





UGM RDkit 2025:

ConfScale: An Open-Source Python Package for Scalable Conformer Generation and Filtration

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I- introduction

II- Data parsing

III- Data parallelism

IV- Filtration

I.a- ConfScale aims

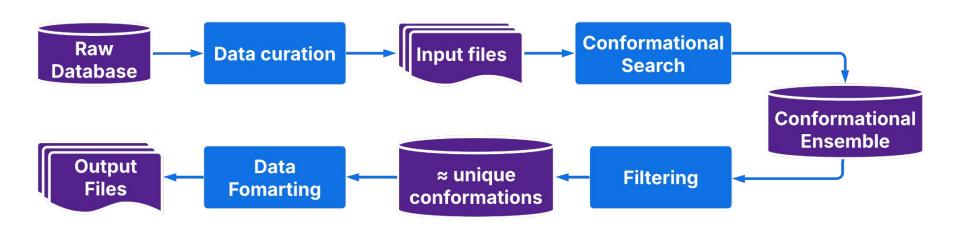
ConfScale is a python package (alpha) that aims at :

- Data formatting of molecular representations
- Data parallelism for conformers generation
- Conformers selections

ConfScale is a utility package to enable downstream Machine learning (ML) and Deep Learning task needing 3D data for *De novo* Drug Design

I.b- Pipeline Overview

ConfScale Workflow



I- introduction

II- Data curation

III- Data parallelism

IV- Filtration

Working with very large library, you may encounter the following problems:

- Loosely define data file format
- Large uncompressed files with uneven distribution
- Little to no metadata and data type

Loosely define data file format

SMILES (.smi)

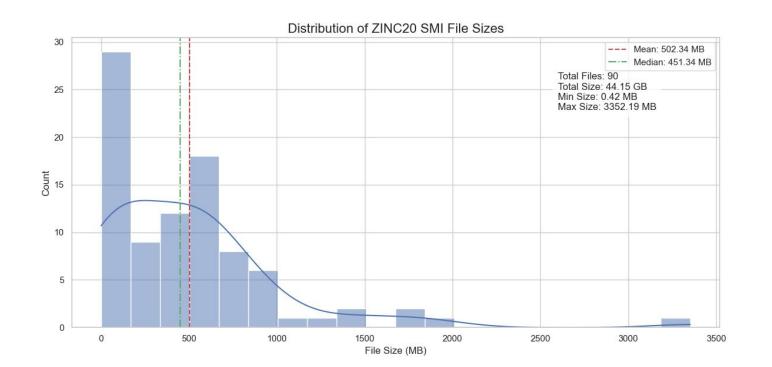
Import and Export fully support the SMILES file format.

→ Background & Context

- MIME type: chemical/x-daylight-smiles
- SMILES chemical format.
- Commonly used to describe the structure of chemical molecules.
- SMILES is an acronym for Simplified Molecular Input Line Entry Specification.
- Used in cheminformatics applications and in chemistry databases to represent chemical formulas.

- ASCII format.
- Uses a linear notation to represent the connectivity graph of a molecule.
- Can store data for multiple molecules.
- Additional properties can be stored on the same line as the SMILES string.
- Developed in the 1980s by Arthur Weininger and David Weininger.

Large uncompressed files with uneven distribution



Little to no metadata and data type

Head of a file .smi file

```
smiles zinc_id
0=C(N[C@H](CO)C(=0)0)c1n[nH]c2ccccc12 19263719
CCC(=0)c1c(N)n(C)c(=0)n(C)c1=0 26421459
C[C@H](C(=0)NC1CC1)N1CCCNCC1 26513959
CC[C@@H](CO)NC(=0)[C@@H](NC(N)=0)C(C)C 35607305
Cn1cc(CNCC2CCC2)c(=0)n(C)c1=0 37179490
CN(C)S(=0)(=0)NCC[C@@H]1CCCNC1 37717456
CS(=0)(=0)CCNC(=0)CCNC1CC1 37740334
Cc1ccc(C(=0)NCCNCC(N)=0)cc1 37902923
0=C(Nc1ccon1)C(=0)N1CCOCC1 38725124
```



Apache Parquet is a free and open-source column-oriented format:

- (Fast) compression and encoding
- Load an arbitrary number of columns
- Explicitly defined data type and support metadata
- Interoperable with existing software



Apache Parquet is a free and open-source column-oriented format:

- (Fast) compression :
 - o gzip
 - zstd
 - Snappy (default)
 - Lz4
- Efficient encoding of low cardinality data :
 - Dictionary encoding
 - Bytes packing
 - Delta encoding



Apache Parquet is a free and open-source column-oriented format:

 Each column is completely independent, and can be loaded without reading each row

Tails of dragon molecular descriptor list

4875	Depressant-50	Ghose-Viswanadhan-Wendoloski antidepressant-like index at 50%	Drug-like indices
4876	Psychotic-80	Ghose-Viswanadhan-Wendoloski antipsychotic-like index at 80%	Drug-like indices
4877	Psychotic-50	Ghose-Viswanadhan-Wendoloski antipsychotic-like index at 50%	Drug-like indices
4878	Hypertens-80	Ghose-Viswanadhan-Wendoloski antihypertensive-like index at 80%	Drug-like indices
4879	Hypertens-50	Ghose-Viswanadhan-Wendoloski antihypertensive-like index at 50%	Drug-like indices
4880	Hypnotic-80	Ghose-Viswanadhan-Wendoloski hypnotic-like index at 80%	Drug-like indices
4881	Hypnotic-50	Ghose-Viswanadhan-Wendoloski hypnotic-like index at 50%	Drug-like indices
4882	Neoplastic-80	Ghose-Viswanadhan-Wendoloski antineoplastic-like index at 80%	Drug-like indices
4883	Neoplastic-50	Ghose-Viswanadhan-Wendoloski antineoplastic-like index at 50%	Drug-like indices
4884	Infective-80	Ghose-Viswanadhan-Wendoloski antiinfective-like index at 80%	Drug-like indices
4885	Infective-50	Ghose-Viswanadhan-Wendoloski antiinfective-like index at 50%	Drug-like indices



Apache Parquet is a free and open-source column-oriented format:

 Explicitly defined data type and support metadata with schematics :

Field	Data Type	Description
smiles	String	Simplified Molecular Input Line Entry System (SMILES) notation
zinc_id	UInt32	Unique identifier for each molecule in the ZINC database
tranches	String	Data partitioning information based on logP and molecular weight



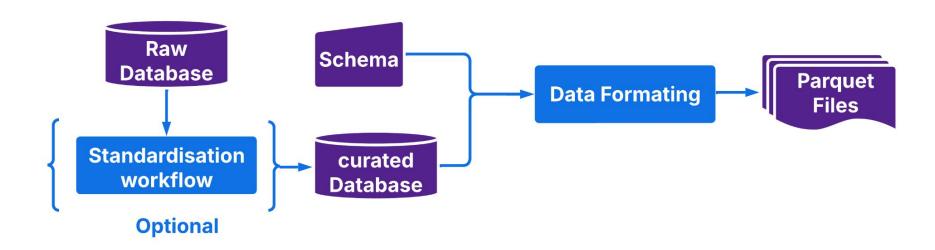
Apache Parquet is a free and open-source column-oriented format:

 Interoperable with existing software and python package like Pandas :

```
df= pd.read parquet("zinc20 drug like.parquet")
df.to parquet("zinc20 drug like.parquet")
```

/!\ Need to install dependencies : pyarrow or fastparquet

II.c- Data curation pipeline



II.d - Use case ZINC database

ZINC20 database drug-like subset is roughly 47,4 GB

Dask Performance Report

Select different tabs on the top for additional information

Duration: 140.71 s

Tasks Information

number of tasks: 3596

compute time: 73m 29s

disk-read time: 123.62 s

disk-write time: 1.69 s

transfer time: 15.93 s

Scheduler Information

Address: tcp://127.0.0.1:34061

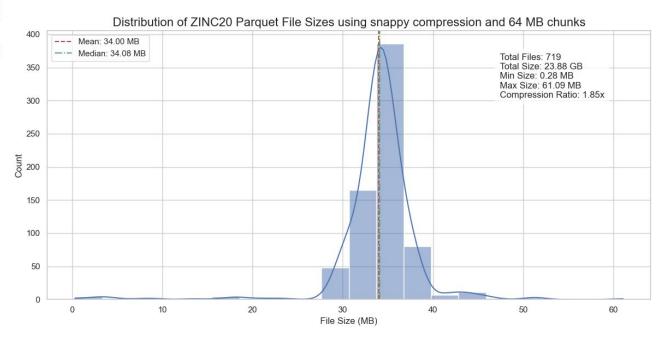
Workers: 18

Threads: 36

Memory: 25.15 GiB

Dask Version: 2025.4.1

Dask.Distributed Version: 2025.4.1



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II.d - Use case : Freedom space

Freedom space 3.0 439 millions enumerated subset original compressed file: **13,8 GB** vs compressed file **62,6 GB**

Dask Performance Report

Select different tabs on the top for additional information

Duration: 20m 43s

Tasks Information

number of tasks: 9776

compute time: 12hr 18m
disk-read time: 17.99 s

disk-write time: 885.93 ms

transfer time: 112.68 s

Scheduler Information

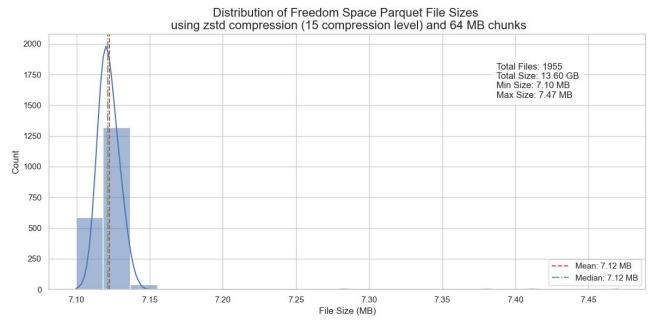
Address: tcp://127.0.0.1:37047

Workers: 18
Threads: 36

Memory: 25.15 GiB

Dask Version: 2025.4.1

Dask.Distributed Version: 2025.4.1



II.e- Take Home Message

Parquet format is good at:

- Data type and Metadata
- Interoperability
- Storing Data as independent column

Parquet format is okay-ish at:

- Compressing High cardinality data
- Readability

II.e- Perspectives

Apache parquet support nested data structure:

- One hot encoding of molecular string representation
- Saving binary array like fingerprints
- store scipy sparse matrix

I- introduction

II- Data curation

III- Data parallelism

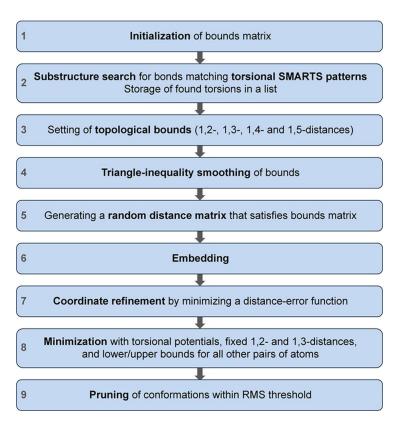
IV- Filtration

III.a - Conformer generation with ETKDGv3

Using RDKit ETKDG algorithm to generate conformers with bias toward crystal-like structures.

Is decently fast with:

- multithreading
- Optimize forcetol = 0.0135



III.b - Data Parallelism with Dask

Overview

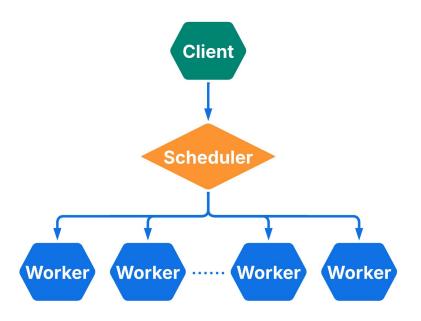
- Open-source **parallel computing library** for Python powered by joblib (like scikit-learn)
- (Easy) integration with existing NumPy, pandas codes
- Supposedly Scales from desktop computer => clusters :
 - Interface with HPC cluster via Dask-Jobqueue
 - Support commercial architecture with Kubernetes and Dask Gateway



III.b - Data Parallelism with Dask

Worker

- A Dask Worker is a process that executes tasks given by the Dask Scheduler
- Runs computations on data partitions (chunks of your dataset)
- Worker can be configure to have n threads



III.b - Parallelism: Process vs Thread

Process

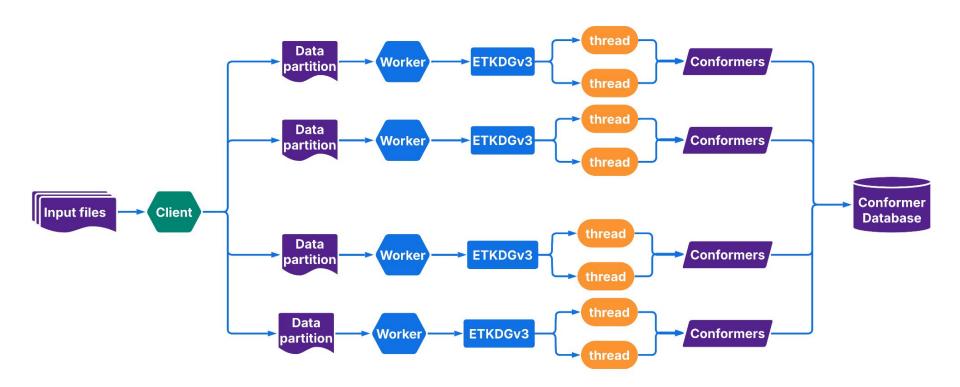
- Independent execution unit
- Has its own memory space and code
- Require time to set up
- Crashes should not affect other processes

Thread

- Lightweight execution unit typically within a process
- Shares memory and code with other threads of the same process
- Faster to create
- A crash can affect the entire process

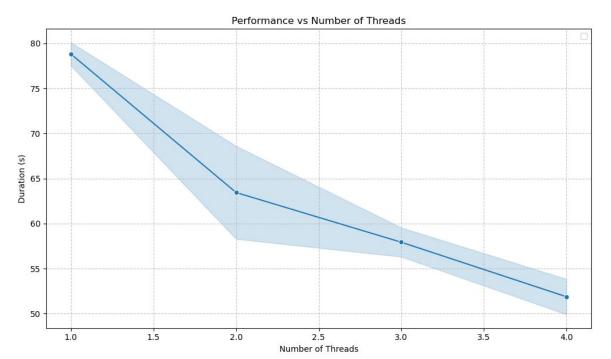
Process are **safer** but more **resource intensive** (python) , thread are **cheaper** but more **risky** (C++)

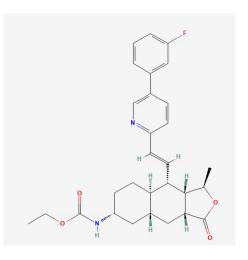
III.b - Combining Multiprocessing and Multithreading



III.c - test case vorapaxar

Experience set up: We setup **5** workers with a dummy set of **5** vorapaxar mol from which generate 1000 conformers. We change the number of thread going from 1 to 4 per worker





III.d- Take Home Message

Dask is good at and with:

- At Horizontal scaling (add lot small workers)
- Data that is well partitioned with well defined type

Dask is difficult with:

- Vertical scaling (big worker)
- Task that require inter-worker communication
- Pre-existing code needs to be carefully adapted

III.e- Perspectives

Dask Dataframe should enable the following fixture:

- GPU accelerated computing with cuda dask worker
- Full integration with existing RDKit PandasTools => distributed pattern search
- Works with python binding of software like Vina

I- introduction

II- Data curation

III- Data parallelism

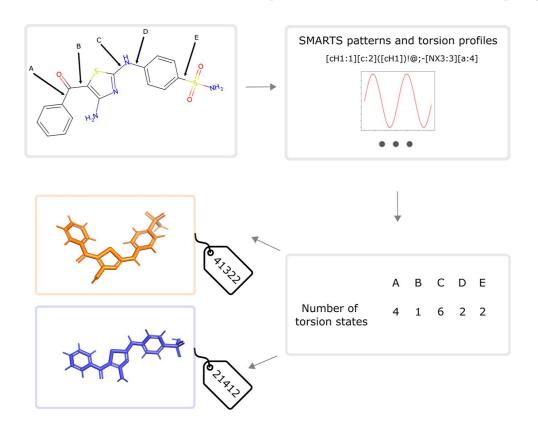
IV- Filtration

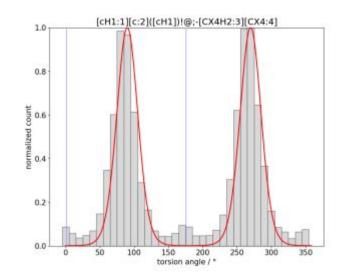
IV.a- The RMSD Filtration problem

RMSD suffers from the following drawbacks:

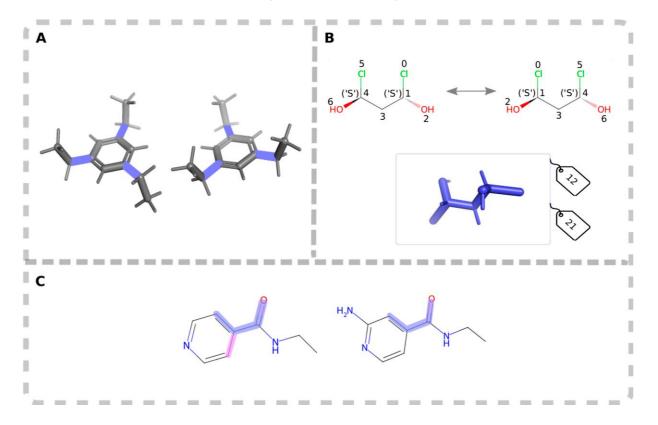
- What is a good reference conformation for alignment
- Pairwise RMSD is resource intensive
- What is an acceptable threshold to consider two conformations different?

IV.b- Torsion Angular Bin String (TABS)





IV.b- Global and local symmetry Problems



IV.b- Proposed alternative for symmetry

TABS maps the molecule using SMARTS querying. If number of mapping >1 => global symmetry

<u>Alternative</u>:

Computing atom canonical ranking without breaking ties:

- If set of canonical indices < nb atoms => global symmetry
- Local symmetry yield identical canonical indices => aggregation and deduplication

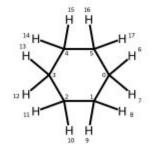
IV.c- Conformational Fingerprint

Categorical labels derived from tabs are transformed into (sim)count fingerprint:

- All torsion angles with same index are aggregated
- Torsion angle with same middle bond are discarded

C

IV.b- Confp: cyclohexane

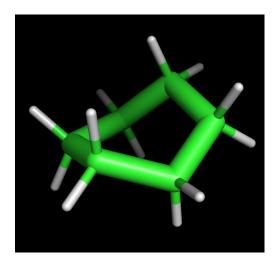


Cyclohexane analysis with ETKDGv3:

- Torsion smarts: [!#1;r{5-8}:1]@[CX4;r{5-8}:2]@;-[CX4;r{5-8}:3]@[!#1;r{5-8}:4]
- Number of angular Bin derived from literature: 3 [0, 120, 240]
- Number of equivalent torsion angle using canonical atom ranking: 6



IV.b- Confp: cyclohexane







III.d- Take Home Message

RMSD is not a very good solution because:

- Need to define reference pose
- Pairwise comparison are expensive
- What defines a good threshold to differentiate two conformers

TABS and confp are:

- Doesn't require alignment
- Can take into account global symmetry (TABS and confp)
- Can take into account some local symmetry (confp)

Conclusion

COnfScale provides some utilities to:

- Format data file to prepare for data parallelism
- Combine multithreading and multiprocessing to accelerate conformer generation
- Provide filtration of conformer that differs from classical RMSD

Perspectives

COnfScale should also provide in the future:

- Support to 3D/2D structural datafile like sdf
- Integration with chemoinformatics projects such as:
 - Scikit-fingerprint
 - EasyDock

Thank You