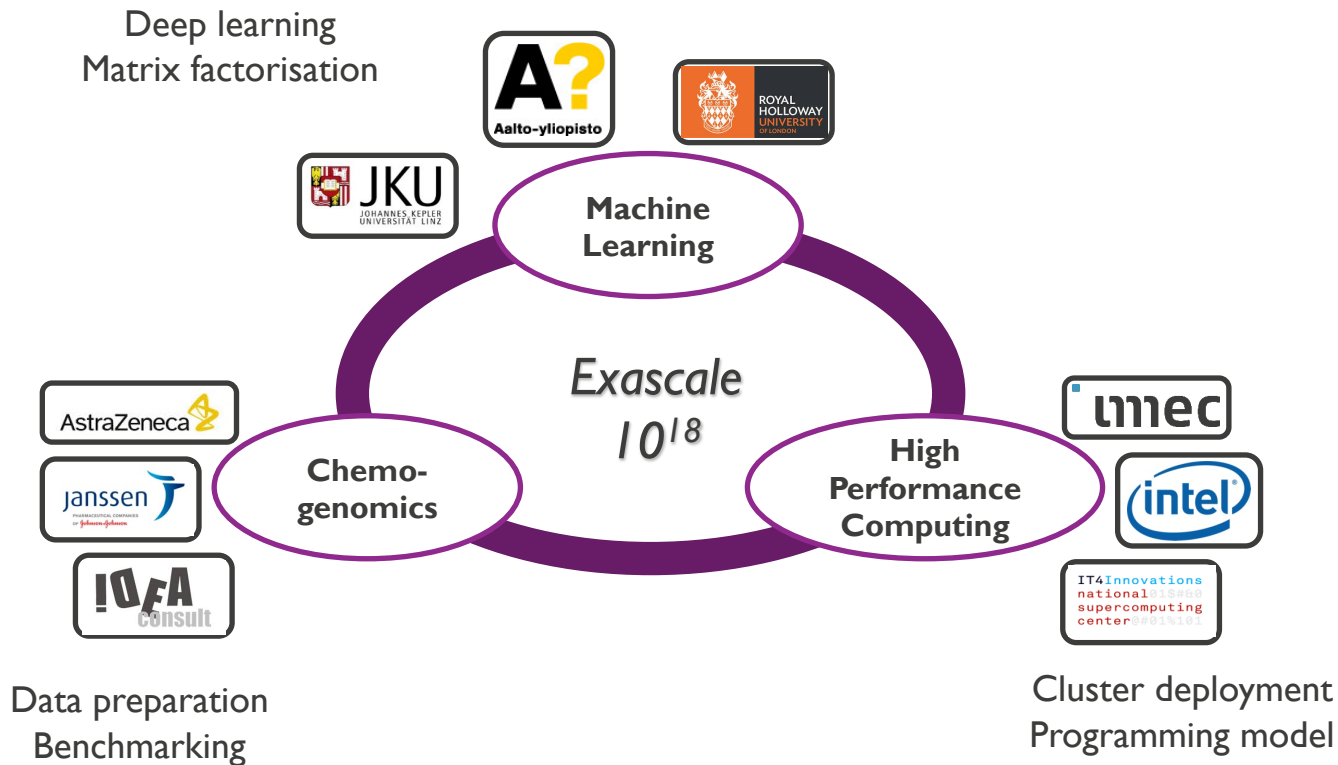
- Predict
 - compound activity on
 - protein target
 - aka chemogenomics
- Like
 - Netflix: users rating movies
 - Amazon: users rating books



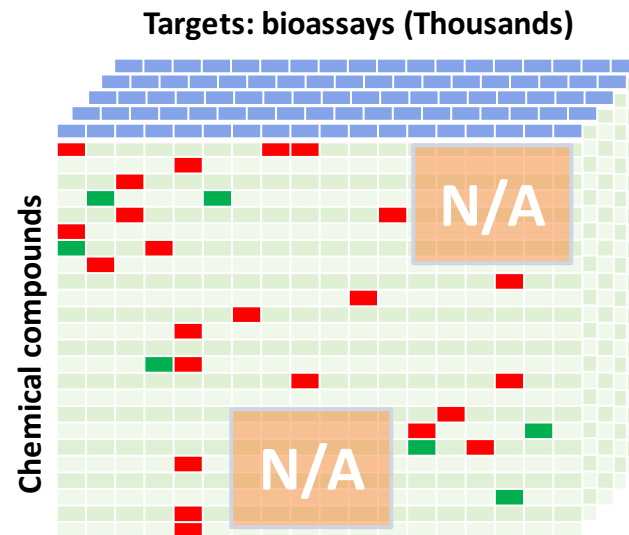
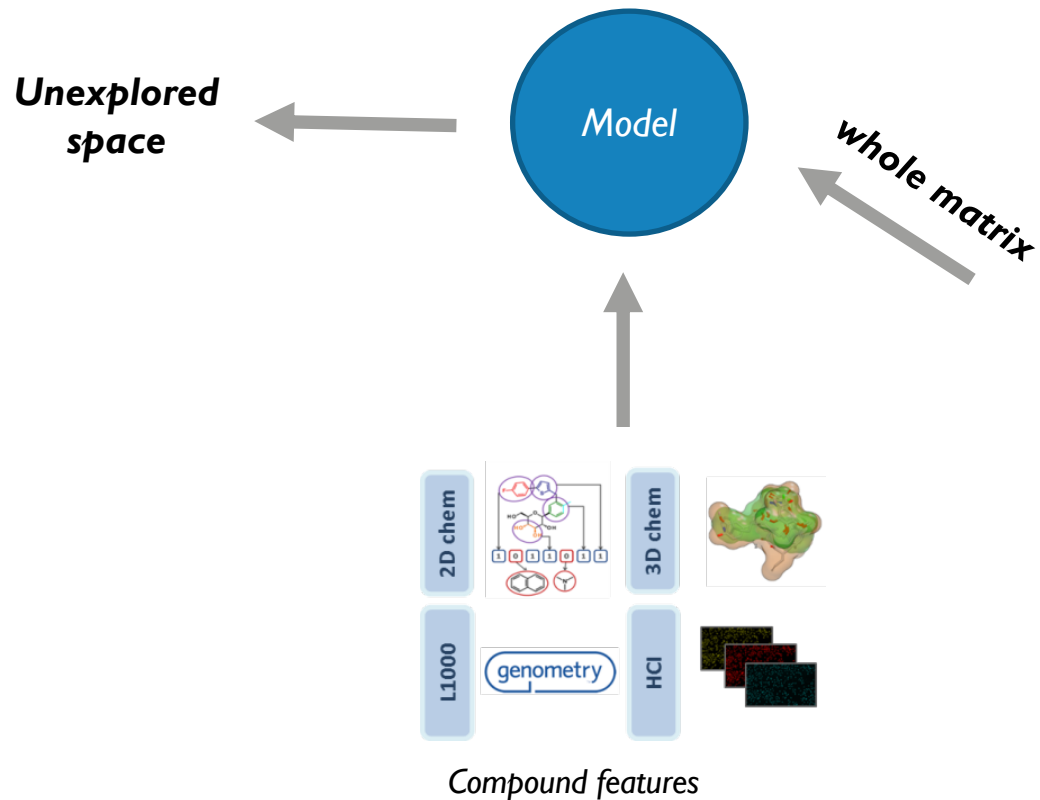


EXCAPE PROJECT

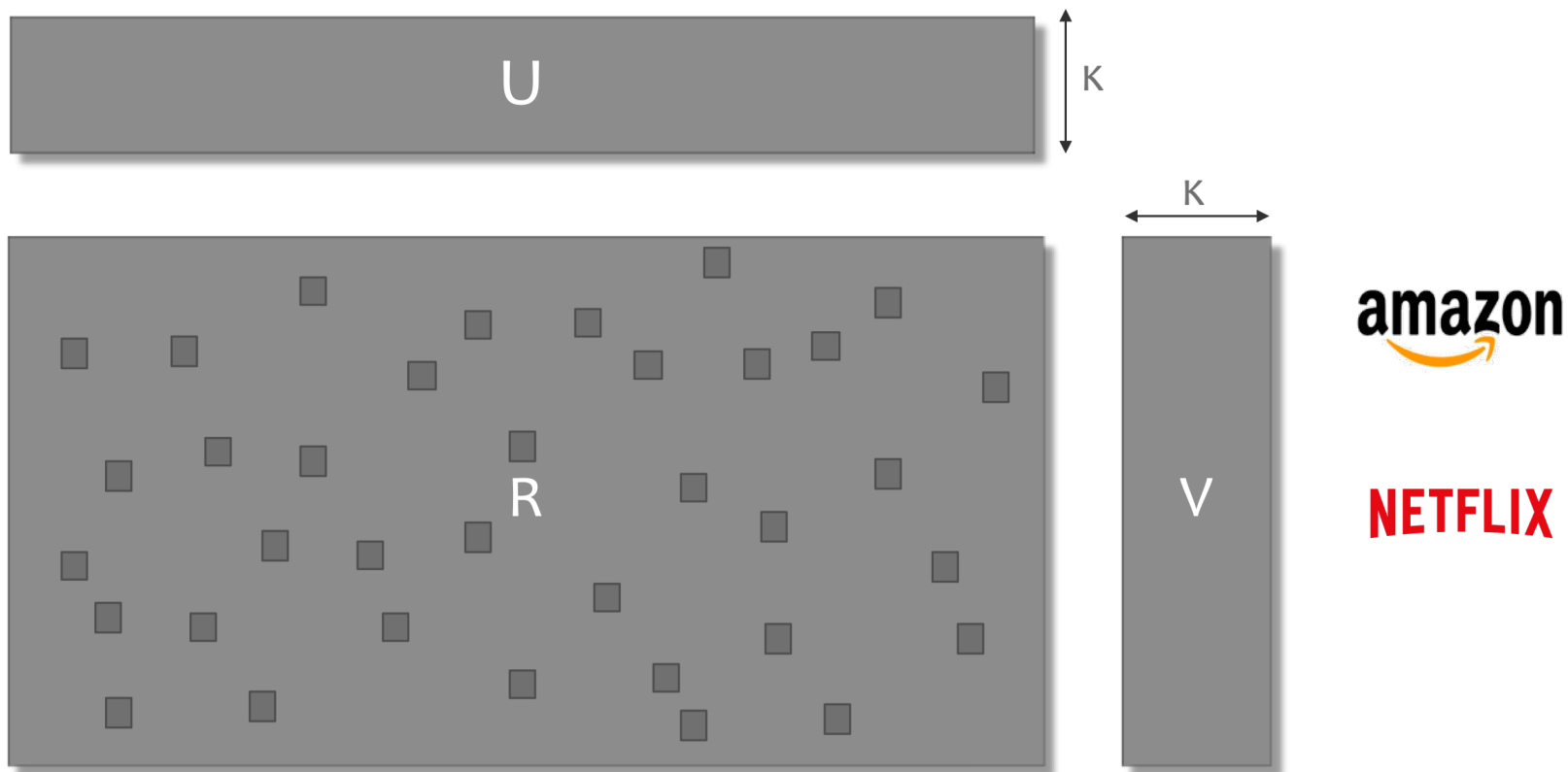
EXASCALE COMPOUND ACTIVITY PREDICTION ENGINES



MULTI TARGET CHEMOGENOMICS

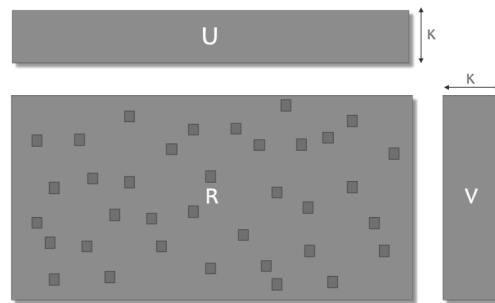
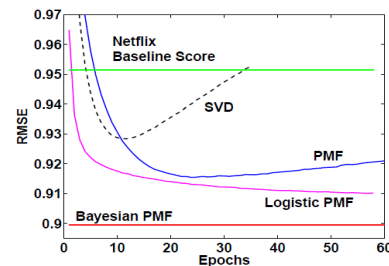


BPMF := LOW-RANK MATRIX FACTORIZATION



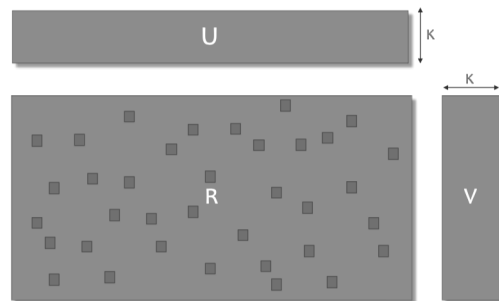
FROM SIMPLE, PROMISING BUT SLOW ...

- BPMF is simple
 - 25 lines of Julia code
 - 35 lines of Eigen C++ code
- BPMF predicts well
 - Bayesian $\rightarrow$ confidence interval
- BPMF is slow
 - Sampling based
 - Julia prototype: 15 days / run

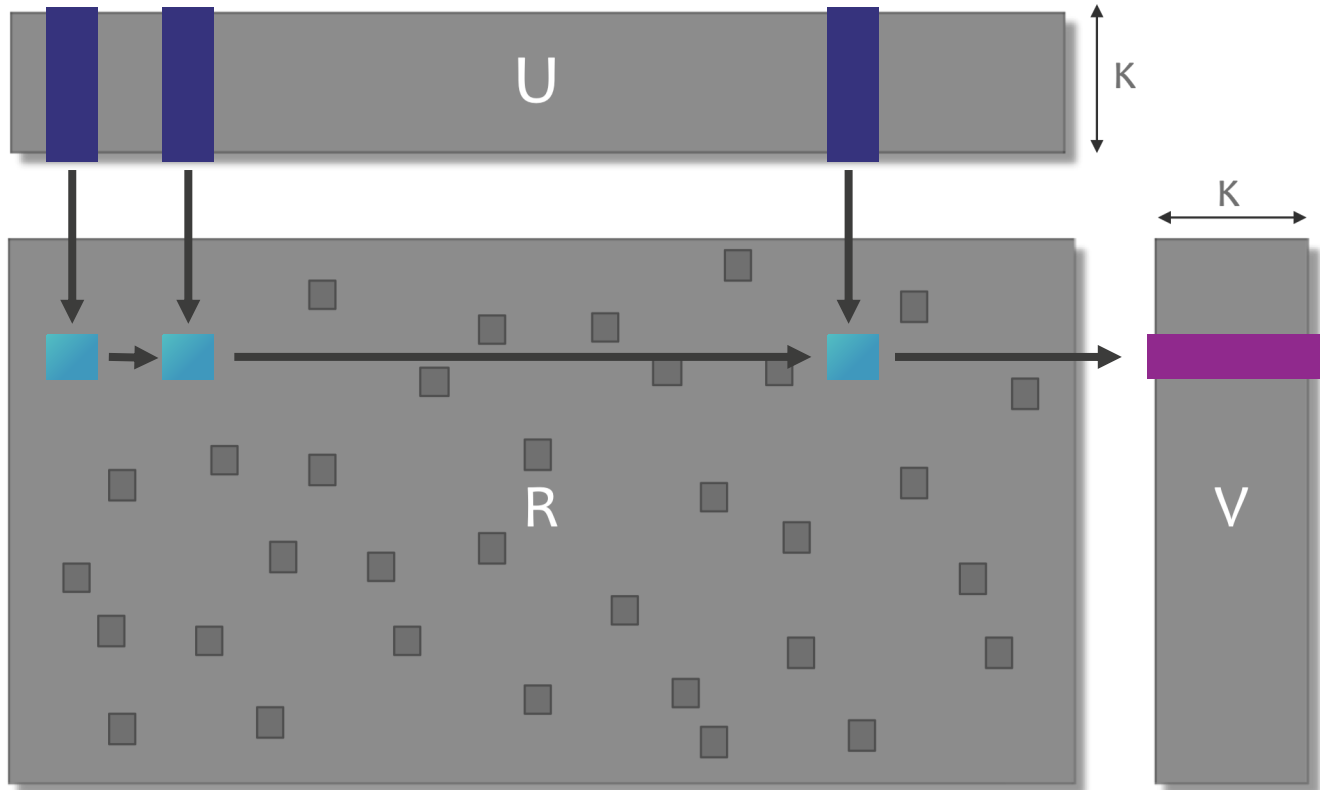


... TO FAST AND COMPLEX

- Many Optimizations
 - Algorithmic
 - Memory Hierarchy
- Multi-core
 - Load Balancing
 - using OpenMP and TBB
- Multi-node
 - Asynchronous communication
 - using MPI and GASPI



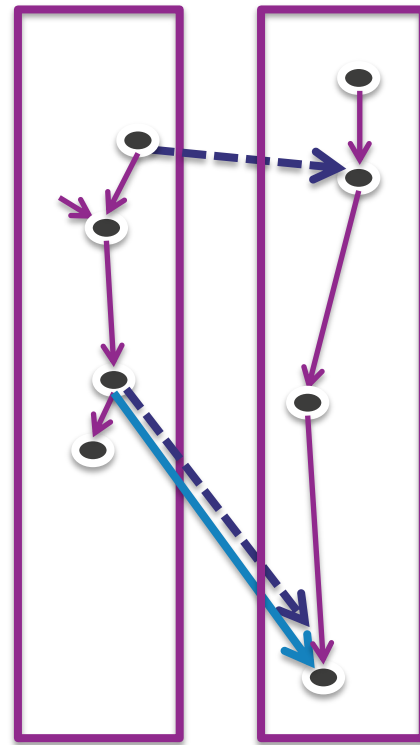
BPMF COMMUNICATION AND COMPUTATION IS DETERMINED BY STRUCTURE OF R



GASPI IN A NUTSHELL



- PGAS API - designed to be
 - Multithreaded
 - Global asynchronous dataflow
 - Interoperability with MPI
- GASPI Specification (gaspi.de)
- GPI-2 Implementation (gpi-site.com)



gaspi_notify

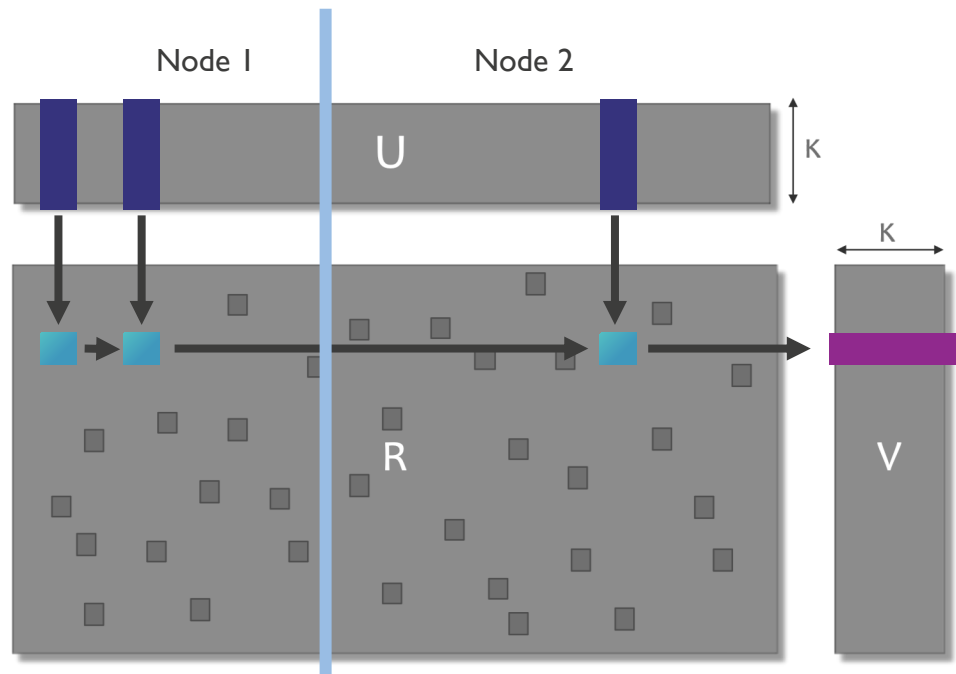


gaspi_write



ASYNCHRONOUS DISTRIBUTED BPMF

- Split both U/V , optimizing:
 1. Load balance (# rows, #nnz)
 2. Communication
- Basic Pattern GASPI
 - Compute a column of U/V
 - Send early

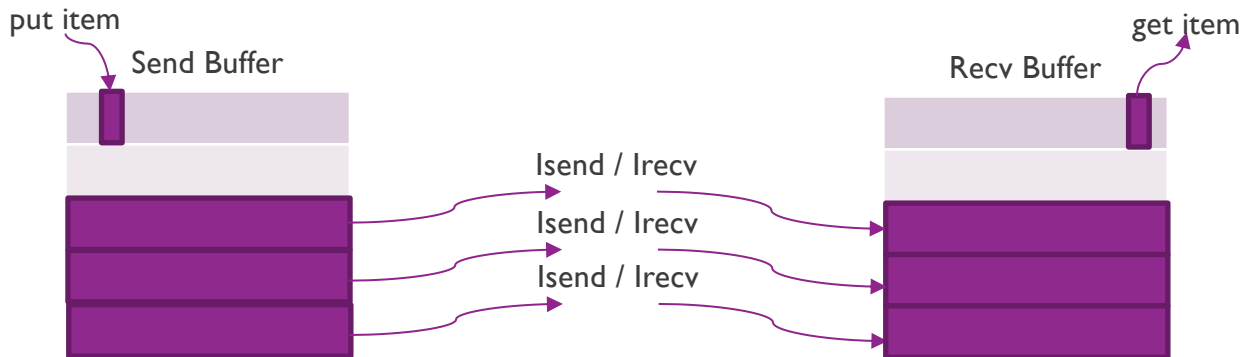


CHALLENGES USING MPI

- MPI is **not thread-safe** by default
 - Multiple work threads, one MPI thread
- MPI calls have **high overhead**
 - Buffer before send
- Many possible MPI primitives
 - **MPI_Bcast**
 - simple, synchronous, does not scale well
 - **MPI_Put**
 - need to split U in multiple MPI Windows, one window per peer
 - actual MPI work delayed until end of epoch
 - **MPI_Isend/Irecv**
 - best at doing background work
 - many irecvs/isends in flight

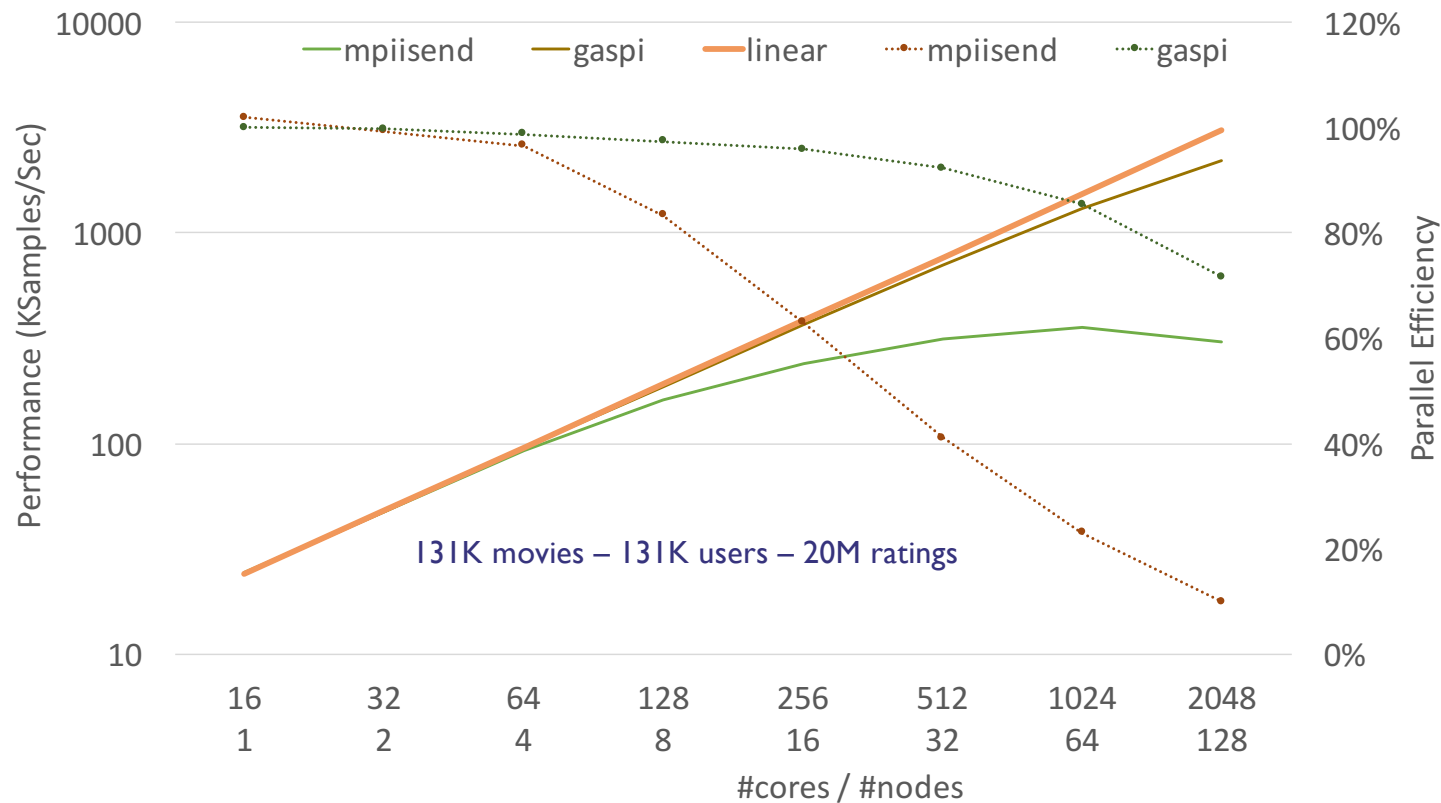
CURRENT BEST MPI IMPLEMENTATION

- Buffered ISend/IRecv
 - One buffer-pair per send-receive pair
 - Several chunks per buffer
 - Several items per chunk

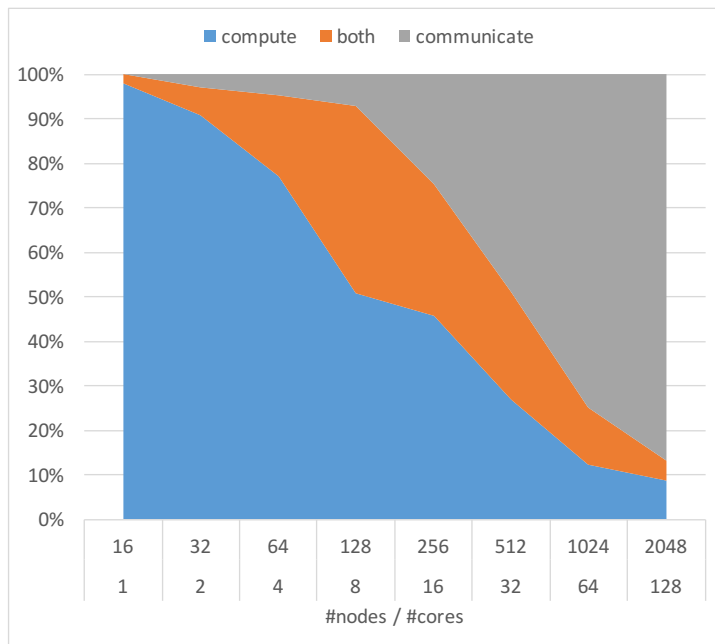


- 5 chunks → maximally 5 Isend/Irecv in flight
- 100 items per chunk

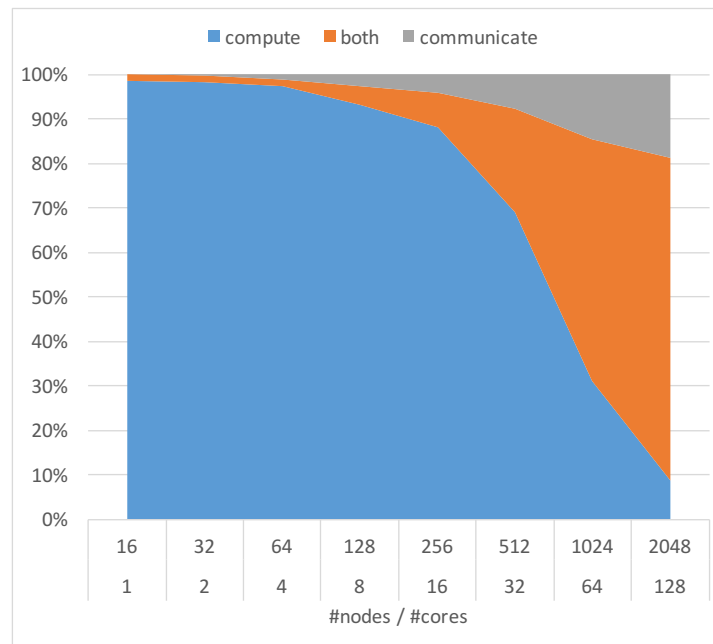
DISTRIBUTED PERFORMANCE – 128 NODES



COMM / COMP OVERLAP



MPI



GASPI

POP COE

- HPC Expertise in ExCAPE (Low to High)
 - Pharma partners
 - Machine Learning Partners
 - HPC Partners (e.g IMEC)
 - POP Partners
- We learned
 - Tools: Extrae, Paraver
 - OpenMP tasks
 - MPI Asynchronous collectives





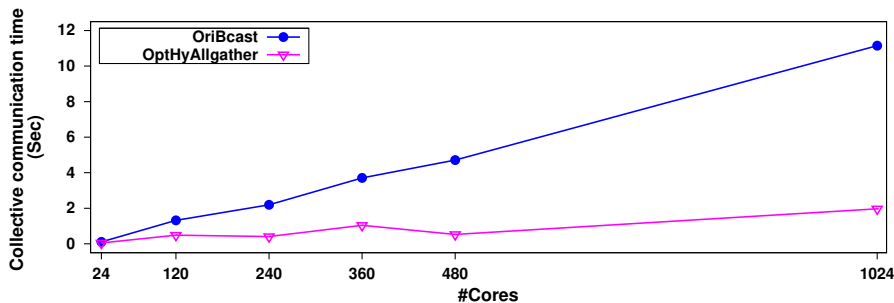
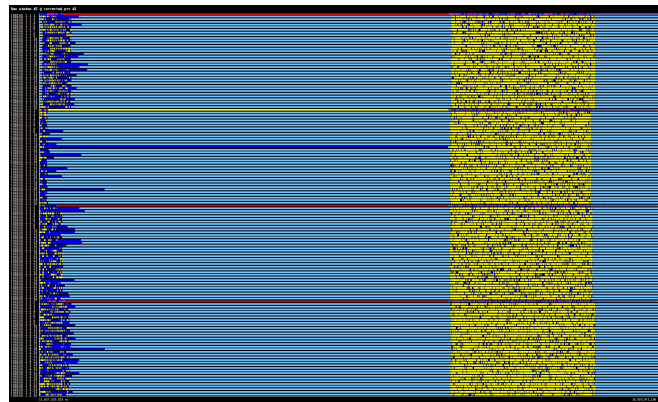
1. Audit Report

- Load imbalanced detected using Extrae and Paraver

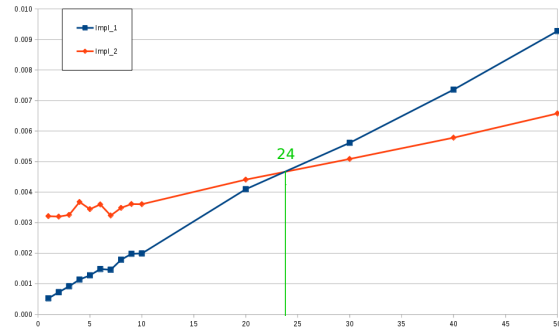
2. OpenMP Optimizations

- Load imbalance fixed with extra arallelism using OpenMP tasks

3. Asynchronous MPI collectives



H L R I S
Optimization: best values of breakpoint 1

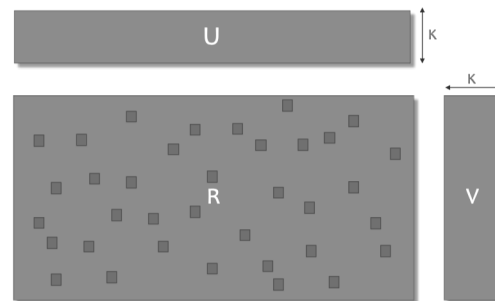


CONCLUSIONS OPTIMIZING BPMF

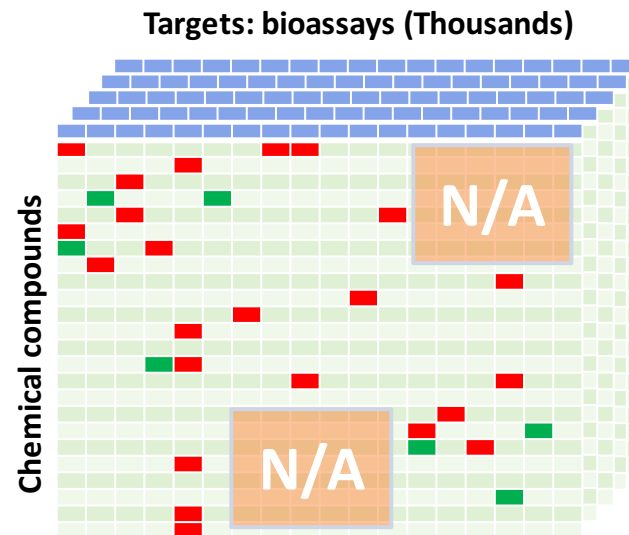
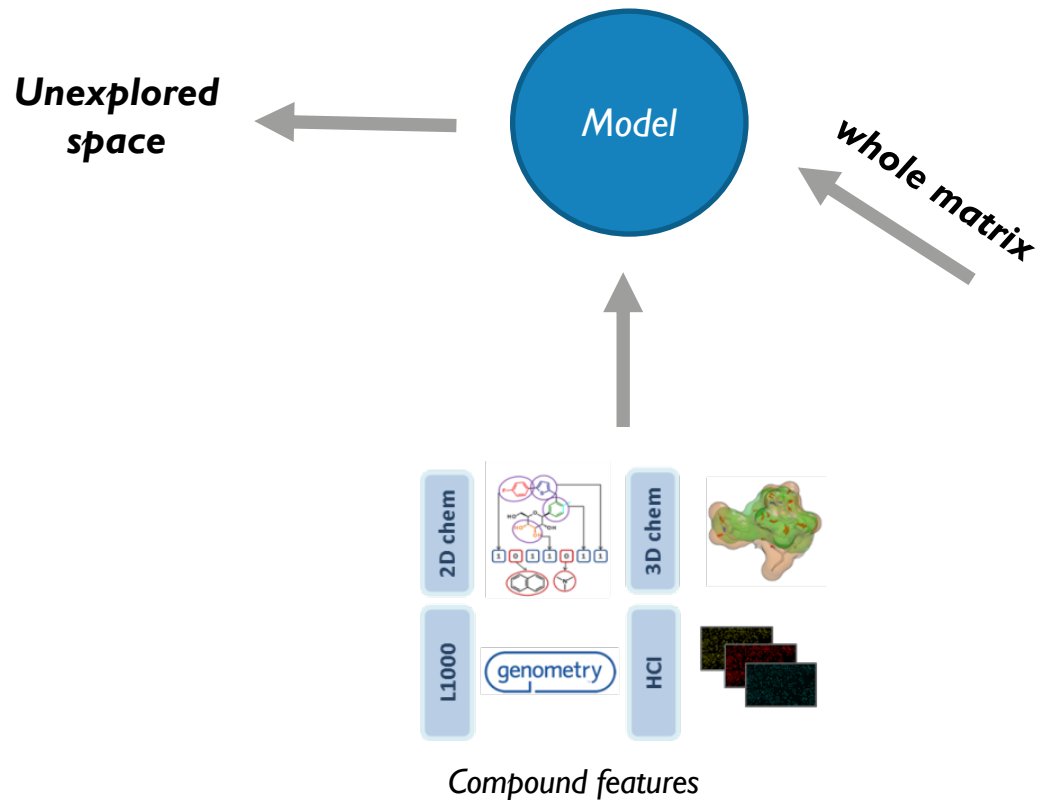
- Reduced runtime on industrial data

Parallelism	Time I Run
Single node - Julia	15 days
Single node - C++ & TBB	1.5 hours
Distributed - C++ & TBB & GASPI	5 minutes

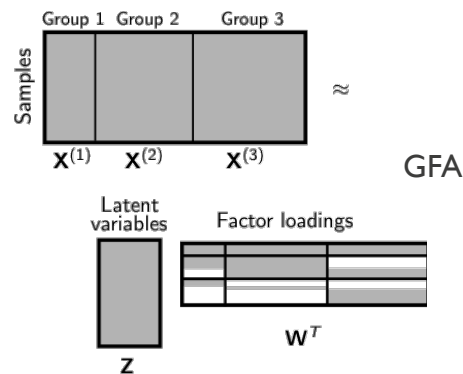
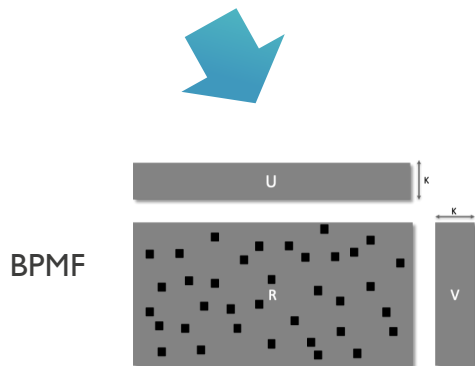
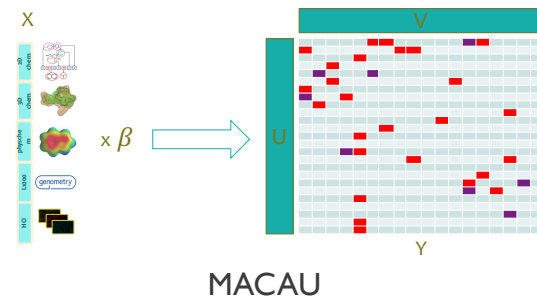
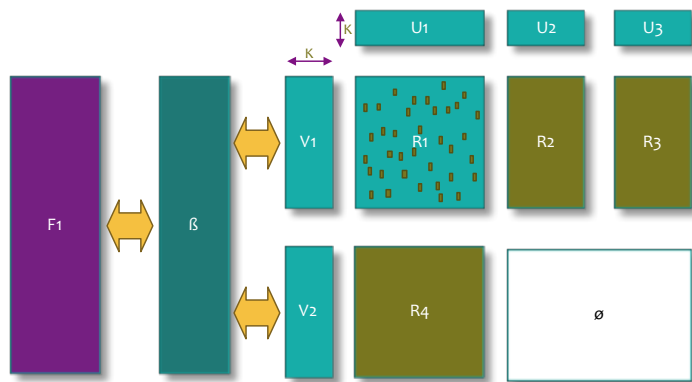
- Parallel efficiency is important
 - Load Balancing and Communication Hiding
- BPMF Released on GitHub
 - <https://github.com/ExaScience/bpmf>



MULTI TARGET CHEMOGENOMICS



EXCAPE SMURFF FRAMEWORK



FROM BPMF TO SMURFF

SINGLE NODE, USER-FRIENDLY VERSION



- Versatile: many matrix & tensor factorization methods
- Maintainable: C++ with OpenMP and MPI
- Easy to use: `conda install smurff`
- Open source: <https://github.com/ExaScience/smurff>



A first example running SMURFF

In this notebook we will run the BPMF algorithm using SMURFF, on compound-activity data.

Downloading the data files

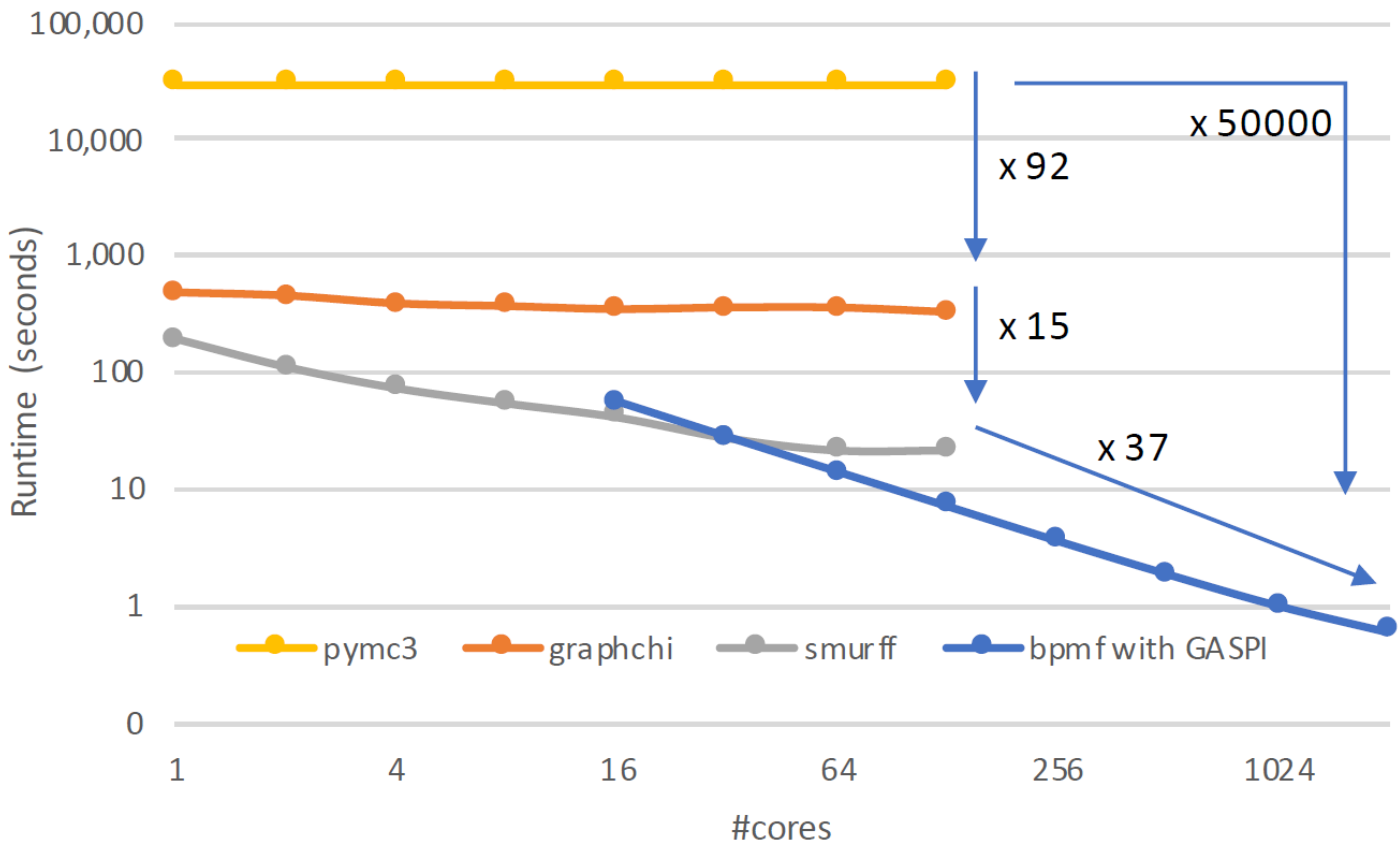
In these examples we use ChEMBL dataset for compound-proteins activities (IC50). The IC50 values are downloaded using this smurff function:

```
In [ ]: import smurff

ic50_train, ic50_test, ecfp = smurff.load_chembl()
```

The resulting variables are all `numpy.ndarray` objects. `ic50_train` is a sparse matrix containing integer

SMURFF PERFORMANCE IS STILL GOOD



ASYNCHRONOUS DISTRIBUTED BPMF WITH POSTERIOR PROPAGATION

Latent factors

Global: $\mathbf{X}_{N \times K}$

Local: $\tilde{\mathbf{X}}_{N_i \times K}^{ij}$

$$\begin{bmatrix} \mathbf{x}^1 & \tilde{\mathbf{x}}^{1j} \\ \mathbf{x}^2 & \tilde{\mathbf{x}}^{2j} \\ \mathbf{x}^3 & \tilde{\mathbf{x}}^{3j} \\ \mathbf{x}^4 & \tilde{\mathbf{x}}^{4j} \end{bmatrix}$$

$$\begin{bmatrix} \mathbf{W}^1 & \mathbf{W}^2 & \mathbf{W}^3 & \mathbf{W}^4 \\ \widetilde{\mathbf{W}}^{i1} & \widetilde{\mathbf{W}}^{i2} & \widetilde{\mathbf{W}}^{i3} & \widetilde{\mathbf{W}}^{i4} \end{bmatrix}$$

$$\begin{bmatrix} \mathbf{Y}^{11} & \mathbf{Y}^{12} & \mathbf{Y}^{13} & \mathbf{Y}^{14} \\ \mathbf{Y}^{21} & \mathbf{Y}^{22} & \mathbf{Y}^{23} & \mathbf{Y}^{24} \\ \mathbf{Y}^{31} & \mathbf{Y}^{32} & \mathbf{Y}^{33} & \mathbf{Y}^{34} \\ \mathbf{Y}^{41} & \mathbf{Y}^{42} & \mathbf{Y}^{43} & \mathbf{Y}^{44} \end{bmatrix}$$

Loading matrix

Global: $\mathbf{W} \in \mathbf{R}^{D \times K}$

Local: $\widetilde{\mathbf{W}}^{ij} \in \mathbf{R}^{D_j \times K}$

Full data: $\mathbf{Y}_{N \times D}$

Subdata: $\mathbf{Y}_{N_i \times D_j}^{ij}$

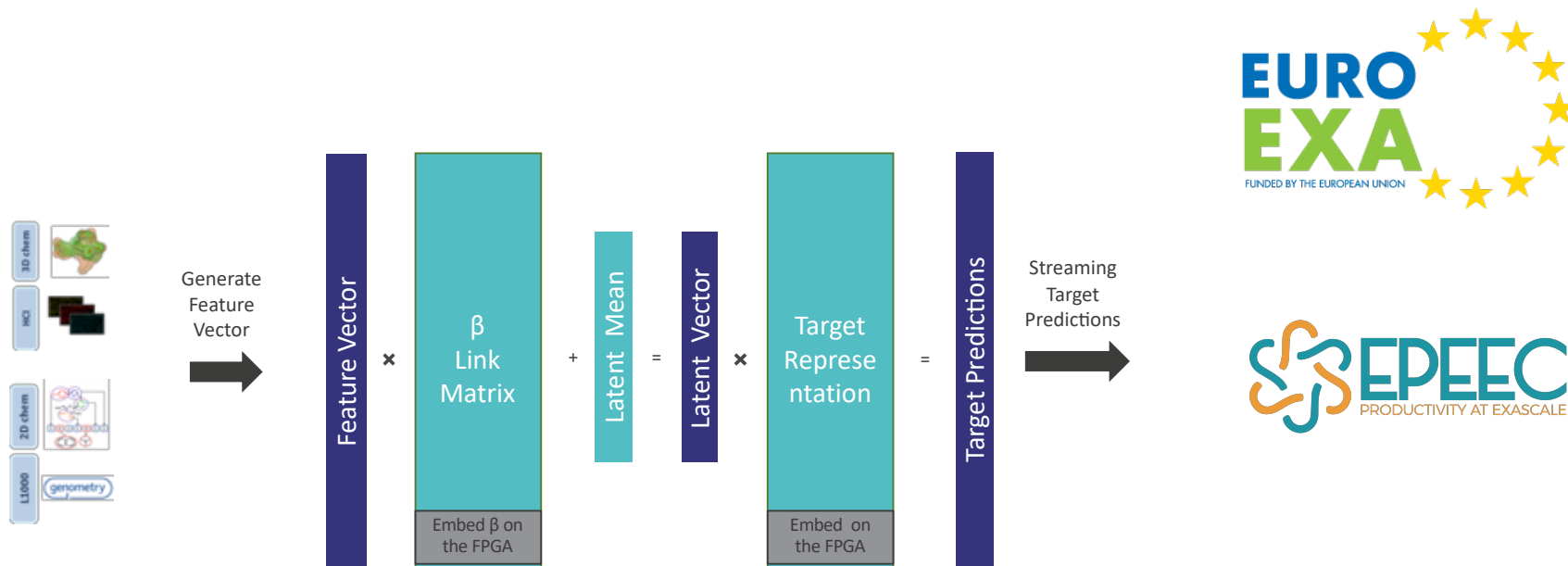


The formulation of submodels in the third stage takes the same form as BPMF, but with different priors for model parameters, i.e.

$$\begin{aligned} \mathbf{y}_n^{(i,j)} &= \widetilde{\mathbf{W}}^{(i,j)} \tilde{\mathbf{x}}_n^{(i,j)} + \epsilon_n, \quad \epsilon_n \sim \mathcal{N}_{D_j}(0, \Sigma) \\ \mathbf{x}_n^{(i,j)} &\sim p(\mathbf{x}_n^{(i,j)} | \mathbf{x}^{(i,1)}) \sim \mathcal{N}_K(\mathbf{y}_n^{(i,j)} | \mu_{\mathbf{x}^{(i,1)}}, \Sigma_{\mathbf{x}^{(i,1)}}) \\ \mathbf{w}_d^{(i,j)} &\sim p(\mathbf{w}_d^{(i,j)} | \mathbf{w}^{(1,j)}) \sim \mathcal{N}_K(\mathbf{w}_d^{(i,j)} | \mu_{\mathbf{w}_d^{(1,j)}}, \Sigma_{\mathbf{w}_d^{(1,j)}}) \end{aligned} \quad (2)$$



VIRTUAL MOLECULE SCREENING ON CPU, GPU, AND FPGA



CONCLUSIONS

- Compound Activity Prediction in the ExCAPE project
- Matrix Factorization
- BPMF with GASPI optimized by POP
- SMURFF - <https://github.com/ExaScience/smurff>
- Virtual Molecule Screening on GPU and FPGA

