

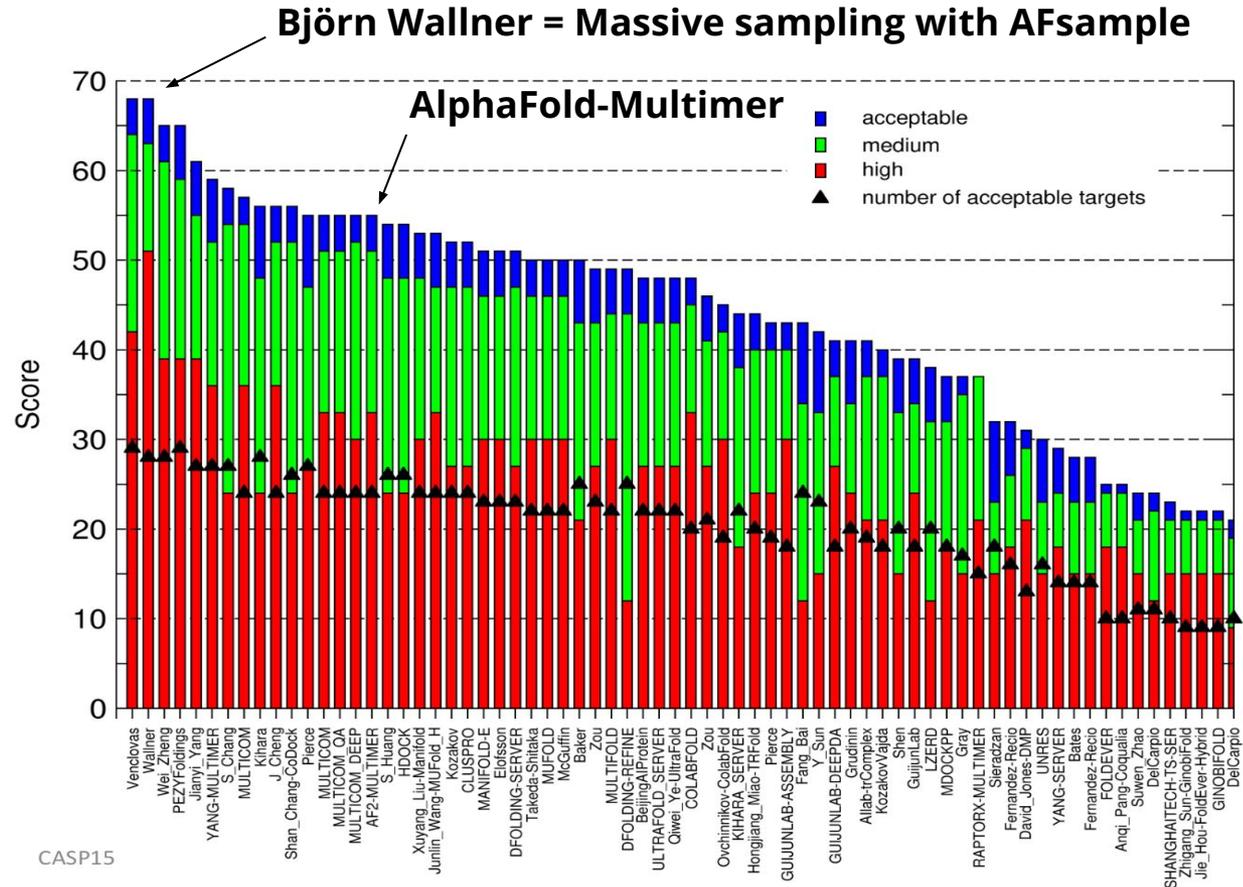
MassiveFold

Massive sampling data shared over CASP16-CAPRI

Nessim Raouraoua, Marc F. Lensink and Guillaume Brysbaert

Guillaume Brysbaert
CNRS - France - Lille

Multimers



Massive sampling:

- thousands of predictions
- diversity parameters: neural network version, dropout, templates, recycles

Limitations:

- cost in GPU hours
- management of such a large computation

CNRS supercomputing cluster "Jean Zay" - France



IDRIS - Paris

Partition CPU



28800 cœurs Intel Cascade Lake 6248 @ 2,5 GHz



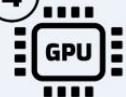
138 To



2,3 PFlop/s

Partitions GPU

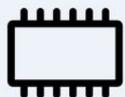
4



1832 GPU V100



OPA 100 Gb/s
par GPU

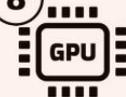


50 To HBM2



17,8 PFlop/s

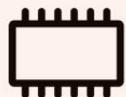
8



416 GPU A100



OPA 100 Gb/s
par GPU

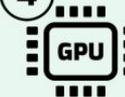


33 To HBM2e



8,2 PFlop/s

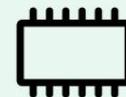
4



1456 GPU H100



IB NDR 400 Gb/s
par GPU



116 To HBM3



99,9 PFlop/s

MassiveFold

Started in March 2023 (GPU Hackathon at IDRIS with NVIDIA)



Nessim Raouraoua
Marc Lensink
Guillaume Brysbaert



Claudio Mirabello
Björn Wallner



MUDIS4LS
Christophe Blanchet



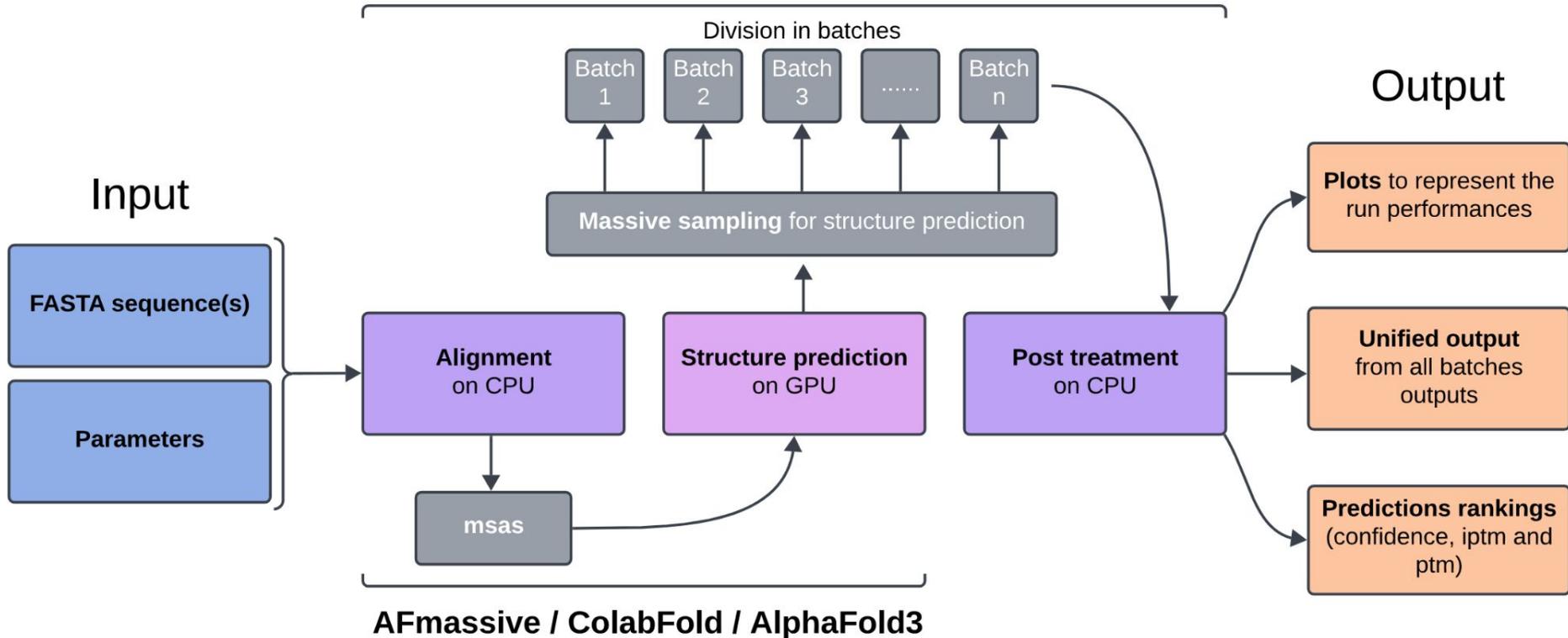
IDRIS
Supercomputing cluster Jean Zay
Thibaut Véry

Goals:

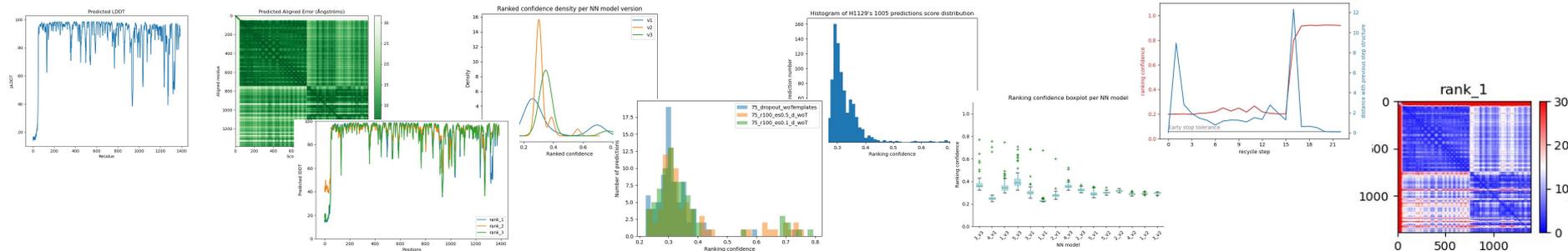
- Update **AFsample** => **AFmassive**, to use on the national cluster
- Optimization of the computing through **parallelization**

MassiveFold

Computing managed by workload manager



AFmassive / ColabFold / AlphaFold3



CASP16/CAPRI - 2024

Statement:

- CASP16 (February 2024): several groups ran massive sampling
- for CASP16-CAPRI, many groups would certainly do the same
- unfair for predictors who don't have access to many GPUs

Motivation for CASP16-CAPRI:

- provide massive sampling data to make the competition fairer
- avoid many groups burning GPU hours for the same type of computation
- boost scoring developments

CASP16/CAPRI - 2024

Statement:

- CAPRI 55 (February 2024): several groups ran massive sampling
- for CASP16-CAPRI, many groups would certainly do the same
- unfair for predictors who don't have access to many GPUs

Motivation for CASP16-CAPRI:

- provide massive sampling data to make the competition fairer
- avoid many groups burning GPU hours for the same type of computation
- boost scoring developments

Stage 0: stoichiometry

Stage 1: predictions

Participation as a baseline
Top-5 following the AF confidence score

Stage 2: MassiveFold

Predictions provided to predictors
(including "light" pickle files)

CASP16/CAPRI - 2024

(Up to) 8040 MassiveFold predictions = 8 x 15 NN x 67 predictions

Setup	Dropout Evoformer	Dropout structure module	Templates	Recycles	Structure inference engine
afm_basic			X	21	AFmassive
afm_woTemplates				21	AFmassive
afm_dropout_full	X	X	X	21	AFmassive
afm_dropout_full_woTemplates	X	X		21	AFmassive
afm_dropout_full_woTemplates_r3	X	X		3	AFmassive
afm_dropout_noSM_woTemplates	X			21	AFmassive
cf_woTemplates				21	ColabFold
cf_dropout_full_woTemplates	X	X		21	ColabFold

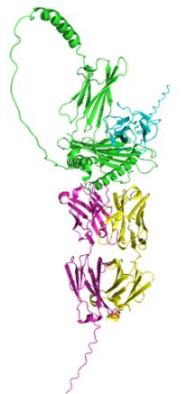
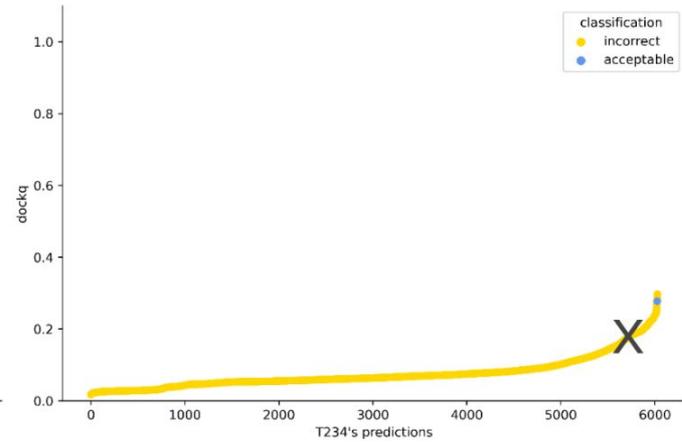
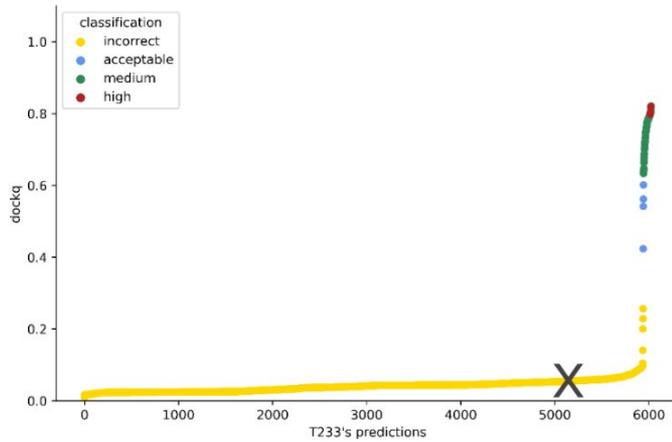
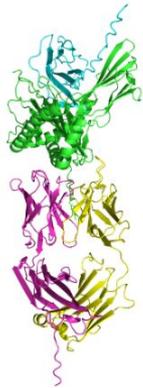
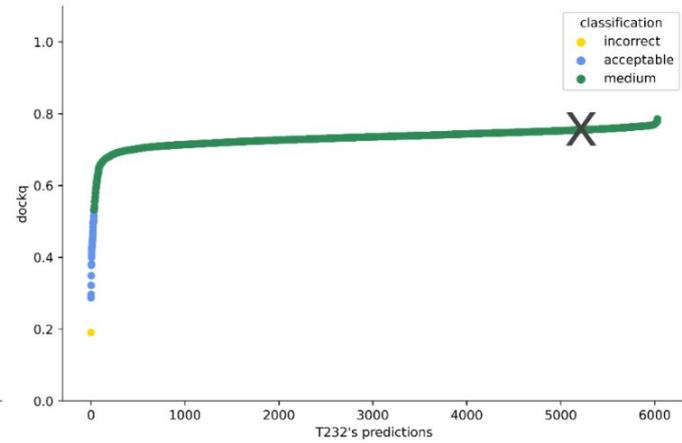
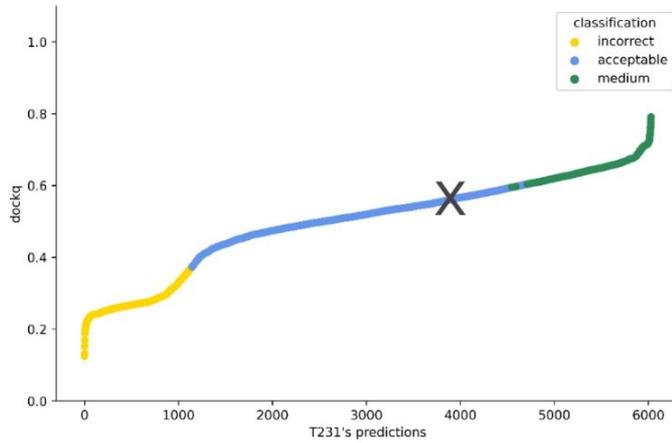
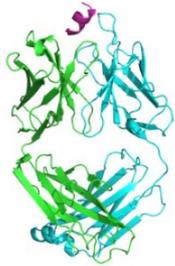
Early stop tolerance set to 0.5

CASP16/CAPRI - 2024 - Computation on Jean Zay

- **265 000 GPU hours** used (eq V100)
- **95 000 € ≈ \$100 000**
- **7.3 CO₂ tons** ≈ **9** round-trip flights Paris/Punta Cana
- **2.2 To** data shared for **73** targets in total (with “light” pickles)

Target type	Number of predictions generated	Number of GPU hours used
Monomers	262 640	43 000
Assemblies	288 605	222 000
Total	551 245	265 000

Expectations like CAPRI round 55



=> scoring

Conclusion

MassiveFold

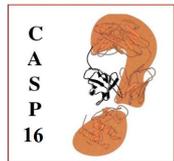
- handles computing with AFmassive and ColabFold on CPU and many GPUs
- now also includes AlphaFold3

CASP16-CAPRI

- stage 1: baseline using AF2 confident score
- stage 2: up to 8040 predictions per target shared / > 500 000 predictions

An accurate **scoring** function is required => let's see CASP16-CAPRI's results!

<https://github.com/GBLille/MassiveFold>
<https://github.com/GBLille/AFmassive>



CAPRI

+ **Nessim's POSTER**



generated with ChatGPT 4

