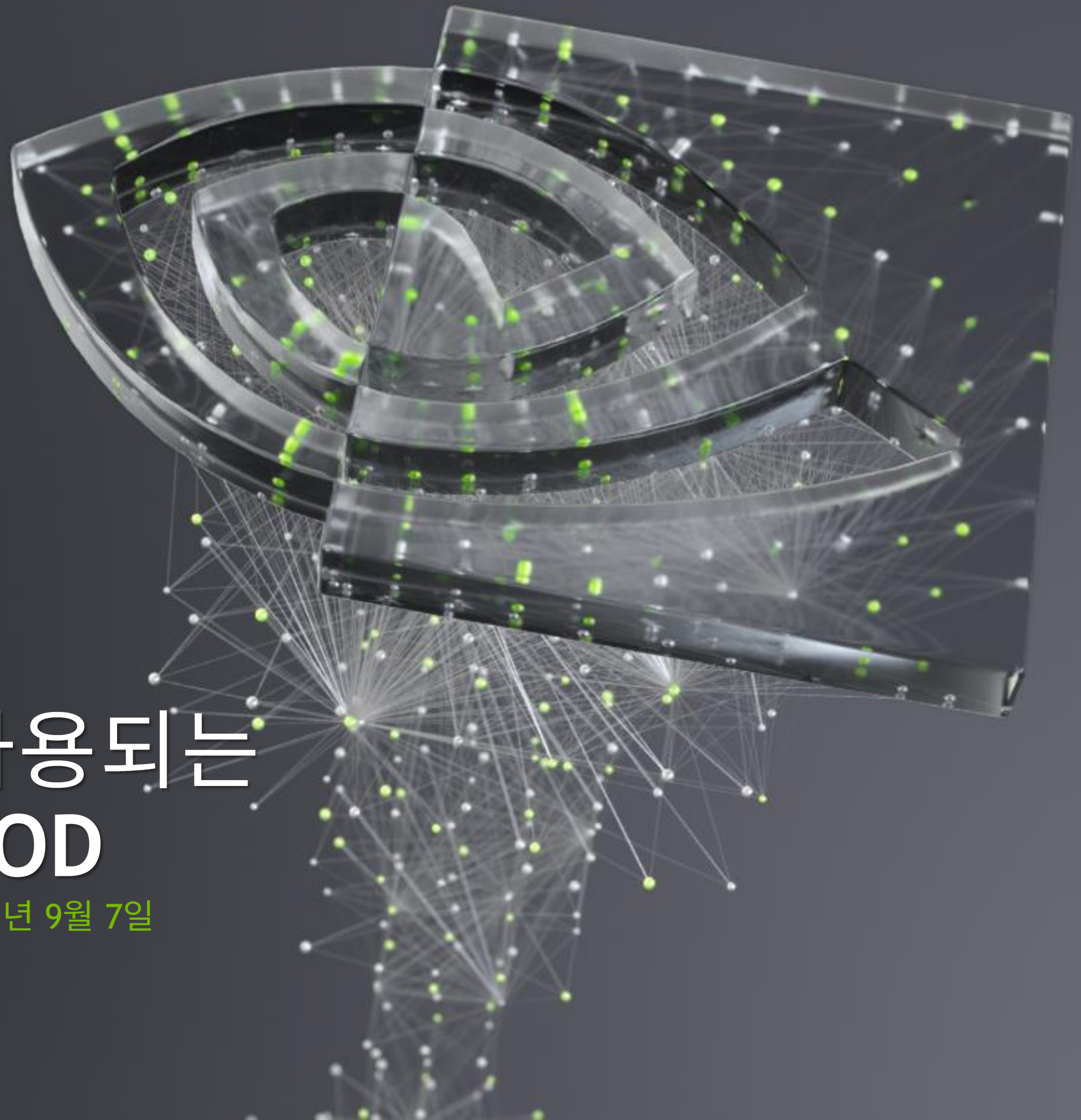




# 신약/신소재 개발에 사용되는 NVIDIA DGX SUPERPOD

정구형 부장, Solutions Architect, NVIDIA Korea, 2021년 9월 7일





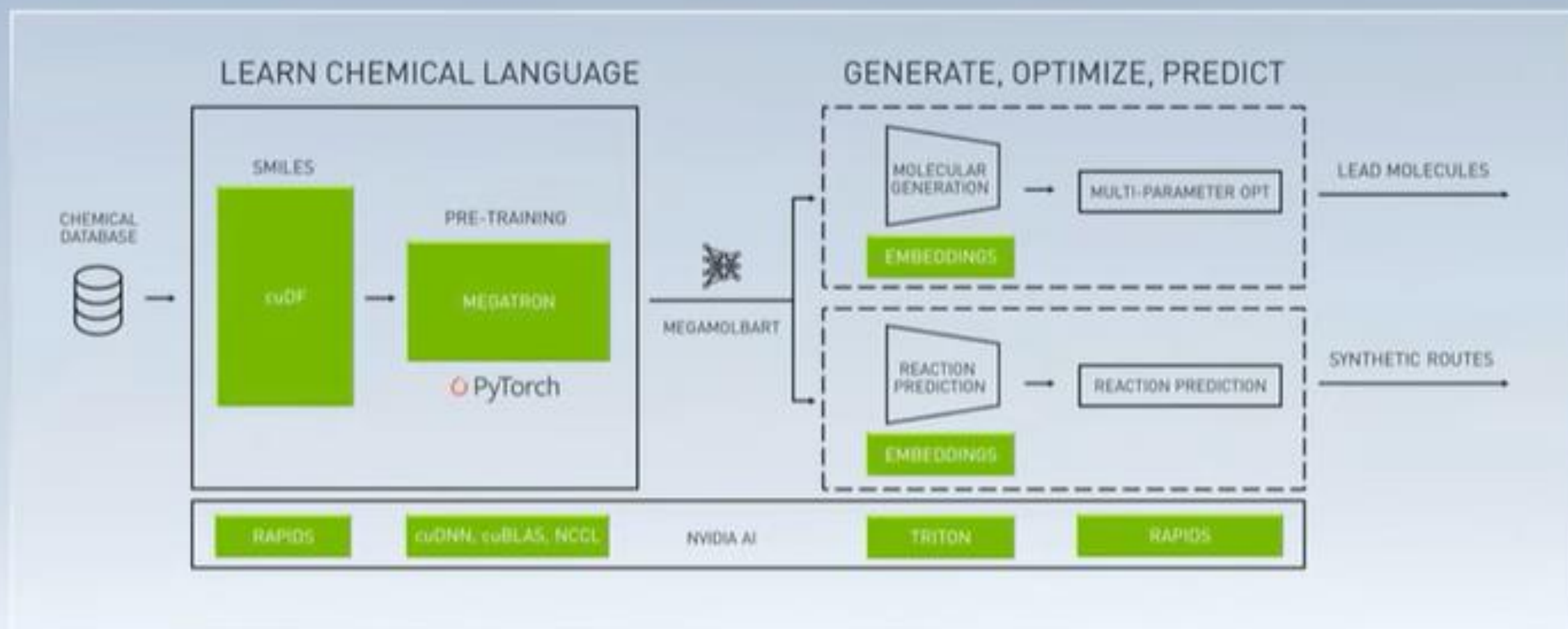
“GPT-3와 같은 초거대 AI 모델을 위한  
NVIDIA DGX SuperPOD”

지난 6월 세션에 이어 이번 발표에서는...



# ANNOUNCING MEGAMOLBART

Understanding the Language of Chemistry



Pre-Training with 1B Molecules in Zinc Database

Megatron Multi-GPU, Multi-Node Training  
Across 32 DGX A100

Triton Inference 250M Molecules/Day on Cambridge-1

Molecule Generation | Molecular Optimization  
Synthesis Prediction

Cambridge-1  
DGX SuperPOD





# NVIDIA SELENE

running molecular dynamics applications

NVIDIA DGX SuperPOD for internal use

4,480 A100 GPUs

560 DGX A100 systems

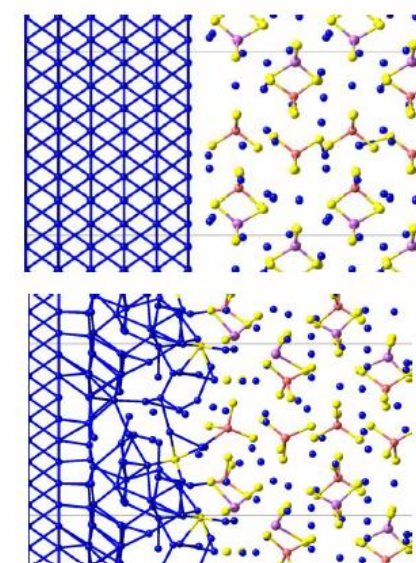
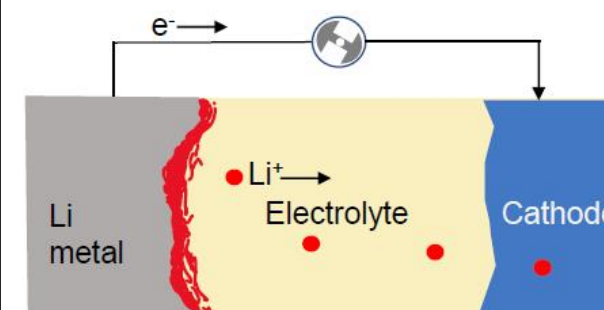
850 Mellanox 200G HDR switches

14 PB of high-performance storage

2.8 EFLOPS of AI peak performance

63 PFLOPS HPL @ 24GF/W

## Batteries with High Power Density



Ab initio molecular dynamics calculations are computationally highly demanding

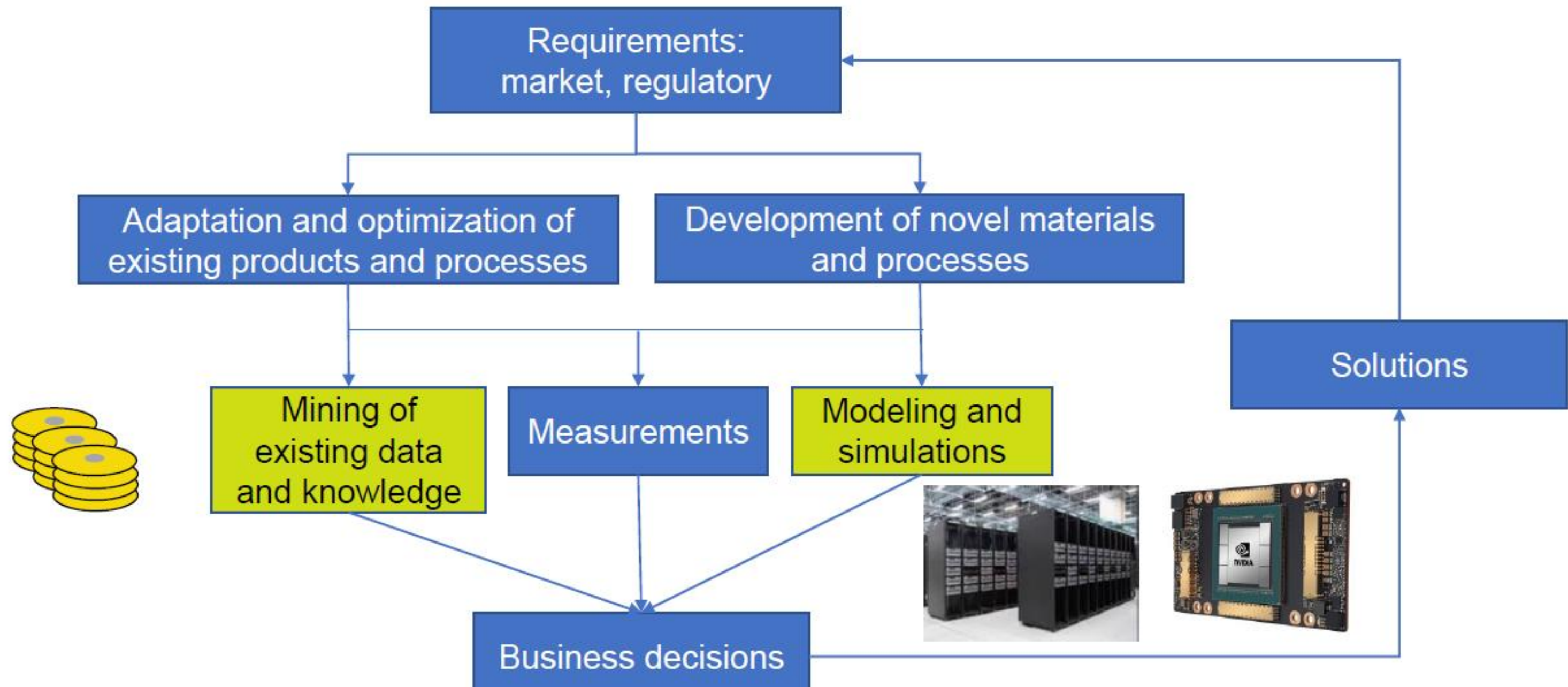






# R&D WORKFLOW

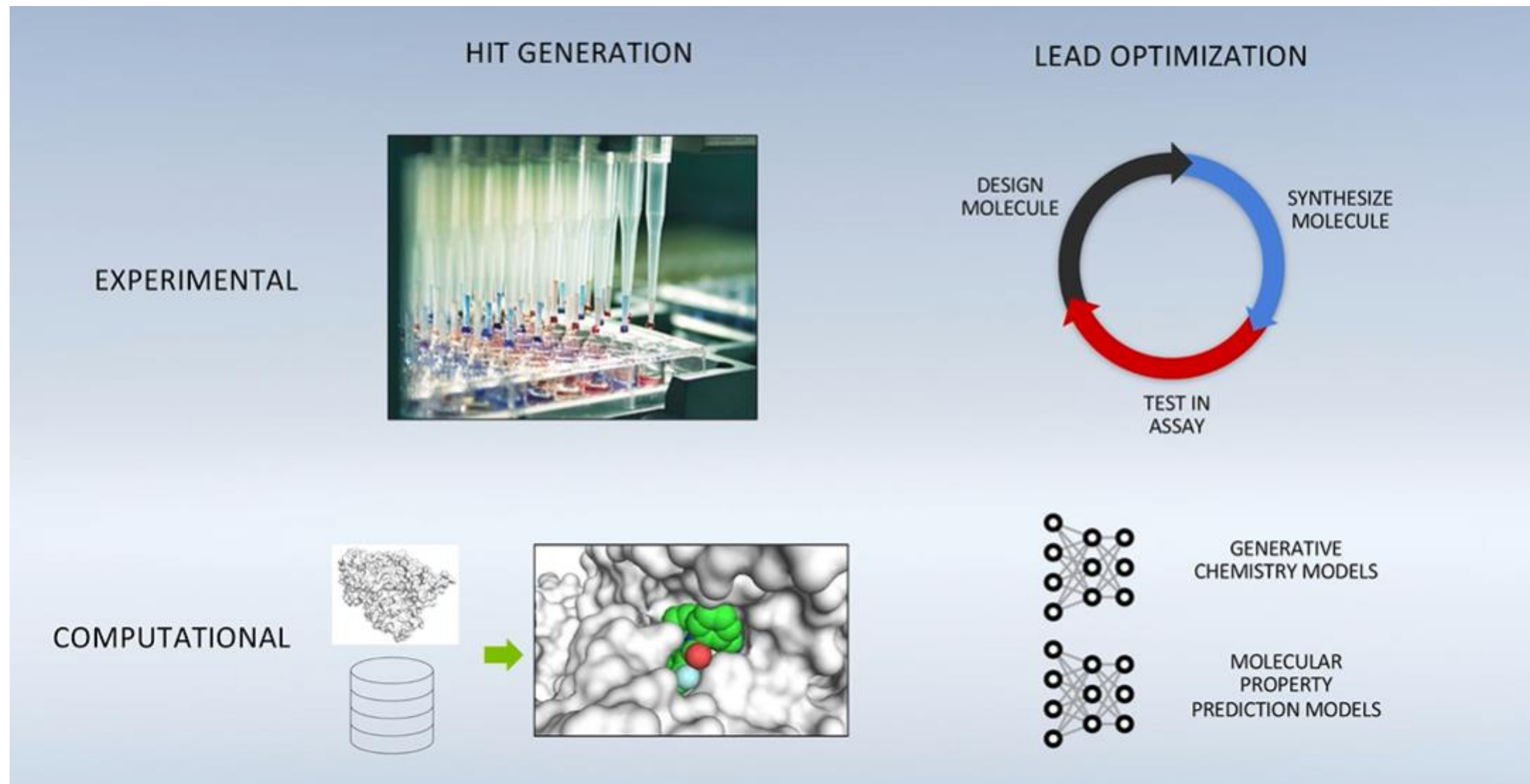
직접 실험 vs. Computational simulation





# 예. 신규 물질 개발

## 직접 실험 vs. Computational simulation

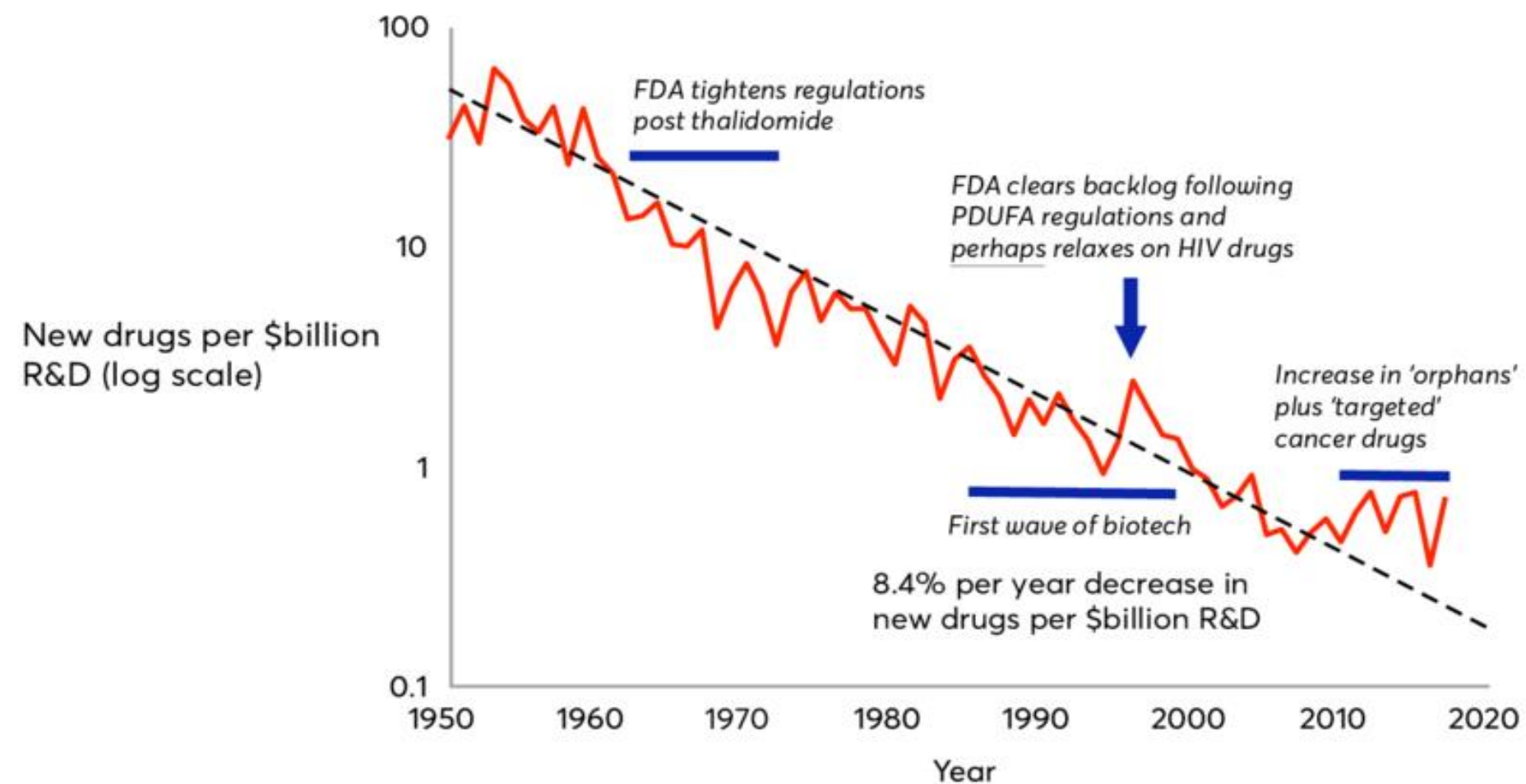


Source: [Accelerating Drug Discovery with Clara Discovery's MegaMolBart](#), NVIDIA, YouTube (2021년 4월)



# EROOM'S LAW - 신약 개발 성공률 저하

평균 10년이 넘는 시간 | 신약 1개 개발시 평균 \$2B 비용 | 신약 개발 실패율 90%



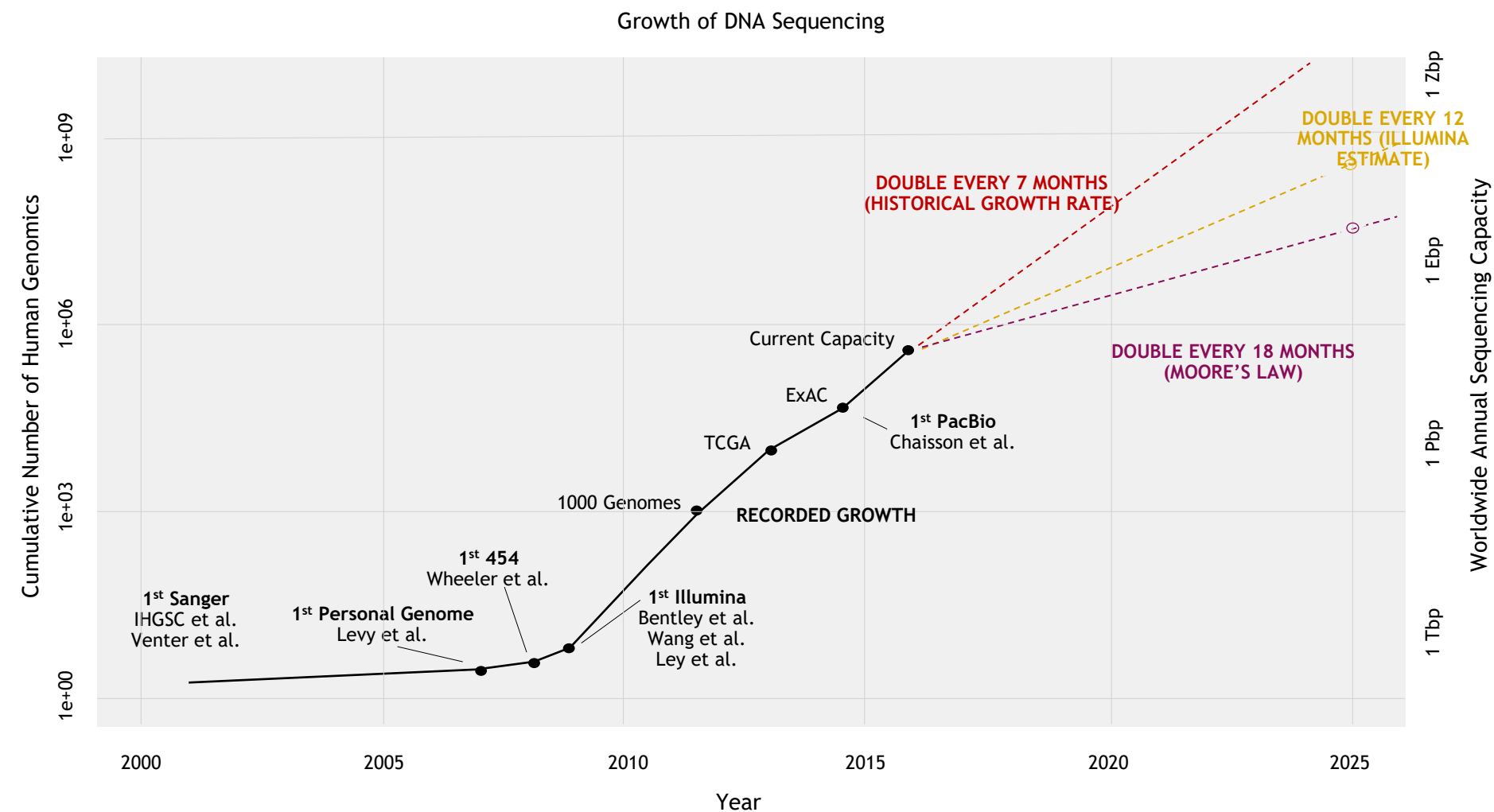
## Eroom's Law

Exponential Decline in Drug Discovery R&D Productivity



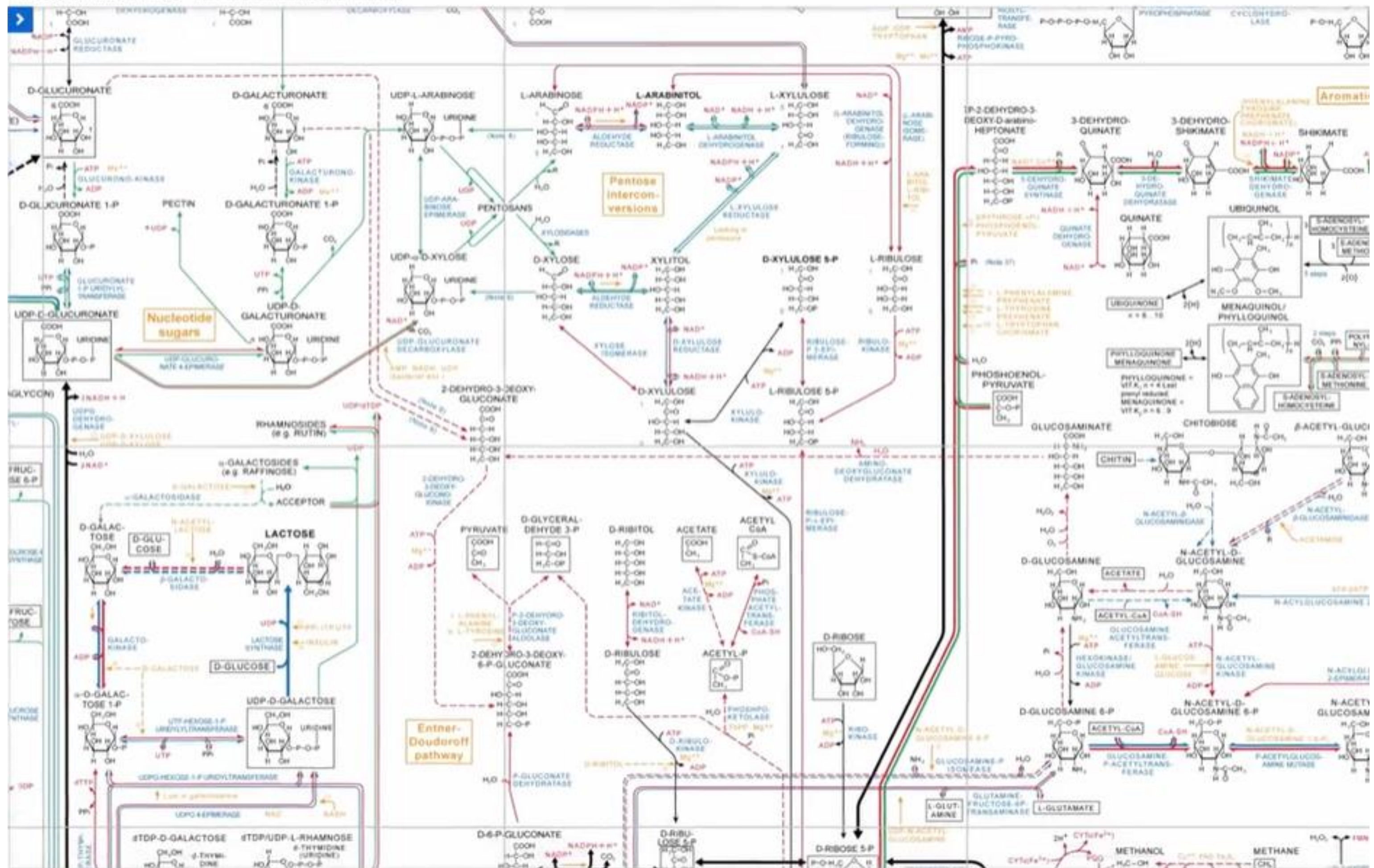
# EROOM'S LAW - 신약 개발 성공률 저하

폭발적으로 늘어나는 biomedical 데이터



Biomedical Data Explosion  
Sequencing, Protein, Imaging



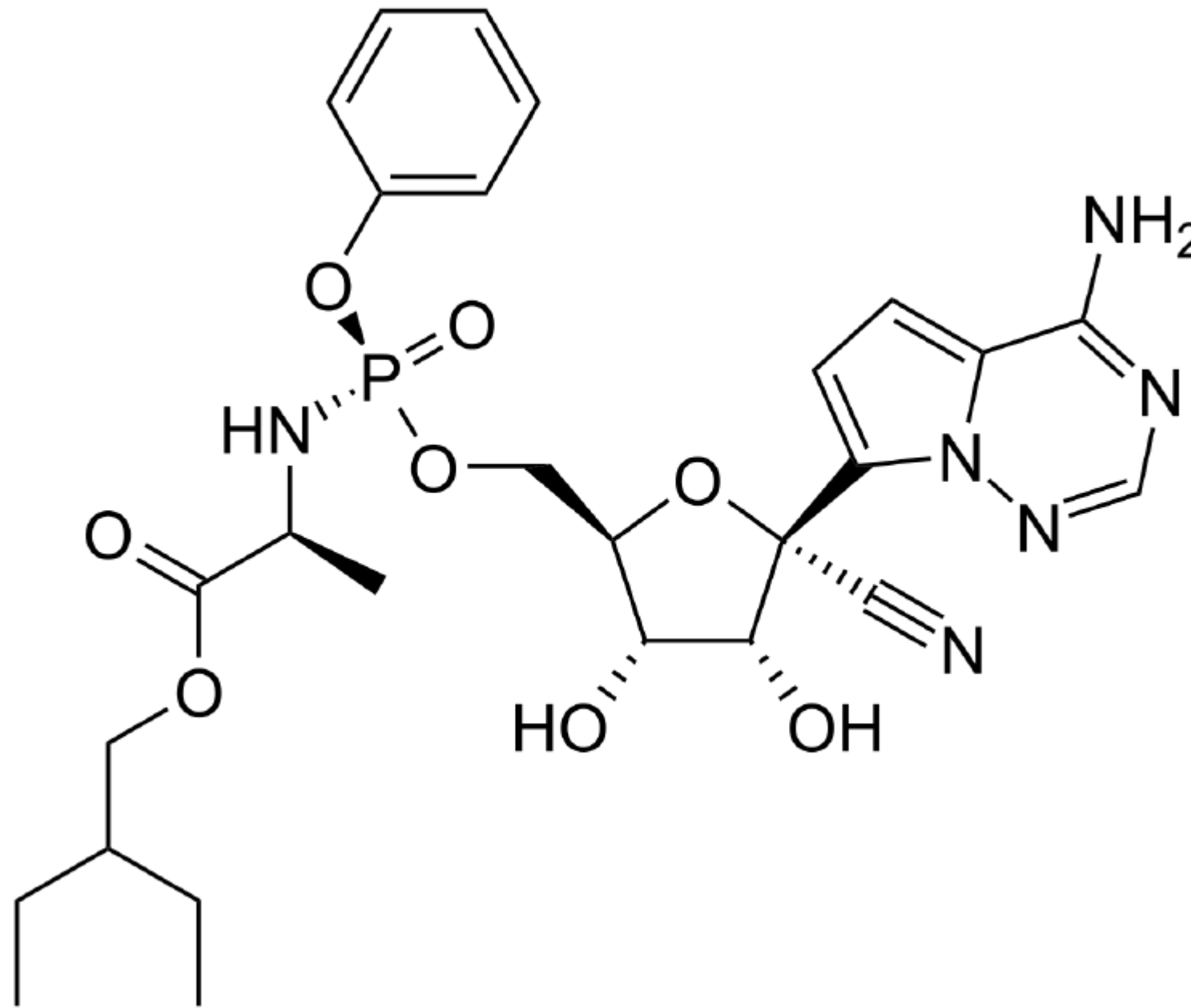






# 신약 개발은 얼마나 힘든 일일까요?

지금 여러분은 하나의 화학 구조물을 보고 계십니다.





## 30개의 원자로 구성할 수 있는 분자 구조 경우의 수

[illegible]

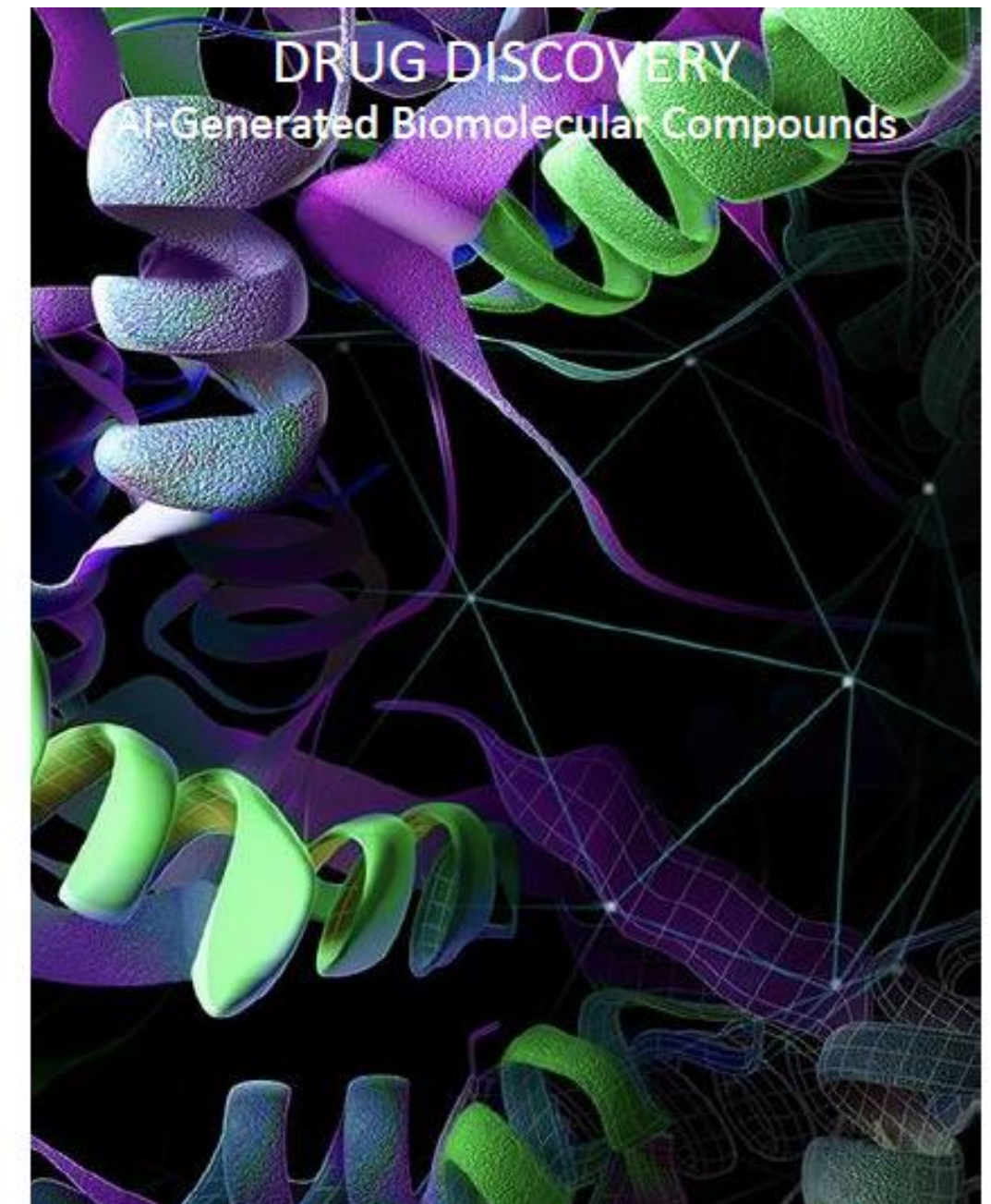
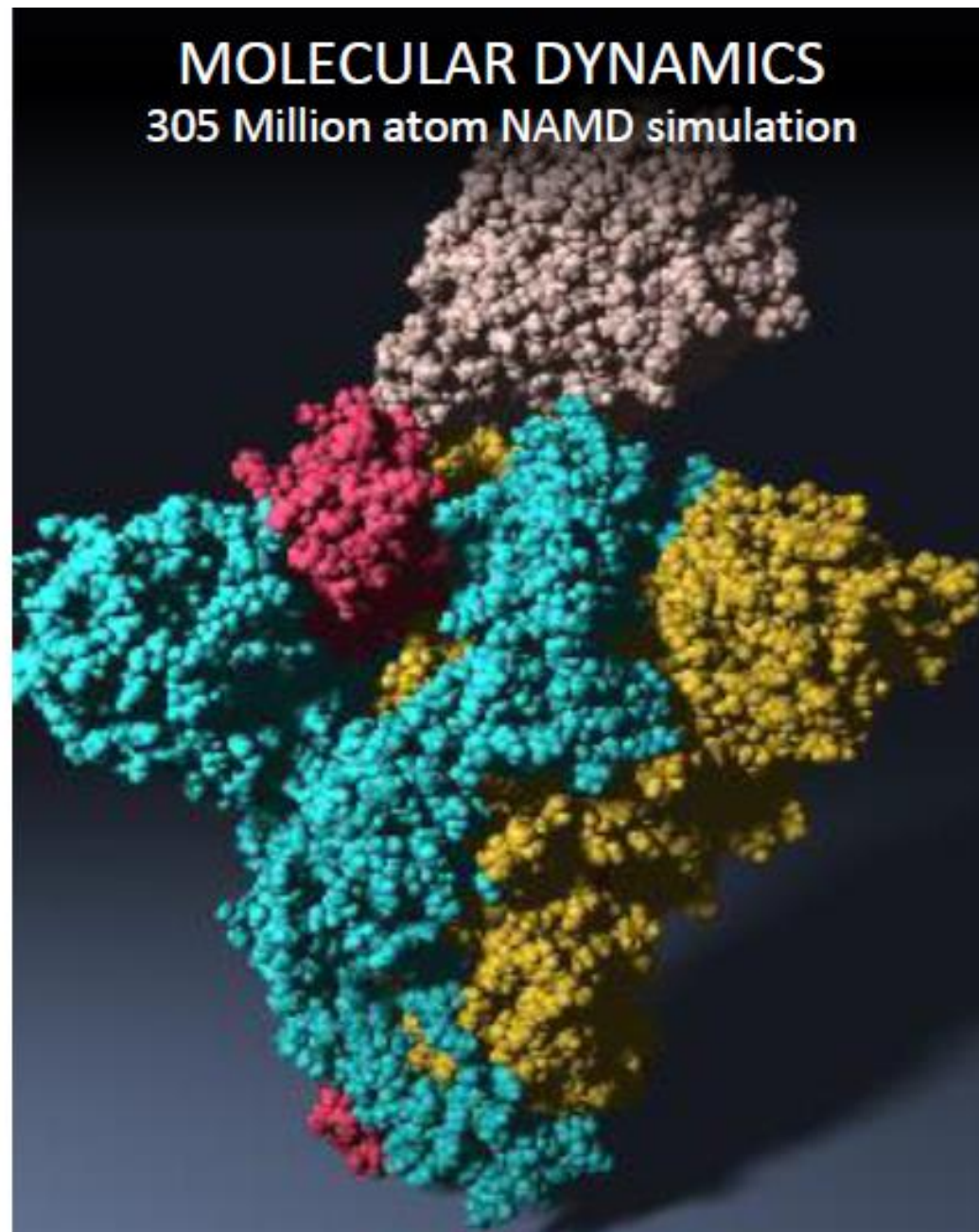
Number of protons/neutrons on Earth ( $10^{24}$  kg /  $10^{-27}$  kg =  $10^{51}$  particles)

Time to compute all structures ( $10^{35}$  years, assuming 200 PF of Summit, 1 structure / FLOP)



# R&D에서 \*SIMULATION\* 중요성 대두

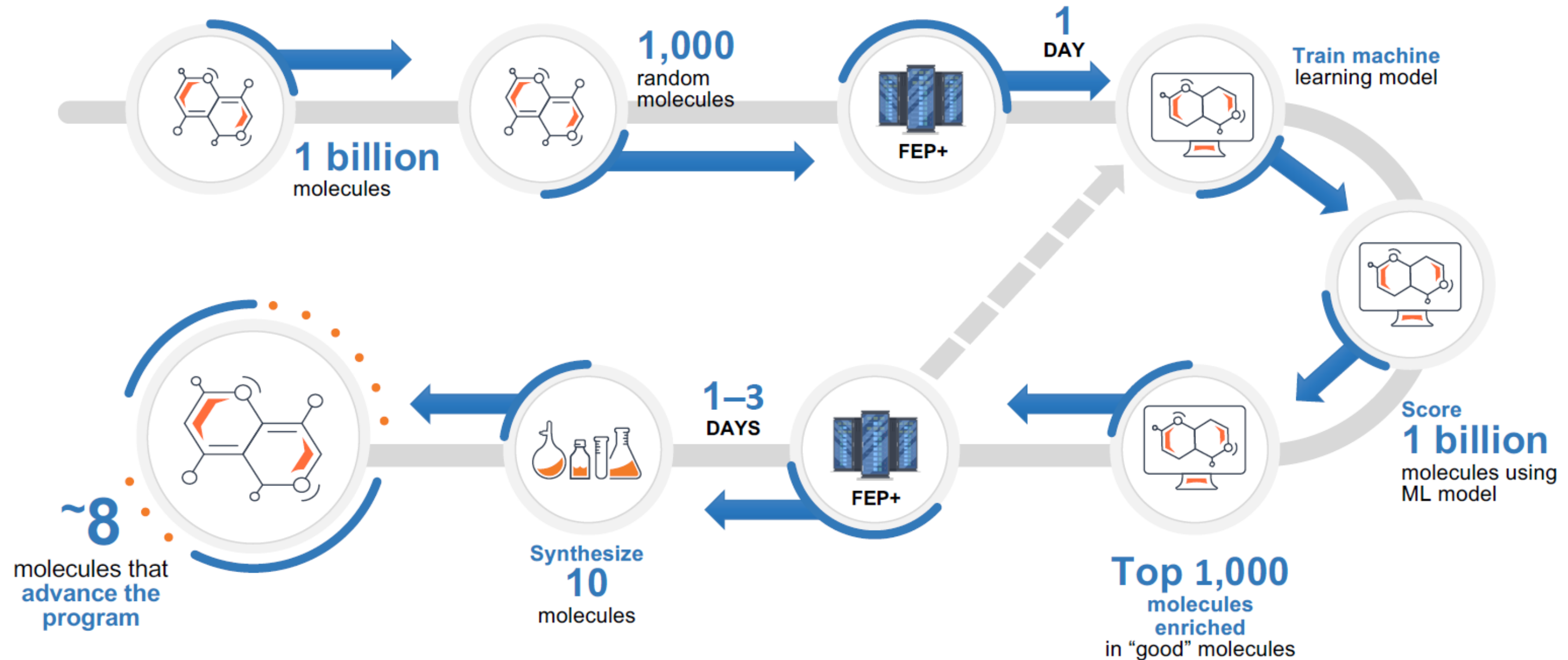
Simulation이 활발히 적용될 수 있는 산업 분야





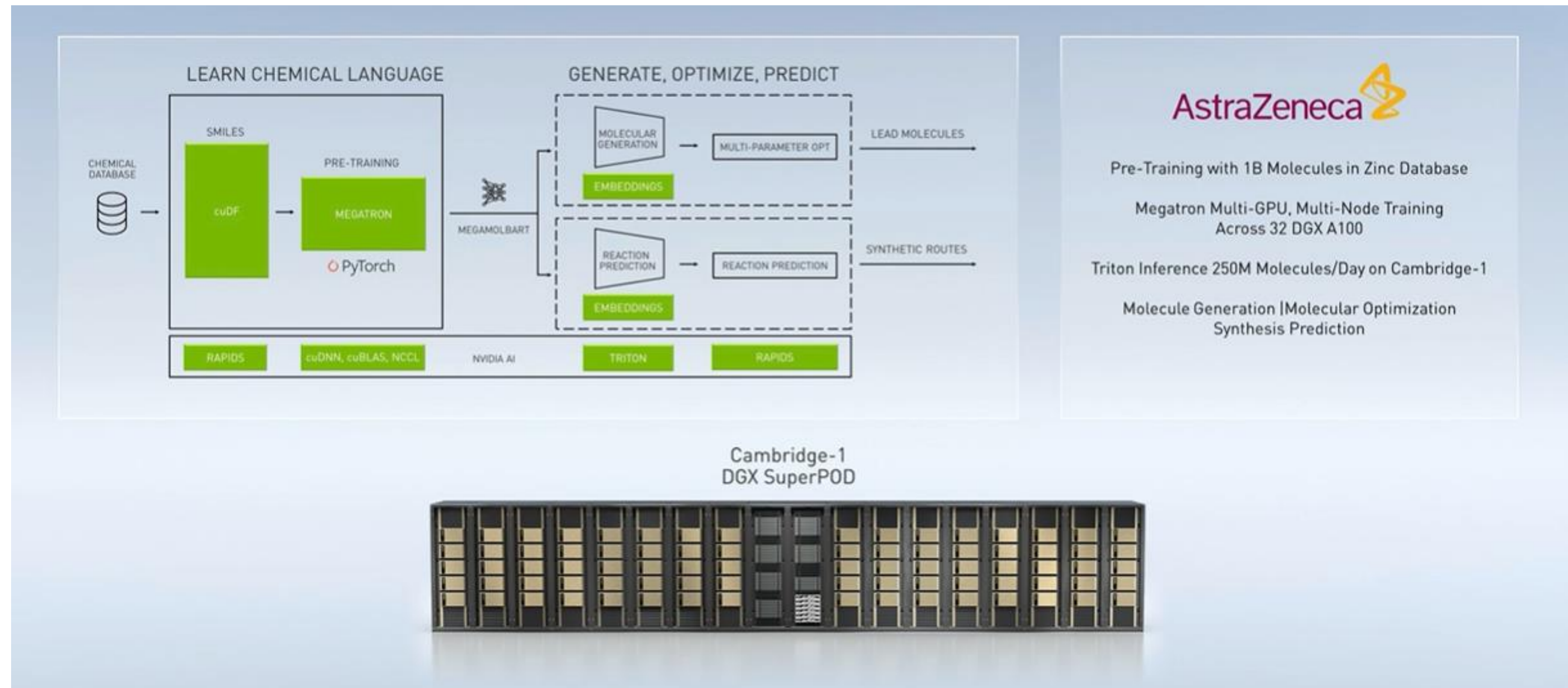
# 신규 물질 개발시 SIMULATION 역할

(1) 얼마나 적합한 후보 물질(HIT)을 찾느냐, (2) 찾은 후보 물질을 얼마나 빨리 시뮬레이션하느냐



# ASTRAZENECA 신약 개발에 활용된 NVIDIA DGX SUPERPOD

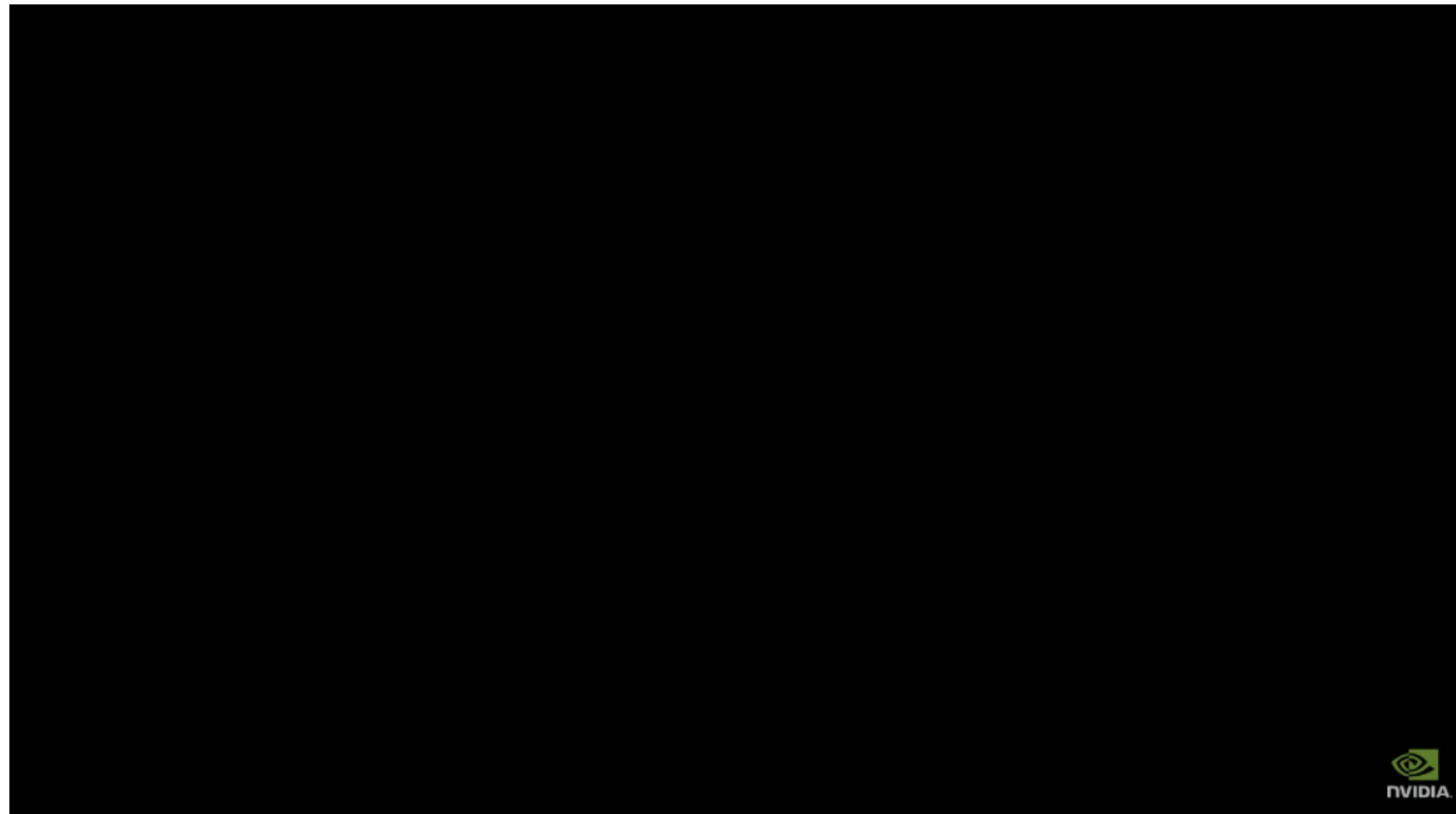
ZINC 데이터베이스에 저장된 10억 여 개 분자 구조 학습 → 타겟 화학 물질에 반응할 후보 hit 생성





# SARS-COV-2에 반응하는 화학 물질 찾기 (VIRTUAL SCREENING)

수 억 개의 분자를 이해하고 있는 AI가 1초에 약 4개 hit 생성 (CPU는 7초에 1개 hit 생성)



Source: [Accelerating Drug Discovery with Clara Discovery's MegaMolBart](#), NVIDIA, YouTube (2021년 4월)

# 타겟 바이러스에 적합한 후보 물질 클러스터링

색깔은 클러스터 구분, 다이아몬드 모양은 클러스터 안에서 후보 hit 분자를 뜻함





# 이렇게 생성된 후보 HIT 분자 2개를 사용자가 지정하면

AI가 자동으로 그 범위 내 추가 후보 hit 분자 생성

**Select Generative Model**

MolBART

**Set number molecules to generate**

5

**Please Select Two**

☒ CHEMBL10188

☒ CHEMBL116438

Generate

Reset

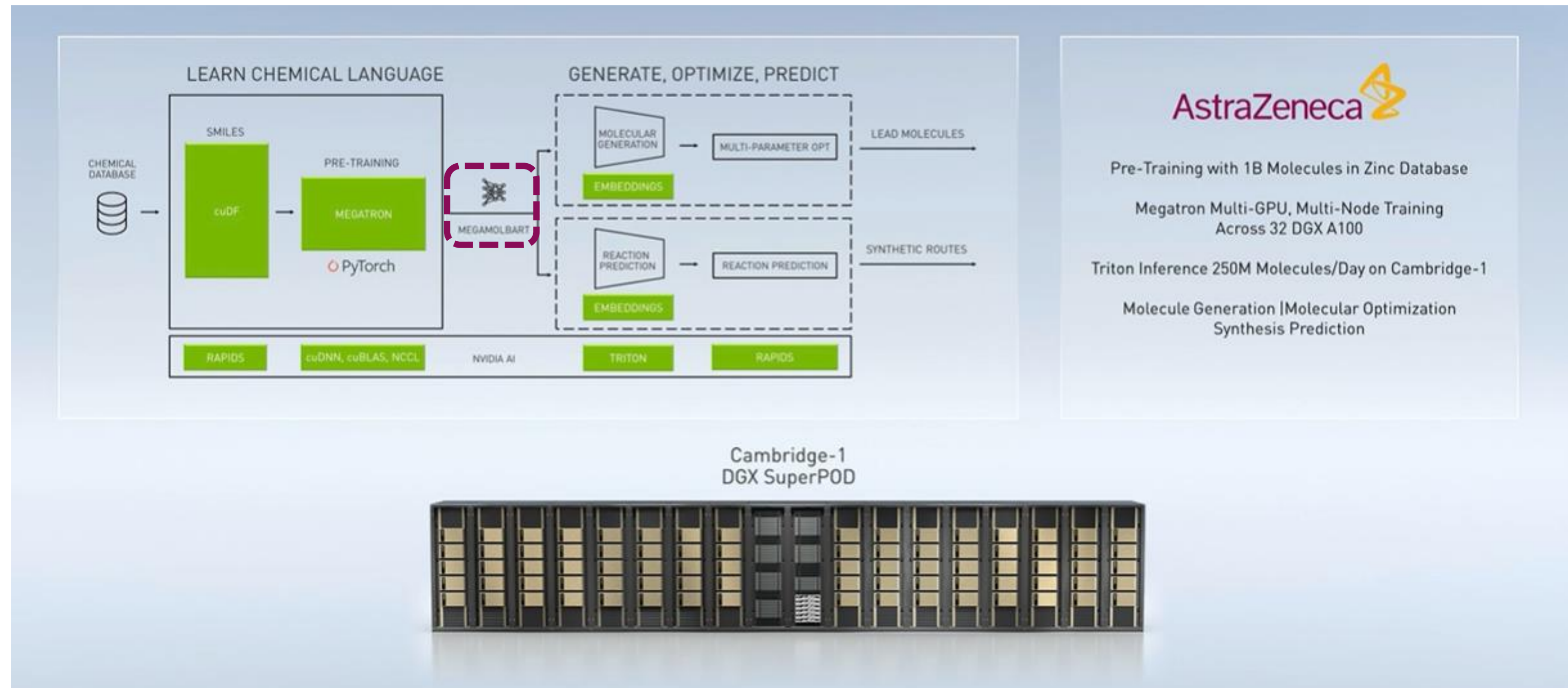
**Select Molecular Property for color gradient**

Select...

SMILES	Generated	Chemical Structure	Molecular Weight	LogP	H-Bond Donors	H-Bond Acceptors	Rotatable Bonds
<chem>CC(C#N)NC1=O/N1Dc1c2ccccc2nc3ccccc13</chem>	False		382.40	5.49	2	3	5
<chem>c1ccc2c(c1)ccc3c2c(c1)nc4ccccc43</chem>	True		345.44	4.15	2	2	5
<chem>c1ccc2c(c1)ccc3c2c(c1)nc4ccccc43</chem>	True		330.43	4.92	1	1	5
<chem>c1ccc2c(c1)ccc3c2c(c1)nc4ccccc43</chem>	True		365.41	4.88	1	4	7
<chem>c1cc(OC)ccc2c(c1)ccc3c2c(c1)nc4ccccc43</chem>	True		328.36	3.82	0	5	7
<chem>c1cc(OC)ccc2c(c1)ccc3c2c(c1)nc4ccccc43</chem>	True		340.38	3.75	1	5	7
<chem>COc1cc(OC)ccc2c(c1)ccc3c2c(c1)nc4ccccc43</chem>	False		368.39	3.85	3	6	7

# ASTRAZENECA의 후보 HIT 생성에 사용된 기술들

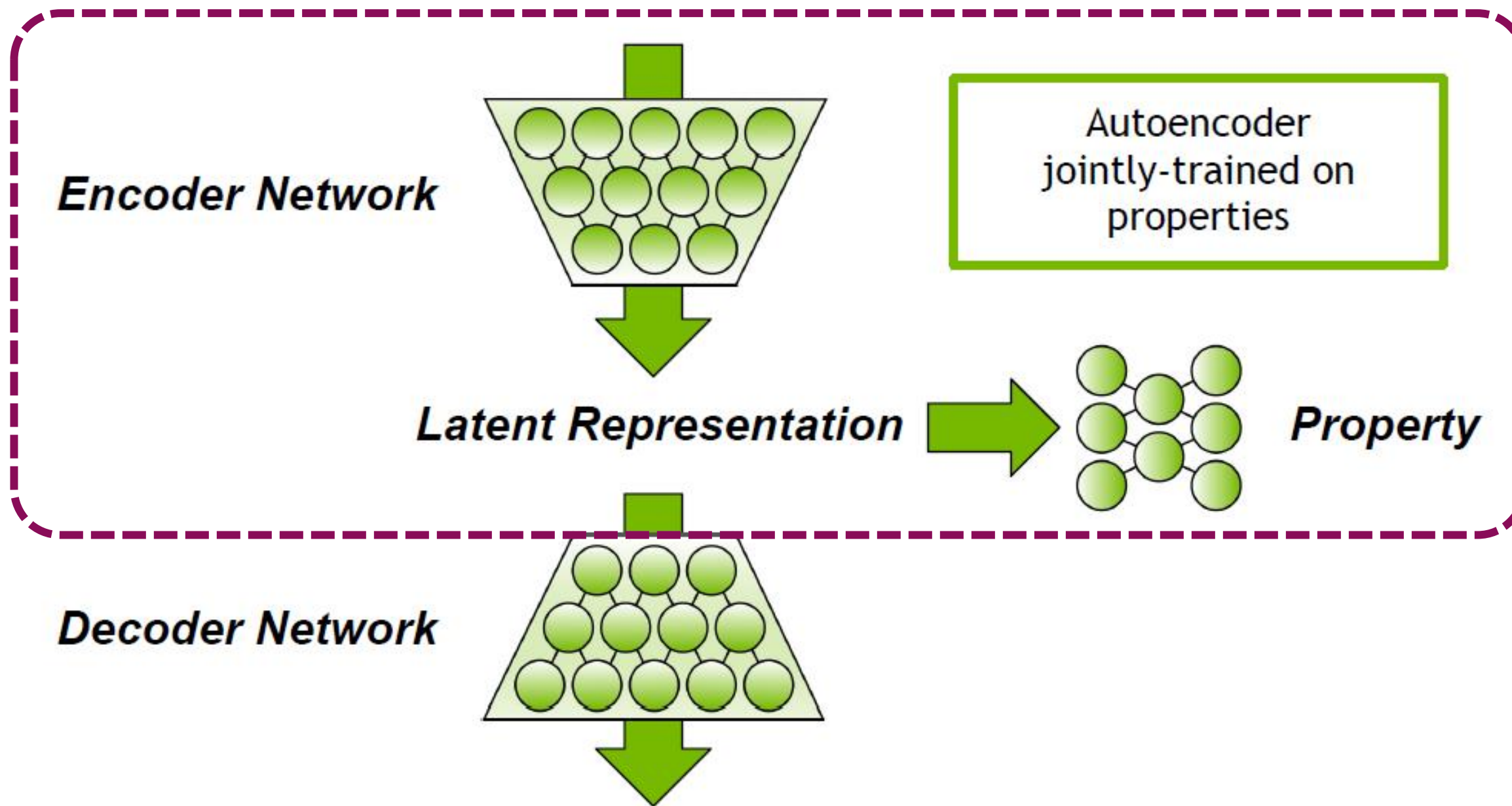
\*MegaMolBART\*, transformer 기반 generative AI 모델 (NVIDIA와 AstraZeneca 협업)



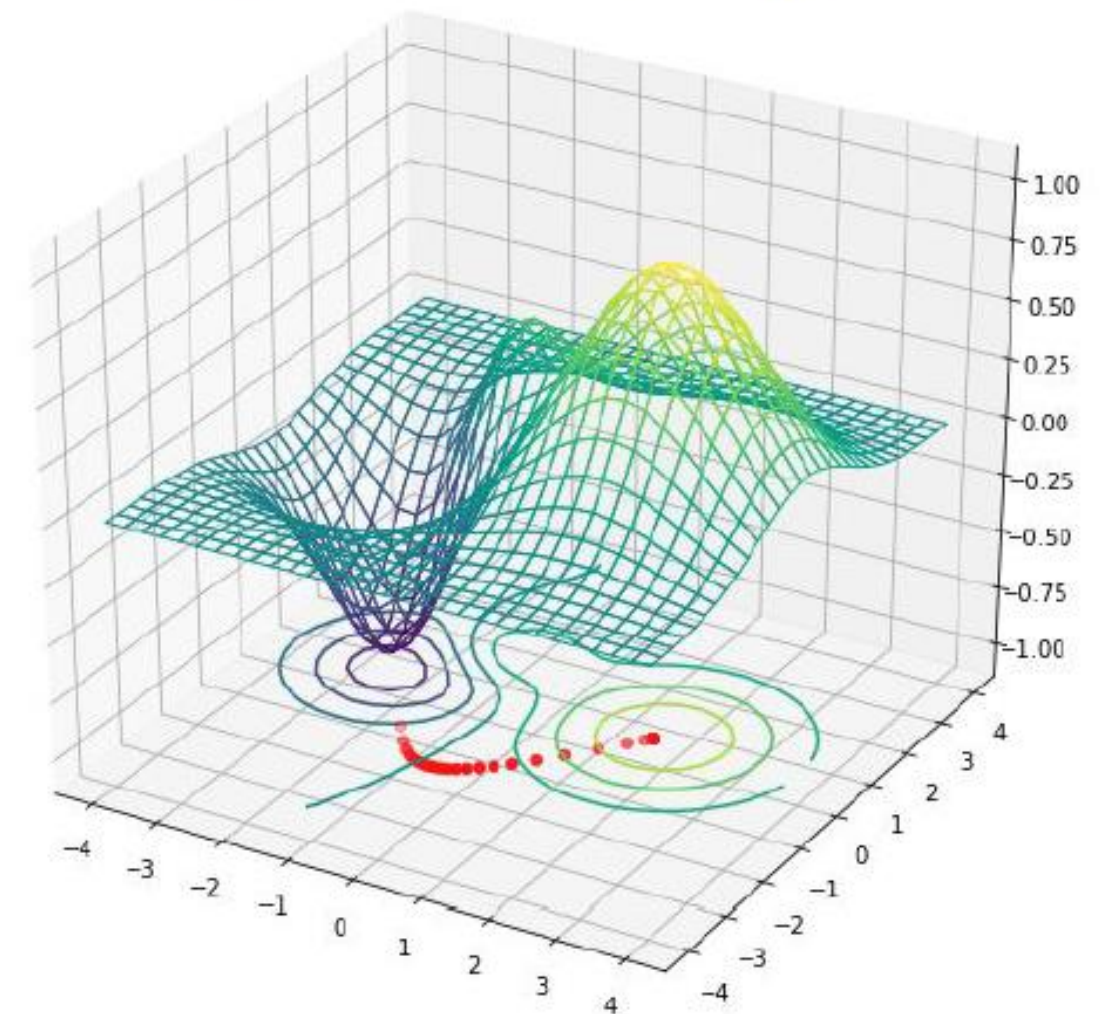


# ASTRAZENECA의 후보 HIT 생성에 사용된 기술들

\*MegaMolBART\*, transformer 기반 generative AI 모델 (NVIDIA와 AstraZeneca 협업)

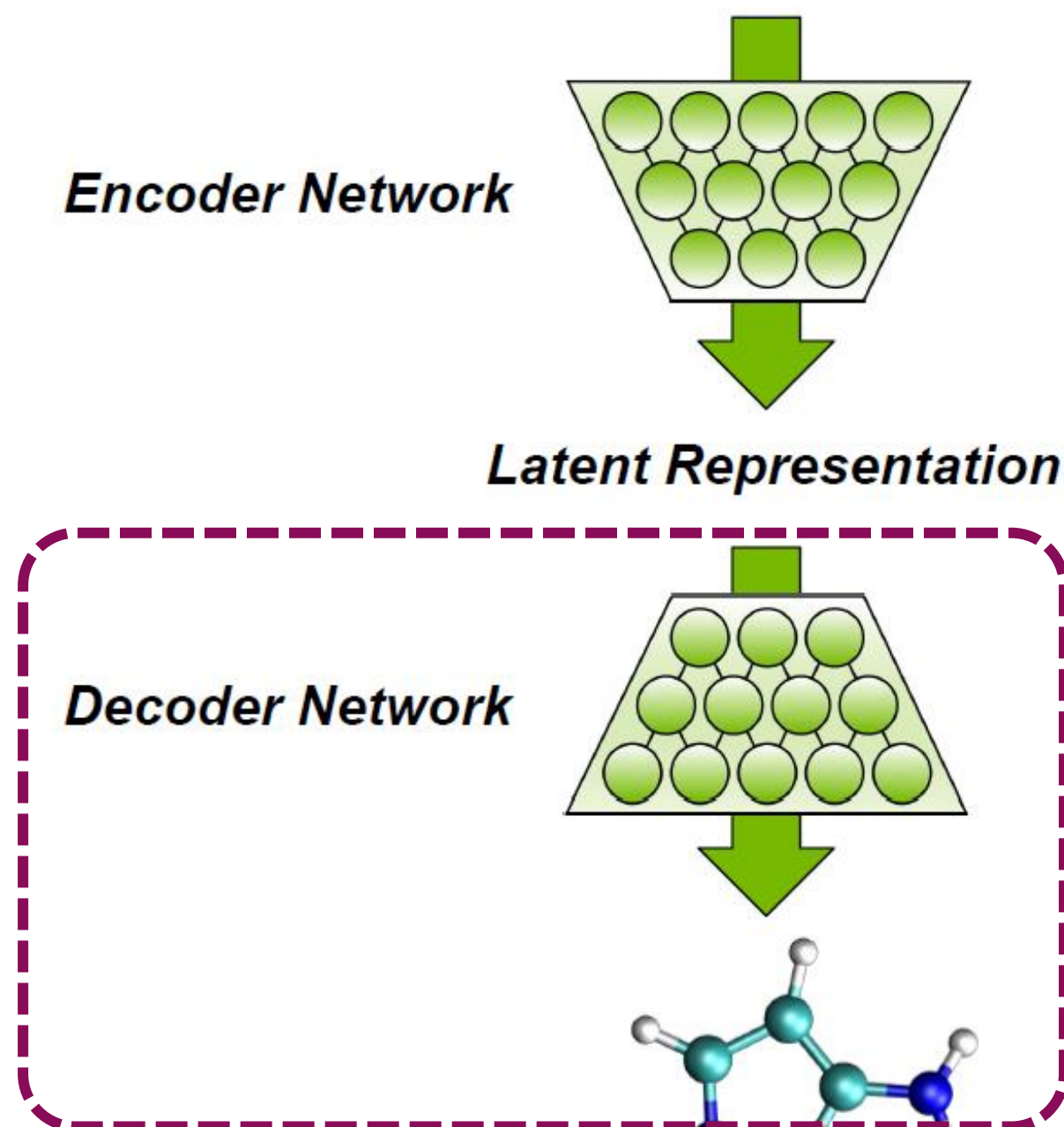


*Organized Latent Space*

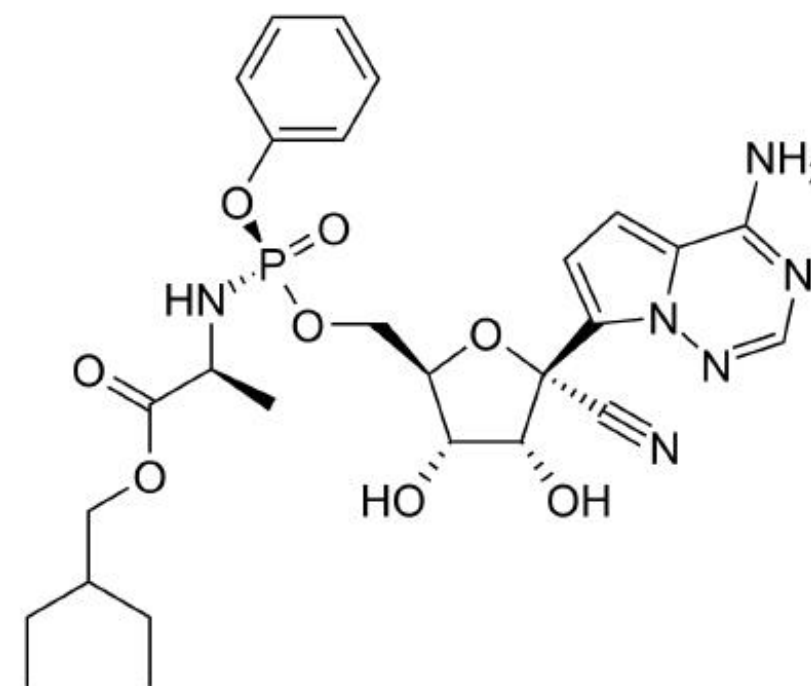


# ASTRAZENECA의 후보 HIT 생성에 사용된 기술들

\*MegaMolBART\*, transformer 기반 generative AI 모델 (NVIDIA와 AstraZeneca 협업)



*How Do We Make This?*

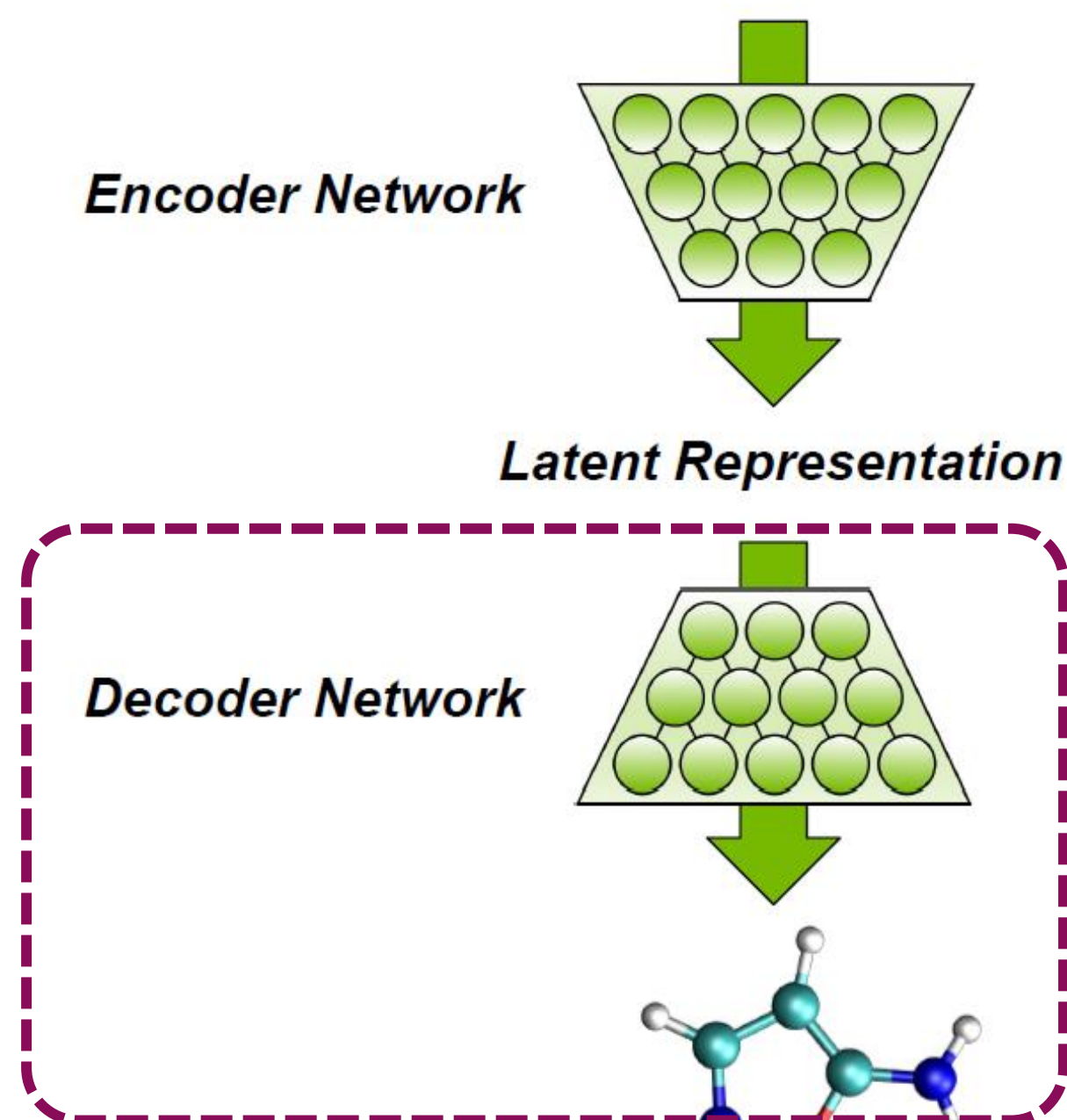


Esben Bjerrum, Ola Engkvist, Ross Irvin, Jiazhen He

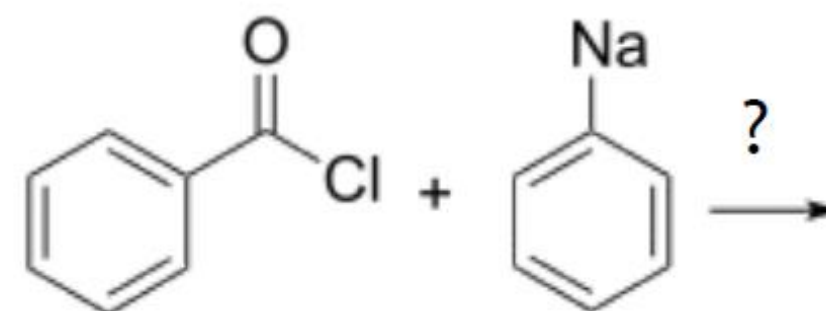


# ASTRAZENECA의 후보 HIT 생성에 사용된 기술들

\*MegaMolBART\*, transformer 기반 generative AI 모델 (NVIDIA와 AstraZeneca 협업)



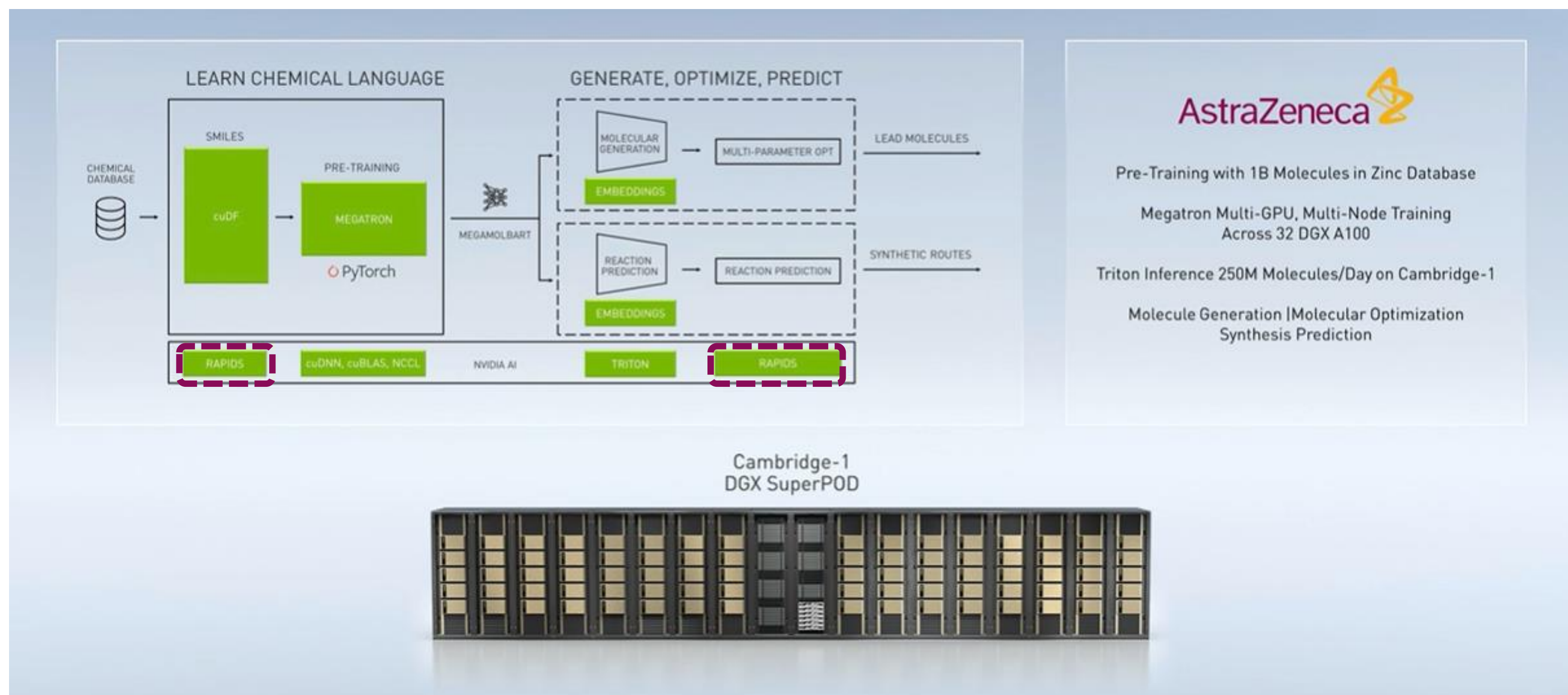
*What Are The Products of This Reaction?*



Esben Bjerrum, Ola Engkvist, Ross Irvin, Jiazhen He

# ASTRAZENECA의 후보 HIT 생성에 사용된 기술들

**\*RAPIDS\*** 활용한 거대 데이터베이스 ELT 처리





# ASTRAZENECA의 후보 HIT 생성에 사용된 기술들

\*RAPIDS\* 활용한 거대 데이터베이스 ELT 처리

## Imports

Here we import cuDF and **CuPy** for GPU-accelerated dataframes and math operations, plus the CPU libraries Pandas and NumPy on which they are based and which we will use for performance comparisons:

In [1]:

```
import cudf
import cupy as cp

import pandas as pd
import numpy as np
```

# ASTRAZENECA의 후보 HIT 생성에 사용된 기술들

**\*RAPIDS\*** 활용한 거대 데이터베이스 ELT 처리

- ▶ Reading 60 million records, entire population of England and Wales from official UK census data

from a local csv file directly into GPU memory:

```
In [2]: %time gdf = cudf.read_csv('./data/pop_1-03.csv')
gdf.shape
```

```
CPU times: user 1.4 s, sys: 996 ms, total: 2.4 s
Wall time: 3.2 s
```

Here for comparison we read the same data into a Pandas dataframe:

```
In [4]: %time df = pd.read_csv('./data/pop_1-03.csv')
gdf.shape == df.shape
```

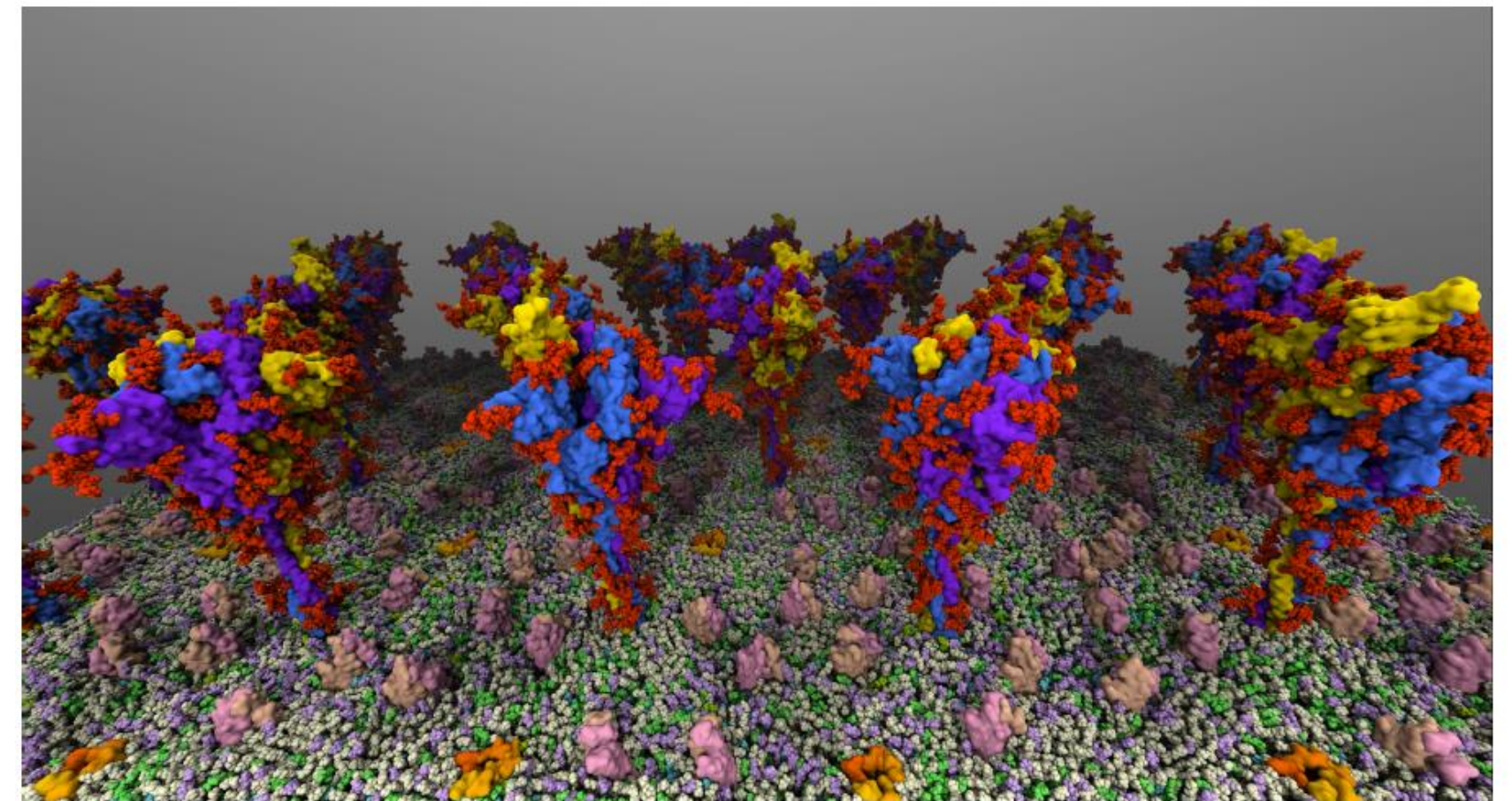
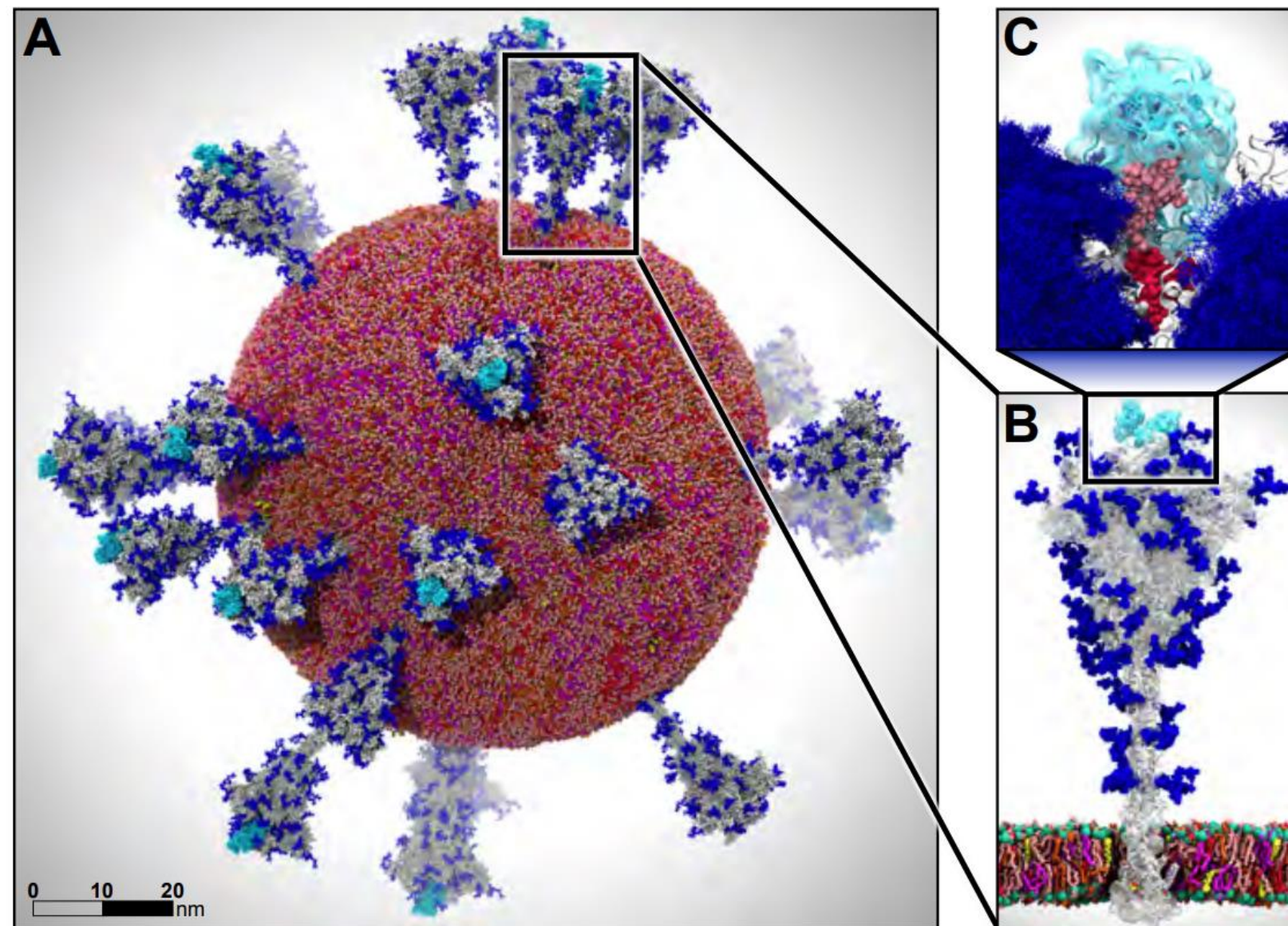
```
CPU times: user 32.1 s, sys: 4.55 s, total: 36.7 s
Wall time: 36.7 s
```



# 이제 후보 화학 물질을 얼마나 신속하게 SIMULATION하느냐

NAMD 소프트웨어 활용한 SARS-Cov-2 simulation (CUDA, NVIDIA GPU, NVIDIA DGX 시스템 활용)

- ▶ SC20 컨퍼런스에서 Gordon Bell Special Prize 차지

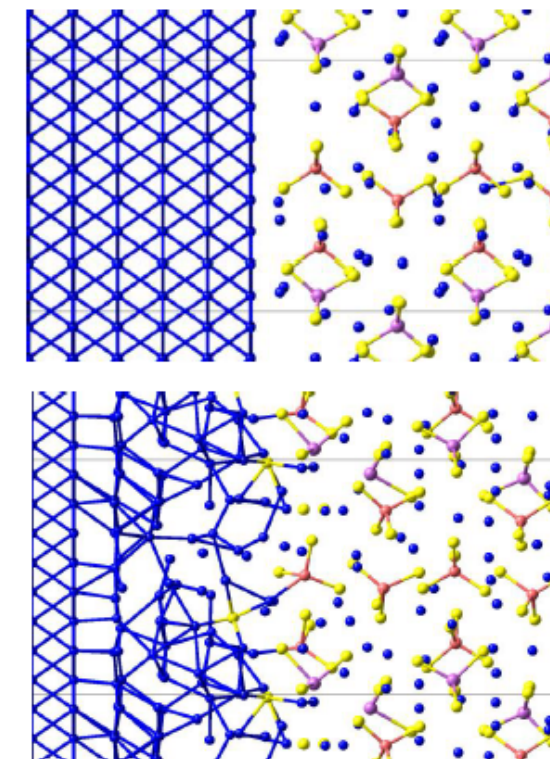
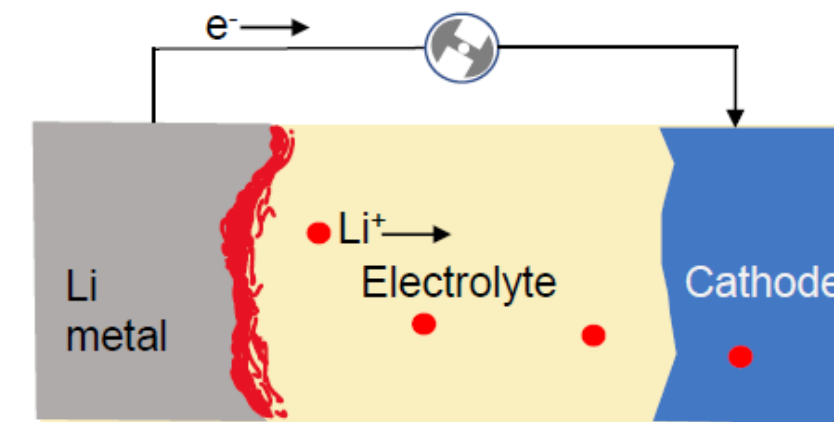




# SIMULATION이 필요한 또 다른 예 - VASP (분자 역학 S/W)

## 리튬 이온 배터리에 사용할 가장 효율적인 전해질 물질 찾기

- ▶ The Challenge: increase the capacity of batteries while maintaining rigorous safety requirements
- ▶ Approach
  - Use Li metal rather than Li in graphite
  - Replace liquid electrolytes by solid state electrolytes
- ▶ The bottlenecks
  - Find solid state electrolytes with high ionic conductivity
  - Control the reaction of Li metal with the electrolyte
  - Find cathode materials with good mechanical match with solid state electrolytes
- ▶ The solution
  - Use large-scale accurate atomistic simulations to find optimal materials
  - Use quantum chemical calculations to understand and control the chemical reactions at interfaces

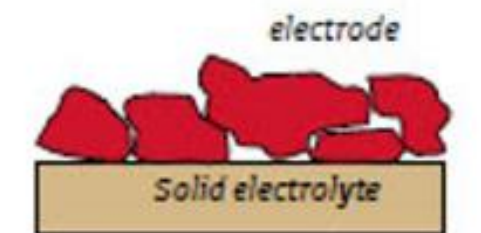


Ab initio molecular dynamics calculations are computationally highly demanding

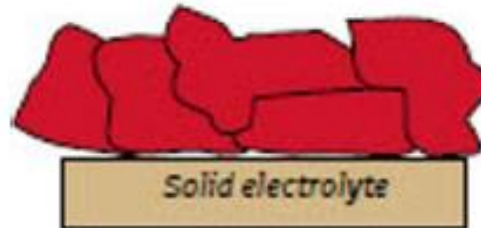


# VASP 활용한 고효율 리튬 이온 배터리 전해질 찾기

충전과 방전 반복시 변형이 최소로 발생하는 전해질 찾기



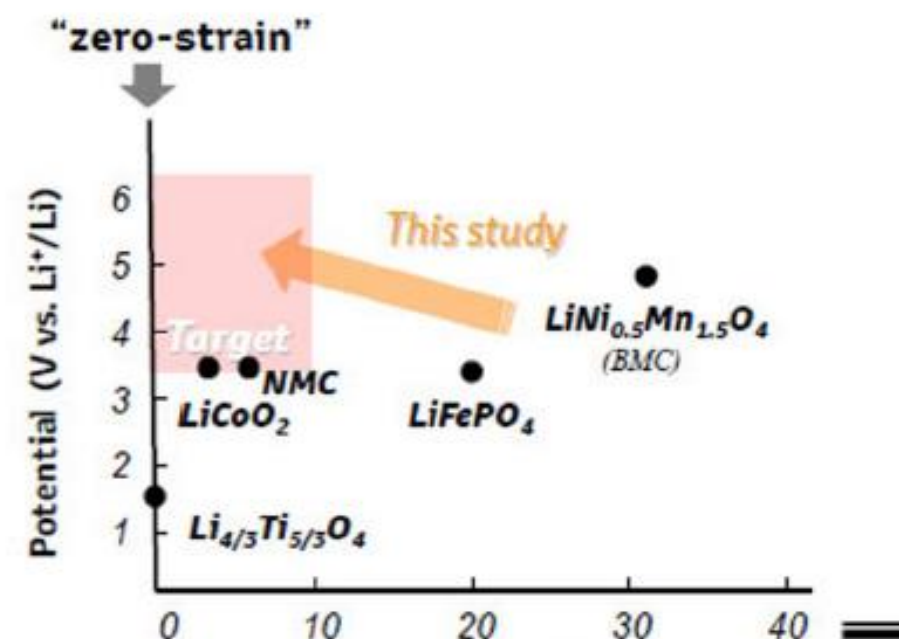
Discharge



Charge



► Computational screening of candidates with Medea VASP



Source: [THE INNOVATIVE FORCE OF HIGH PERFORMANCE COMPUTING IN MATERIALS SCIENCE](#), NVIDIA, Webinar (2021년 7월)

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Organization  
International Bureau

(43) International Publication Date  
4 December 2014 (04.12.2014)



(10) International Publication Number  
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H01M 4/505 (2010.01) H01M 10/0562 (2010.01)

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(22) International Filing Date:

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(25) Filing Language:

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(26) Publication Language:

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(71) Applicant: TOYOTA MOTOR EUROPE NV/SA  
[BE/BE]; Avenue du Bourget 60, B-1140 Brussels (BE).

(72) Inventors: ROSCIANO, Fabio; Milcampsiaan 127, B-1030 Schaarbeek (BE). CHRISTENSEN, Mikael; Branningevagen 1, S-120 54 Arsta (SE). EYERT, Volker; Baumschulenweg 6A, 14469 Potsdam (DE). MAVROMARAS, Alexander; Bergandsgatan 43, S-133 41 Saltsjobaden (SE). WIMMER, Erich; 3 avenue du Commerce, F-78000 Versailles (FR).

(81) Designated States (unless otherwise indicated, for every kind of national protection available): AE, AG, AL, AM, AO, AT, AU, AZ, BA, BB, BG, BH, BN, BR, BW, BY, BZ, CA, CH, CL, CN, CO, CR, CU, CZ, DE, DK, DM, DO, DZ, EC, EE, EG, ES, FI, GB, GD, GE, GH, GM, GT, HN, HR, HU, ID, IL, IN, IS, JP, KE, KG, KN, KP, KR, KZ, LA, LC, LK, LR, LS, LT, LU, LY, MA, MD, ME, MG, MK, MN, MW, MX, MY, MZ, NA, NG, NI, NO, NZ, OM, PA, PE, PG, PH, PL, PT, QA, RO, RS, RU, RW, SC, SD, SE, SG, SK, SL, SM, ST, SV, SY, TH, TJ, TM, TN, TR, TT, TZ, UA, UG, US, UZ, VC, VN, ZA, ZM, ZW.

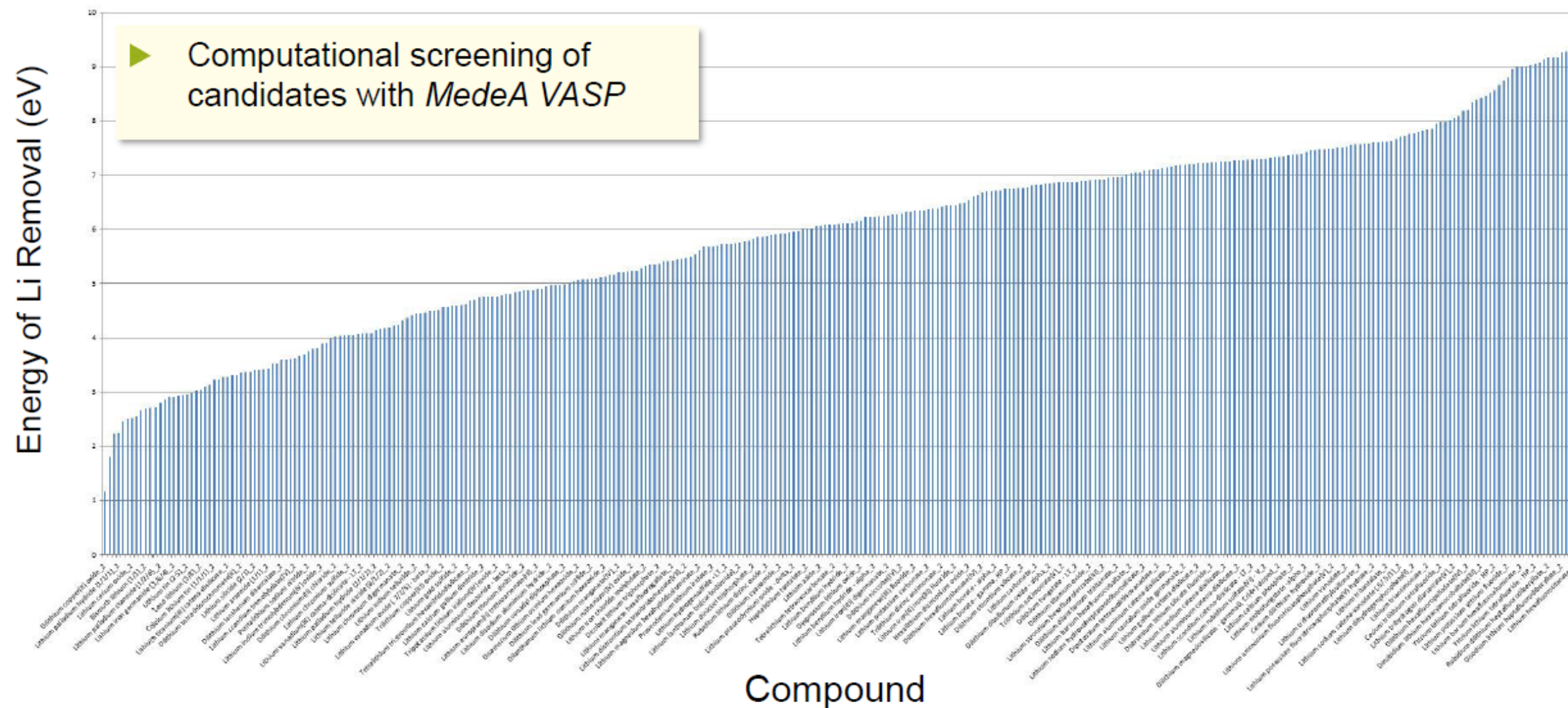
(84) Designated States (unless otherwise indicated, for every kind of regional protection available): ARIPO (BW, GH, GM, KE, LR, LS, MW, MZ, NA, RW, SD, SL, SZ, TZ, UG, ZM, ZW), Eurasian (AM, AZ, BY, KG, KZ, RU, TJ, TM), European (AL, AT, BE, BG, CH, CY, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HR, HU, IE, IS, IT, LT, LU, LV, MC, MK, MT, NL, NO, PL, PT, RO, RS, SE, SI, SK, SM, TR), OAPI (BF, BJ, CF, CG, CI, CM, GA, GN, GQ, GW, KM, ML, MR, NE, SN, TD, TG).

Published:

# VASP 활용한 고효율 리튬 이온 배터리 전해질 찾기

직접 실험을 한다면 현실적으로 불가능한 후보 물질 수, VASP 활용한 computational screening 활용

## Search of compounds with optimal Li binding energy





# VASP 활용한 핵발전 SIMULATION

Zr(지르코늄)과 H<sub>2</sub>O와의 반응 simulation (반복되는 핵융합에도 원료가 최대한 오래 지속되도록)

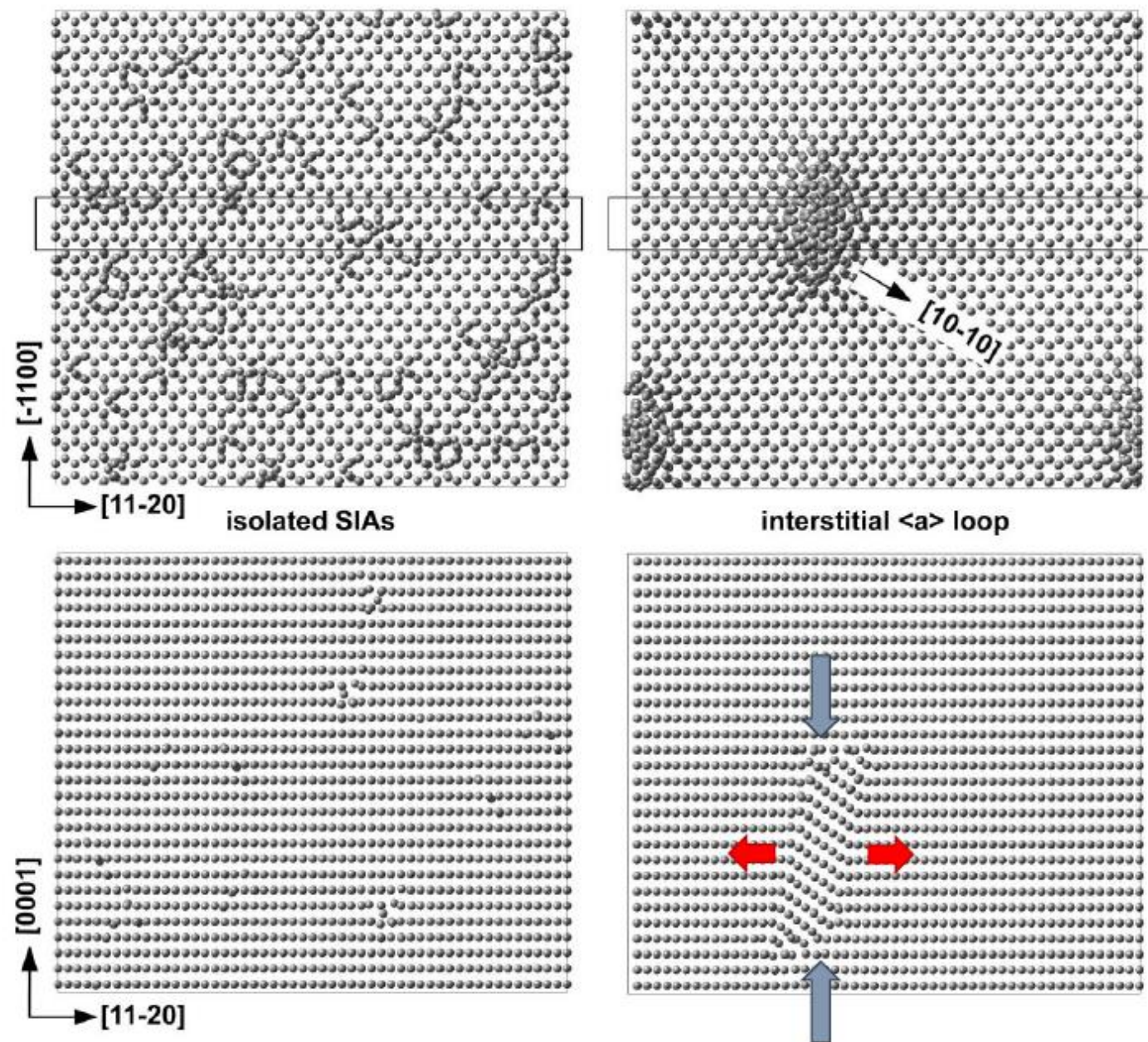
- ▶ The Challenge: increase the life-time of materials in the reactor while maintaining their safe operation
- ▶ Approach
  - Use materials modeling to identify the key degradation mechanisms under irradiation
  - Develop a predictive computational approach
  - Predict the performance of improved and new materials prior to experimental testing which is expensive and time consuming
- ▶ The bottleneck
  - Highly accurate multi-scale models
  - 3D simulations require large-scale simulations
- ▶ The solution
  - HPC enables simulations of high complexity and accuracy with predictive power, thus accelerating the development and certification of advanced materials.





# VASP 활용한 핵발전 SIMULATION

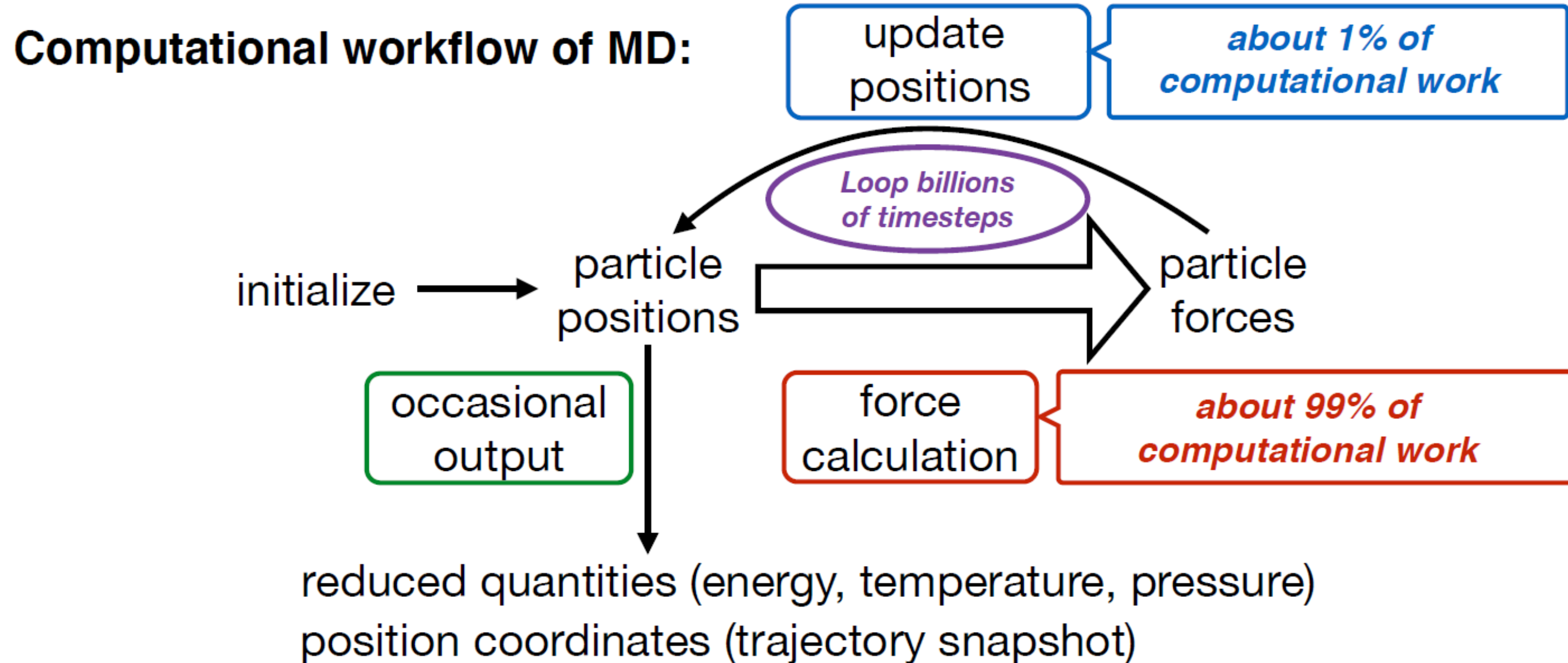
Zr(지르코늄)과 H<sub>2</sub>O와의 반응 simulation (반복되는 핵융합에도 원료가 최대한 오래 지속되록)





# SIMULATION에서 요구되는 COMPUTATIONAL WORK

원자간 force calculation

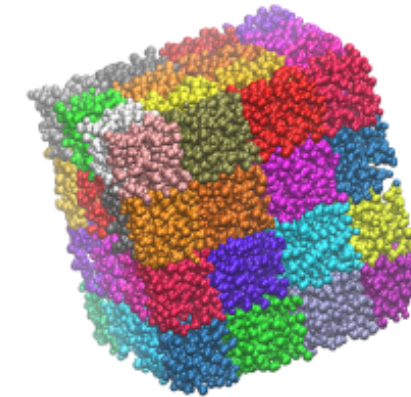


# 분자 역학 SIMULATION에서 분산(병렬) 컴퓨팅의 중요성

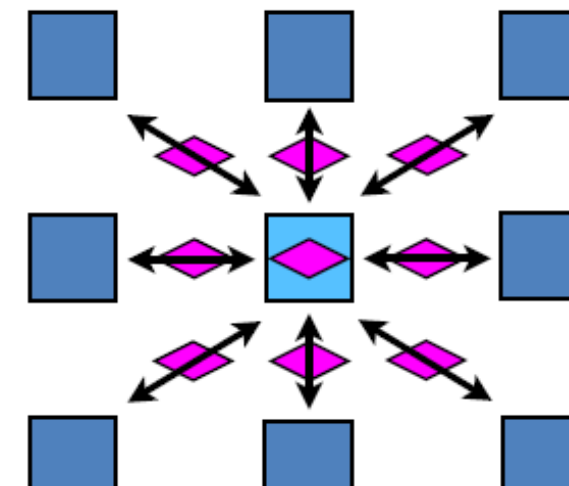
(준비) Patch라 불리는 공간에 원자들 배치 → (Simulation) 원자간 힘 적용 → 변화된 원자들 위치 적용

- Atoms are decomposed into fixed volume *patches* within the system
- Forces that move atoms are calculated in parallel at each step between adjacent patches
- Migrate atoms to adjacent patches, updating domain decomposition after every *cycle* (e.g. 20 steps)
- Performance is measured in **ns/day** — number of nanoseconds of simulated time achieved per day of running. (More is better!)

Spatial decomposition of atoms into patches



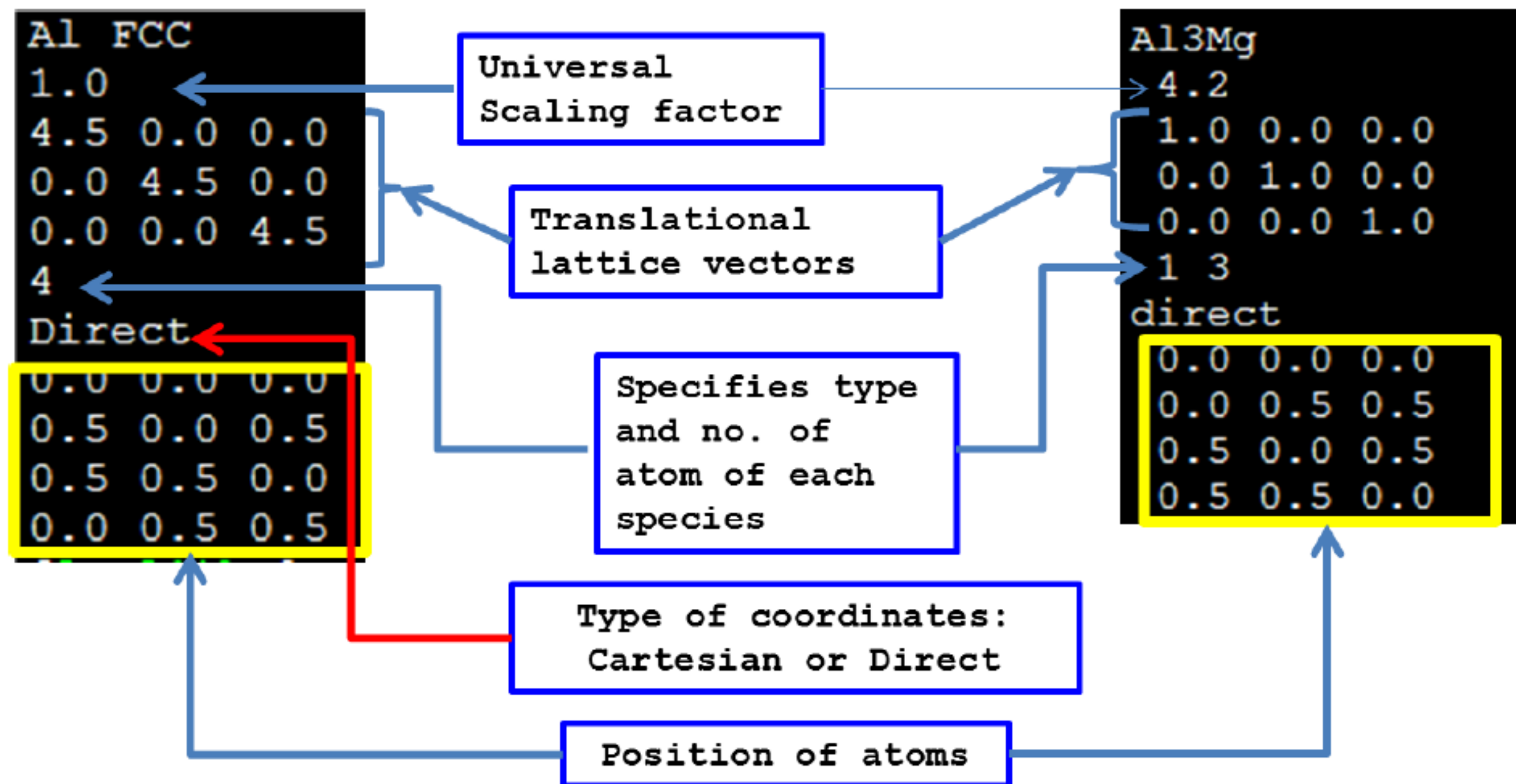
Work decomposition of patch interactions





# VASP SIMULATION에 필요한 INPUT FILES

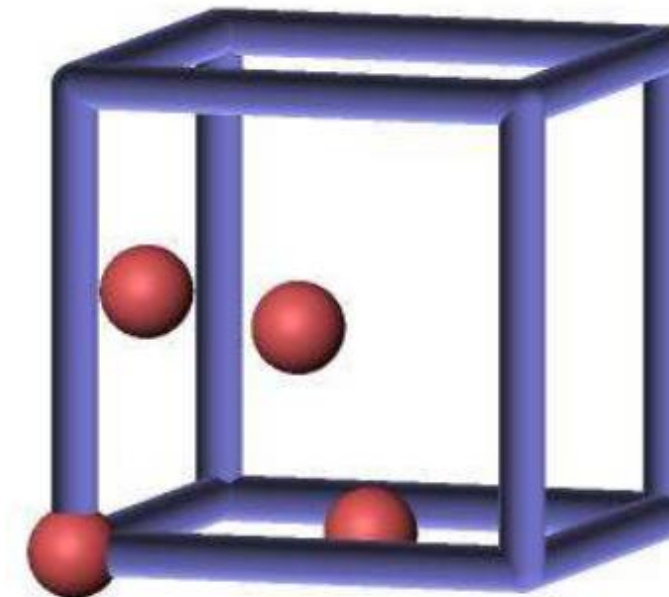
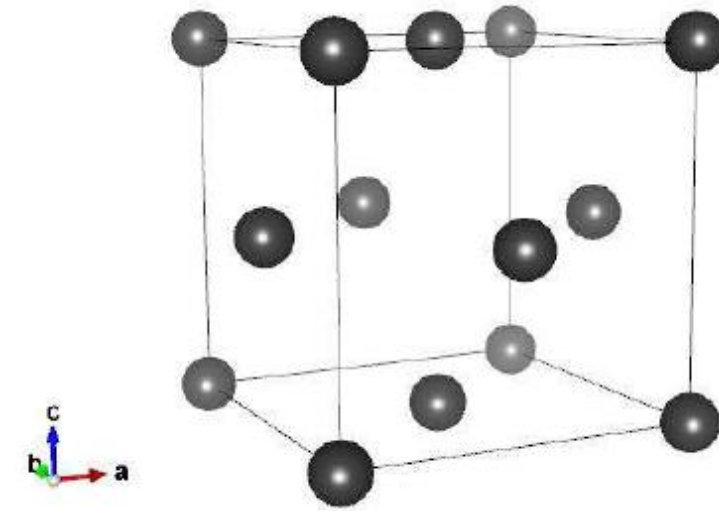
중 \*POSCAR\* 파일에 명시되는 원자들 위치 (원자 개수 예. 200개, 2000개, LAMMPS 경우 80M도)



# VASP SIMULATION에 필요한 INPUT FILES

중 \*POSCAR\* 파일에 명시되는 원자들 위치 (원자 개수 예. 200개, 2000개, LAMMPS 경우 80M도)

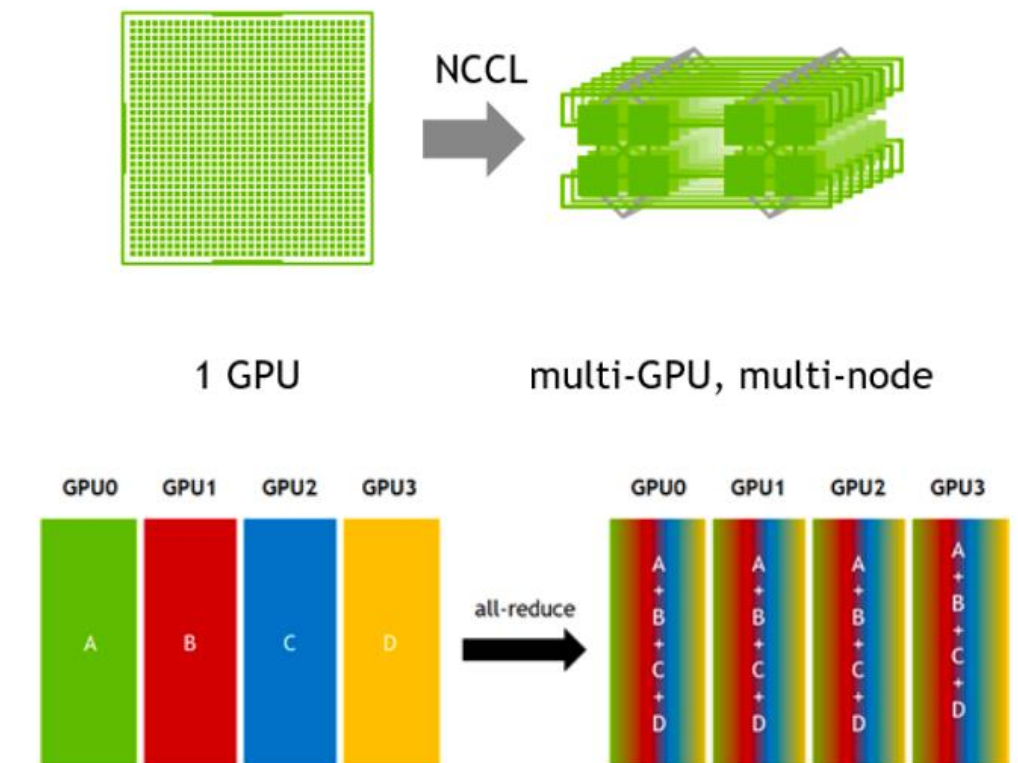
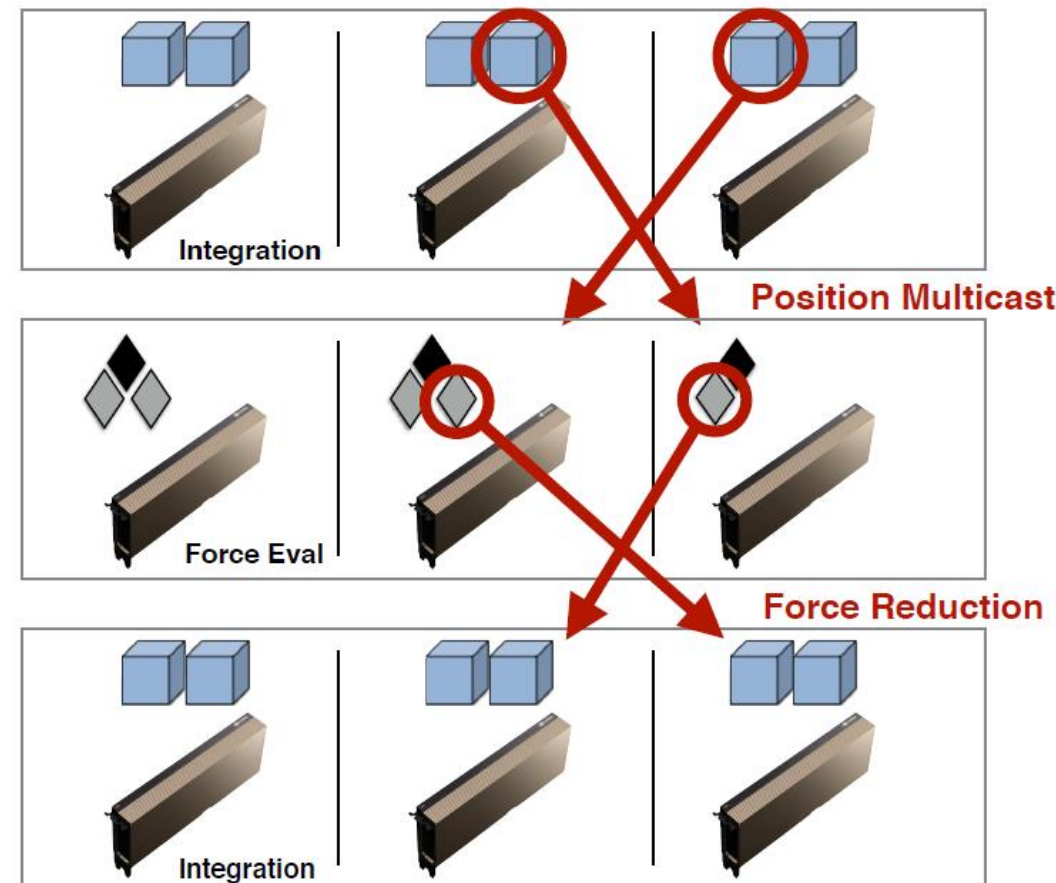
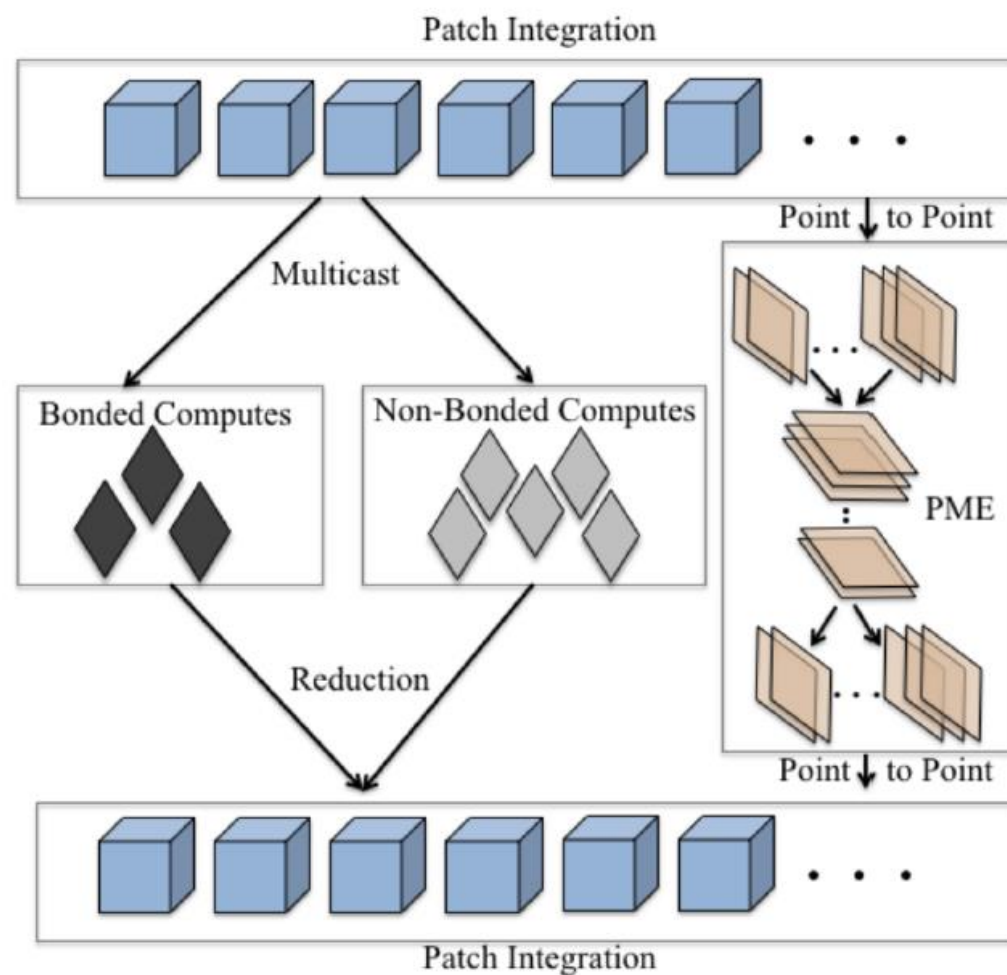
- 4 atoms, fcc structure
  - Translational lattice vectors
    - $a_1 = (4.0; 0.0; 0.0)$
    - $a_2 = (0.0; 4.0; 0.0)$
    - $a_3 = (0.0; 0.0; 4.0)$
  - Basis vectors
    - $0.0; 0.0; 0.0$
    - $0.5; 0.0; 0.5$
    - $0.5; 0.5; 0.0$
    - $0.0; 0.5; 0.5$





# 분자 역학 SIMULATION에서 MULTI GPU 및 GPU간 통신 중요성

수많은 patch를 GPU당 하나씩 할당, iteration 끝날 때마다 변경된 원자 위치 모든 GPU에 업데이트



# VASP COMPUTATION ENVIRONMENT

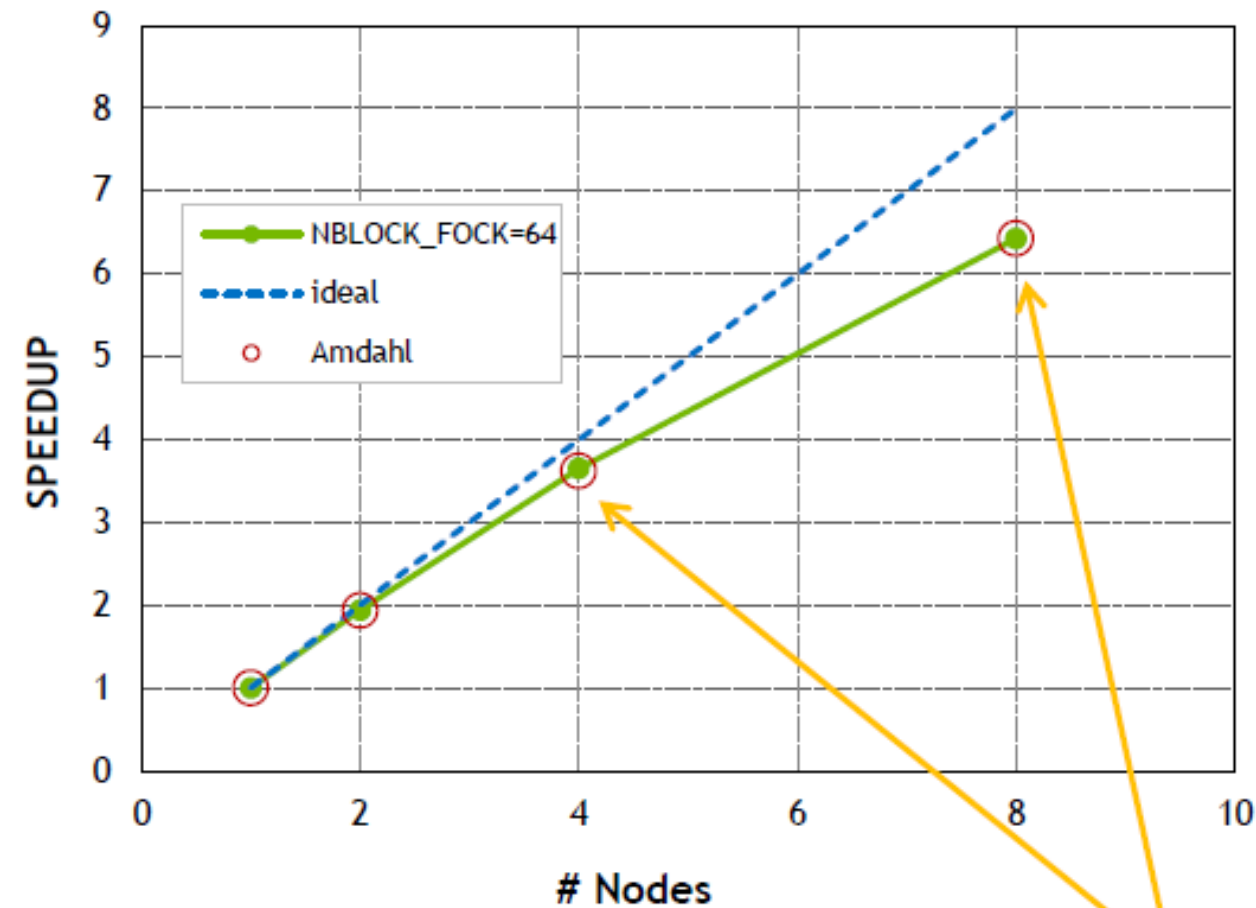
특별히 GPU간 통신 기술 주목

- ▶ H/W : NVIDIA Selene
- ▶ S/W
  - ▶ VASP 6.2.0 & 6.2.1
  - ▶ NVIDIA HPC SDK
  - ▶ CUDA 11.0: FFT libs - cuFFT, cuBLAS, cuSolver 11.0
  - ▶ Communication - openMPI 4.0.6rc1 using UCX 1.10.x branch; NCCL 2.9.9

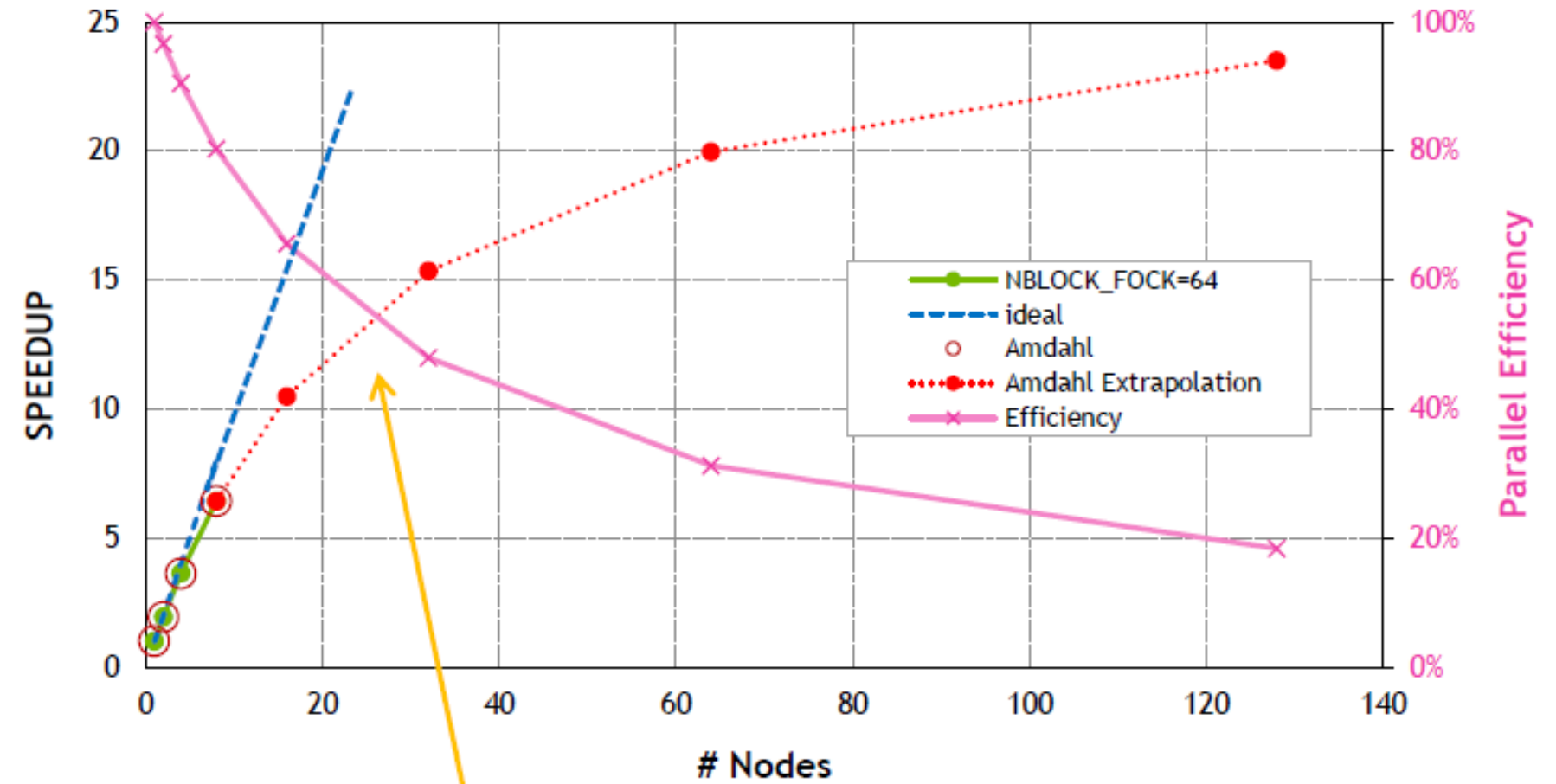


# VASP SIMULATION에서 MULTI GPU 노드의 위력

NVIDIA DGX SuperPOD



With an Amdahl's law numerical fit the approximation is quite good

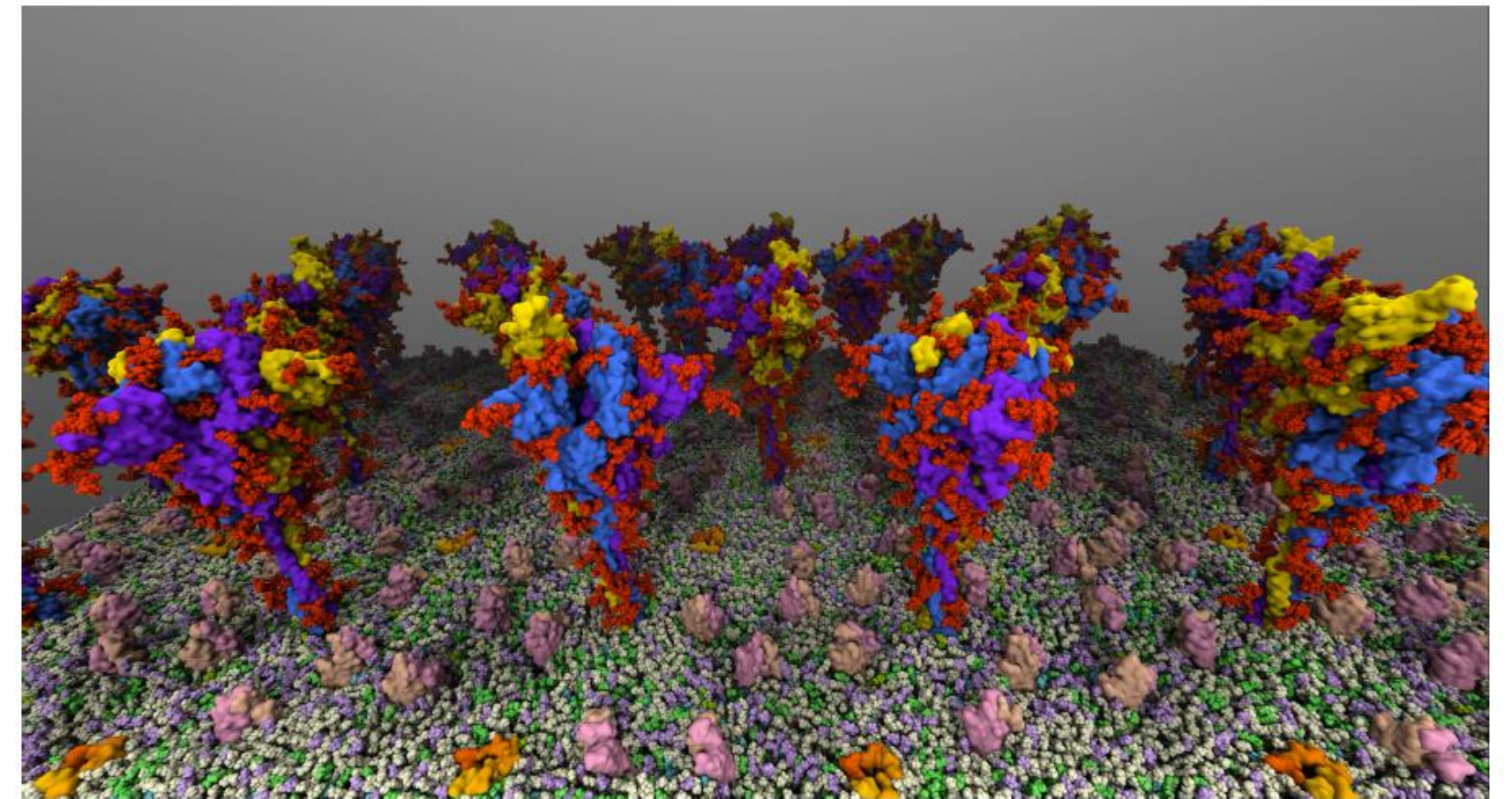
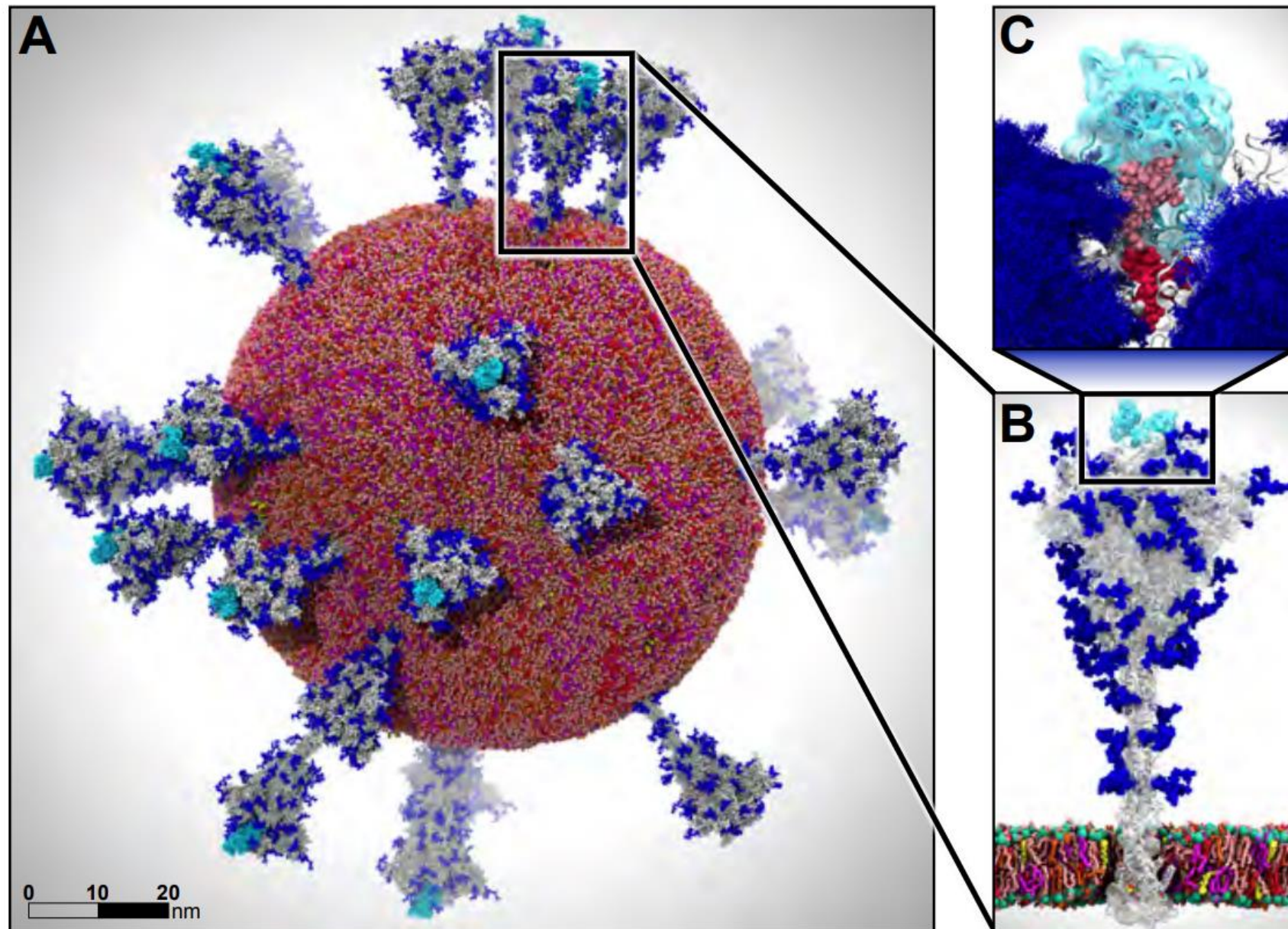


50% Scaling efficiency occurs at 30 nodes in this example



# SIMULATION에서 이뤄지는 추가 움직임

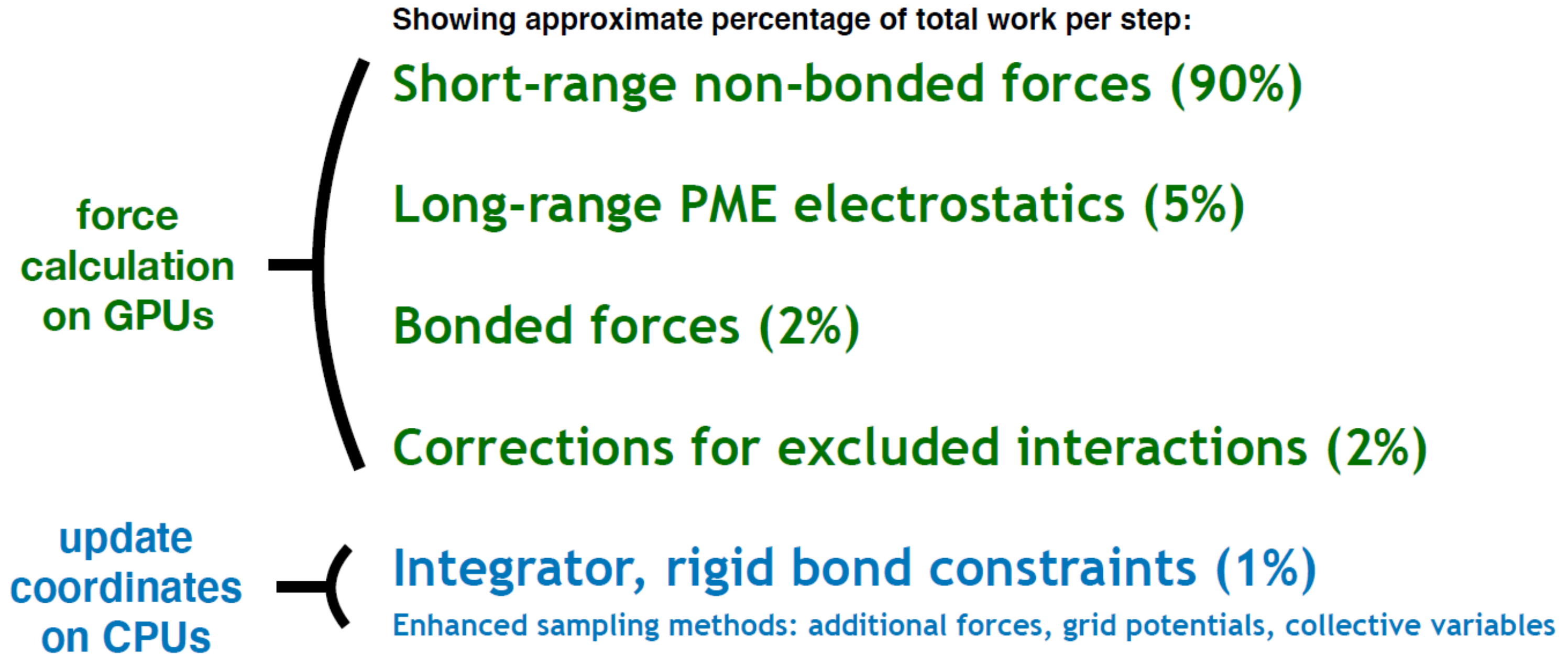
NAMD 소프트웨어, GPU-Offload 에서 GPU-Resident 아키텍처로





# 기존 GPU-OFFLOAD 아키텍처

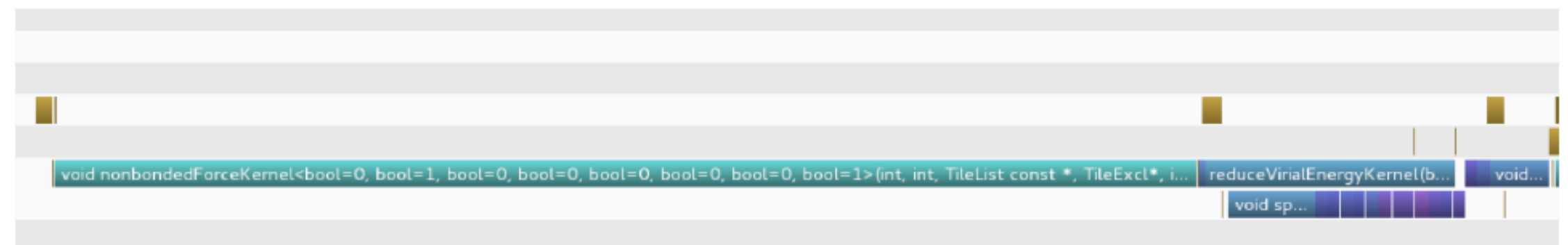
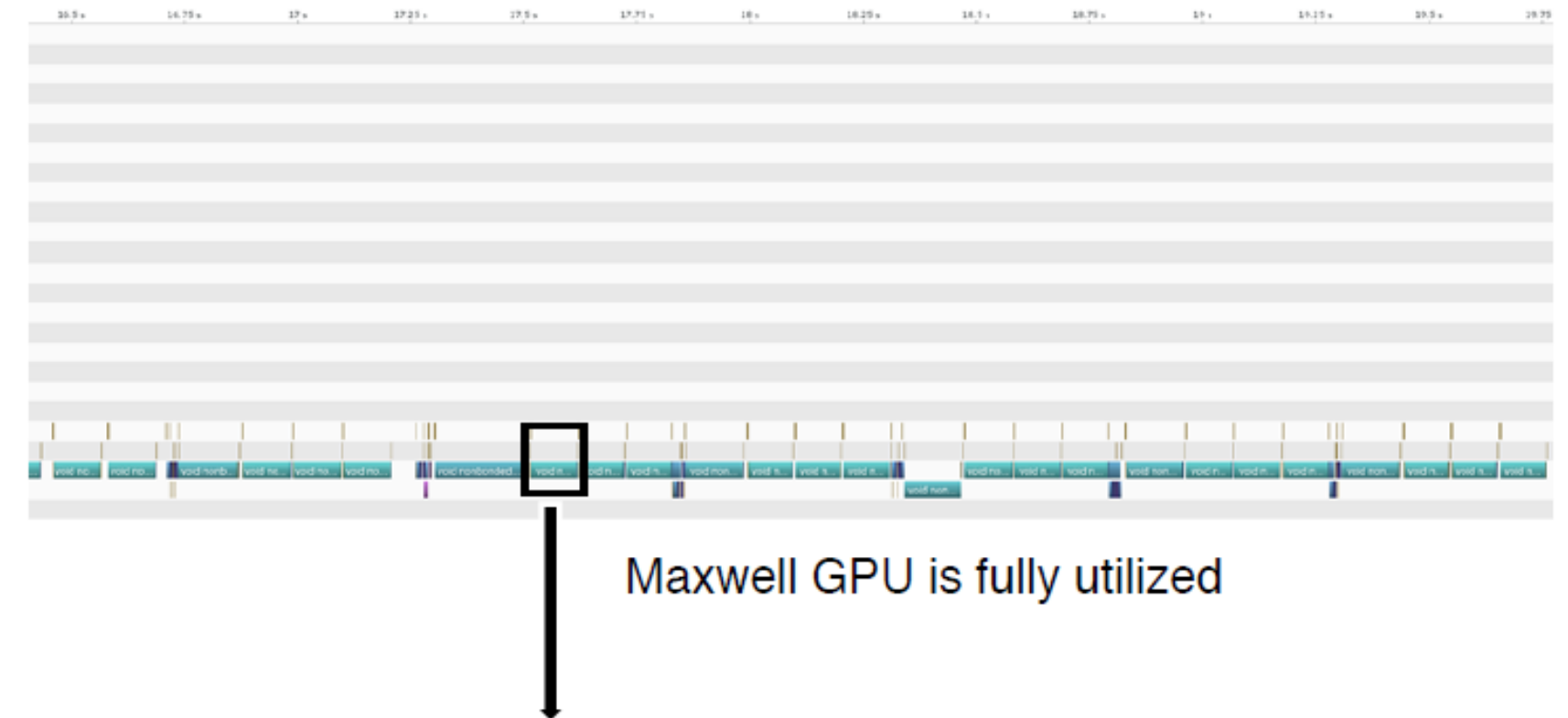
GPU는 force calculation, CPU는 원자 위치 업데이트



# 기존 GPU-OFFLOAD 아키텍처

NVIDIA Pascal GPU까지는 force calculation도 어느 정도 시간 소요되어 CPU 연산과 overlap 됨

- GPUs weren't **that** fast back then
- Profiling shows GPUs are fully occupied by forces - no idle time
- Streaming forces allows overlap of CPU and GPU computation





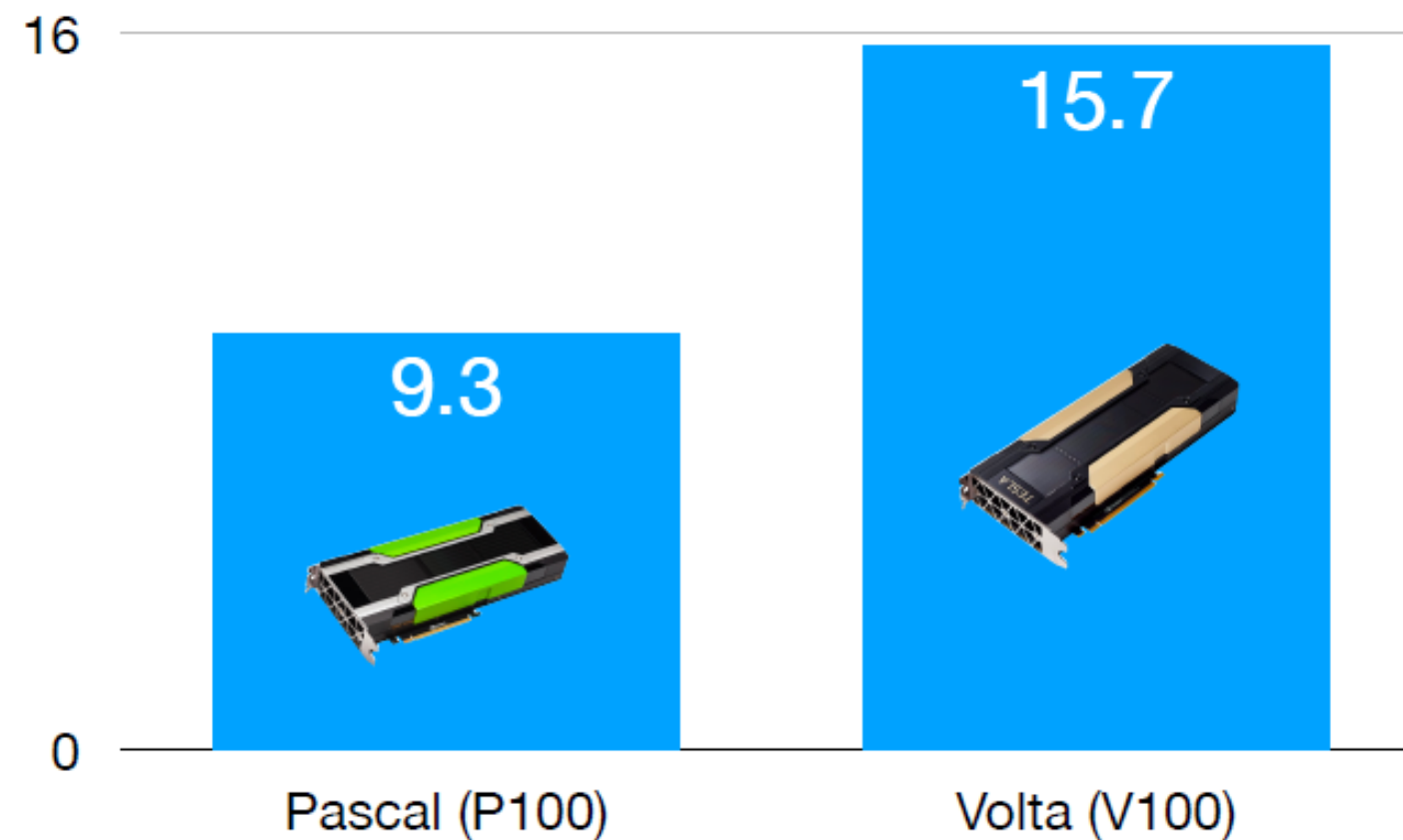
# 기존 GPU-OFFLOAD 아키텍처

신규 GPU 성능 월등히 향상되었지만 NAMD 성능은 그만큼 향상되지 않았음. 왜?

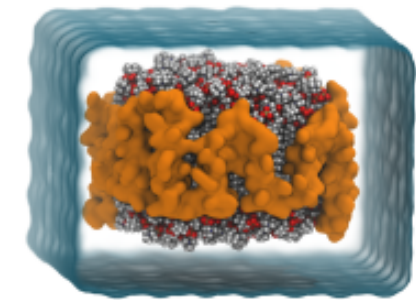
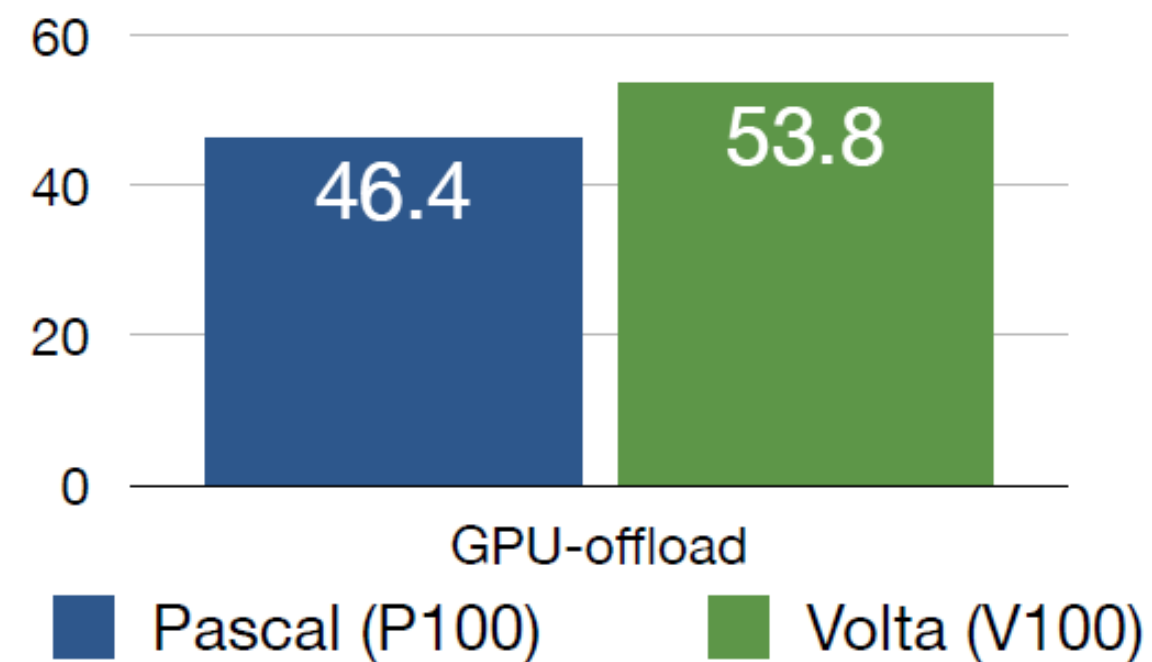
Hardware has ~70% perf improvement!

NAMD (in 2018) less than 20% perf improvement!

Peak Performance in TFLOPS



ns/day



ApoA1  
92k atoms

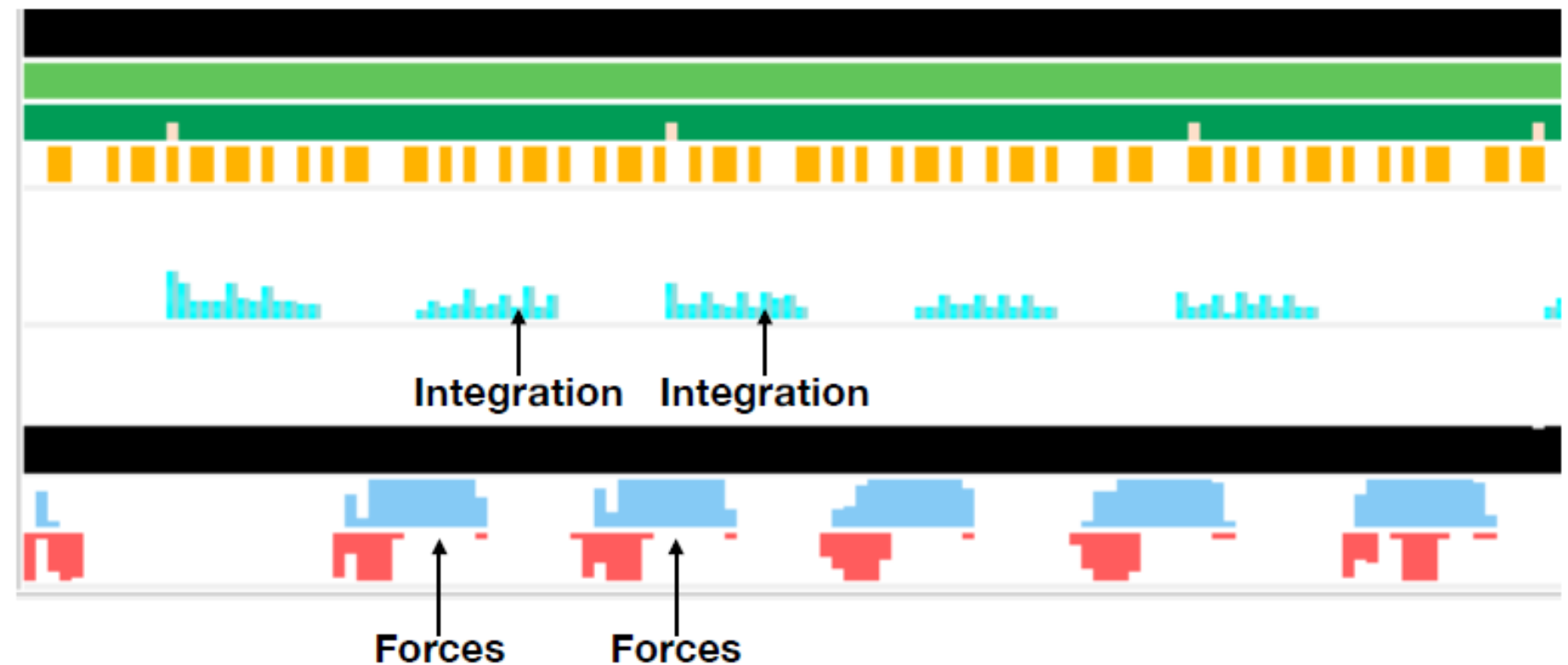
**Simulation details:**  
NVE, CHARMM force field, cutoff distance 12Å,  
MTS with 2fs time step and 4fs PME, rigid bond constraints.  
<https://www.ks.uiuc.edu/Research/namd/benchmarks/>

# 기존 GPU-OFFLOAD 아키텍처

성능 대폭 향상된 GPU, 이제 force calculation 워낙 빨리 끝나 CPU 연산 마칠 때까지 idle time 발생

- GPUs became **much** faster!
- Attempt to overlap CPU and GPU causes performance bottleneck
- Unable to fully utilize GPU

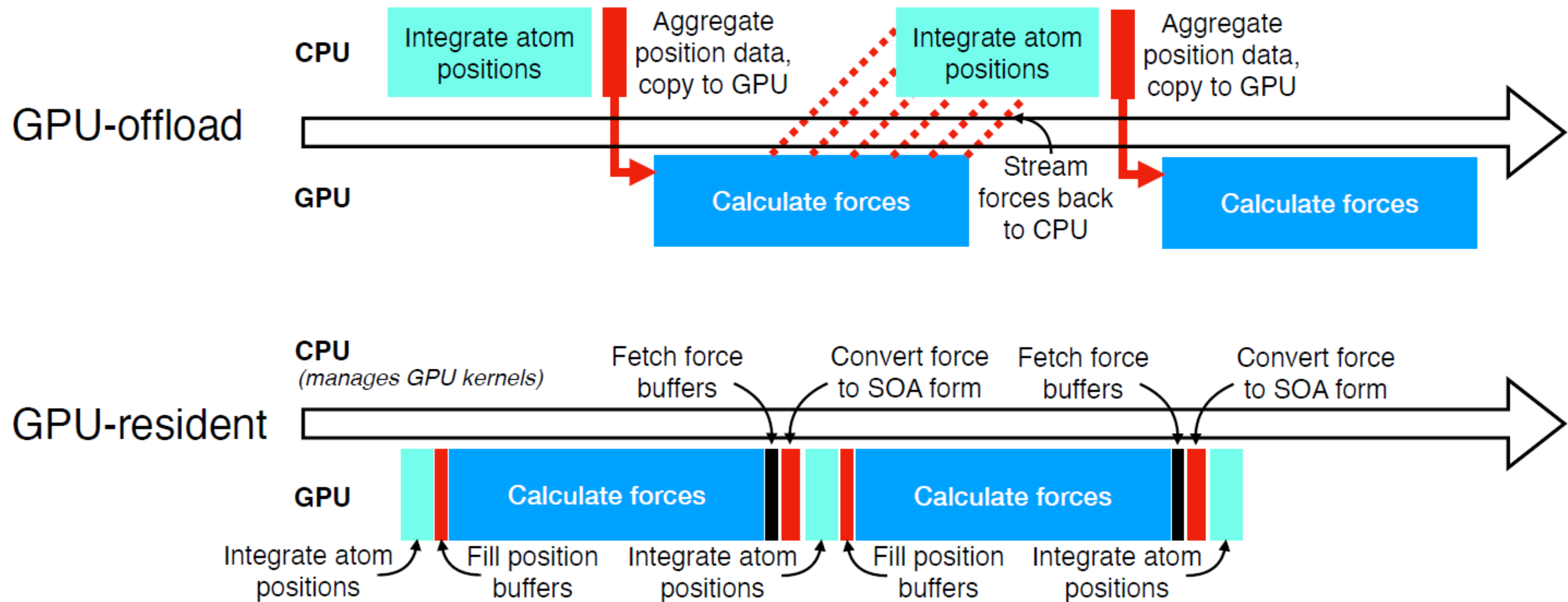
Profile using **Nsight Systems** with NVTX tags to trace execution of CPU kernels:





# 신규 \*GPU-RESIDENT\* 아키텍처

기존 CPU가 하던 원자 위치 업데이트 연산도 이제 GPU로! (모든 연산을 GPU에서, “GPU-Resident”)

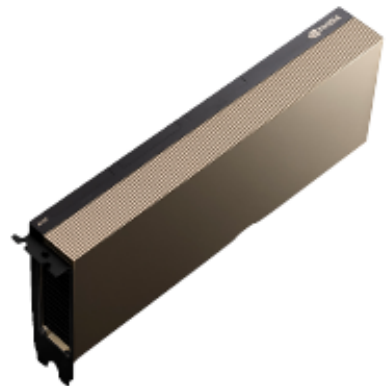


# 신규 \*GPU-RESIDENT\* 아키텍처에서 성능 향상

GPU-Offload 아키텍처 대비



Intel Xeon Gold  
6134 @ 3.2 GHz

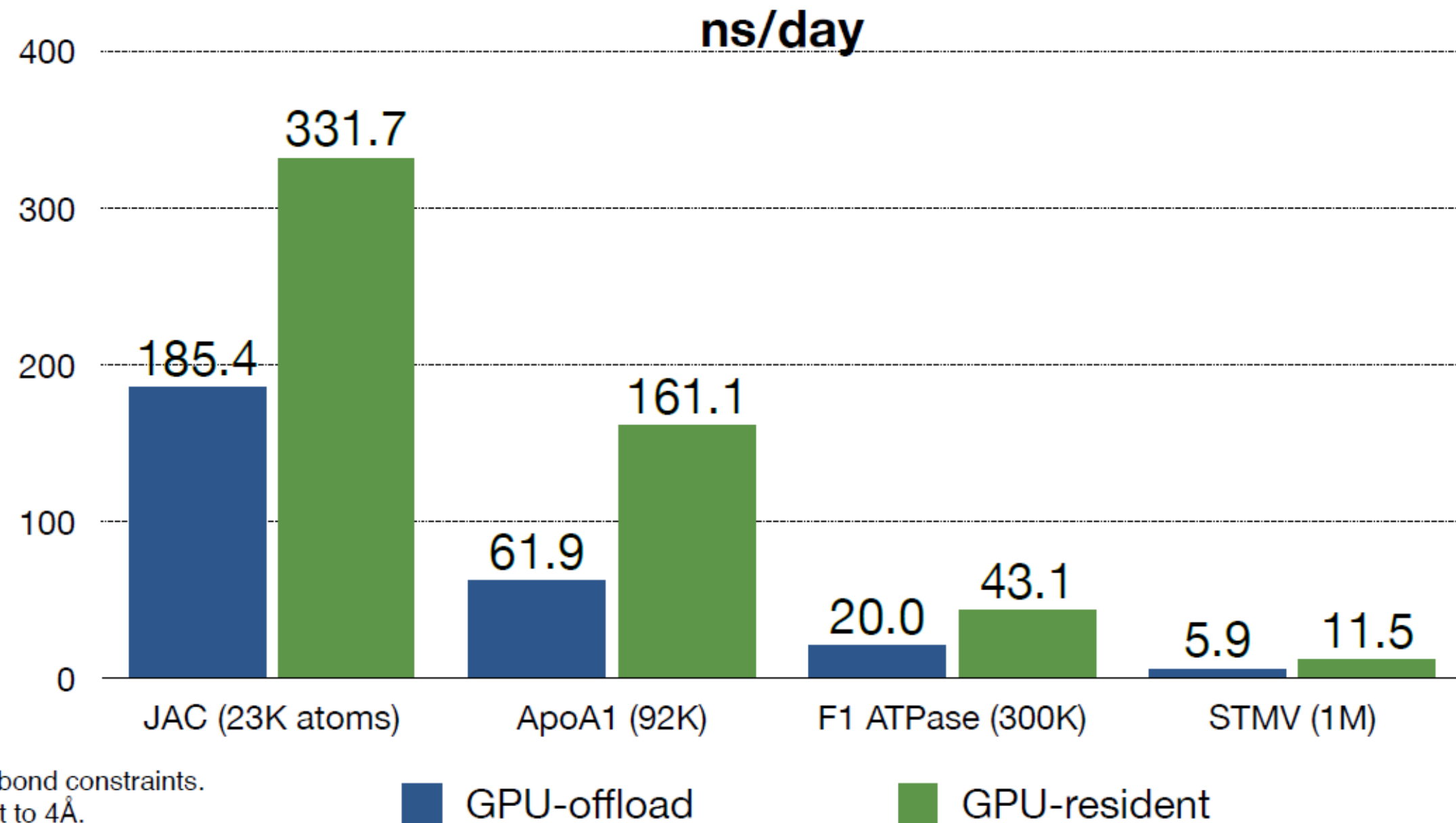


NVIDIA A100-PCIe

## Simulation details:

CHARMM force field, cutoff distance 12Å,  
MTS with 2fs time step and 4fs PME, rigid bond constraints.  
Performance tuning parameter "margin" set to 4Å.

<https://www.ks.uiuc.edu/Research/namd/benchmarks/>





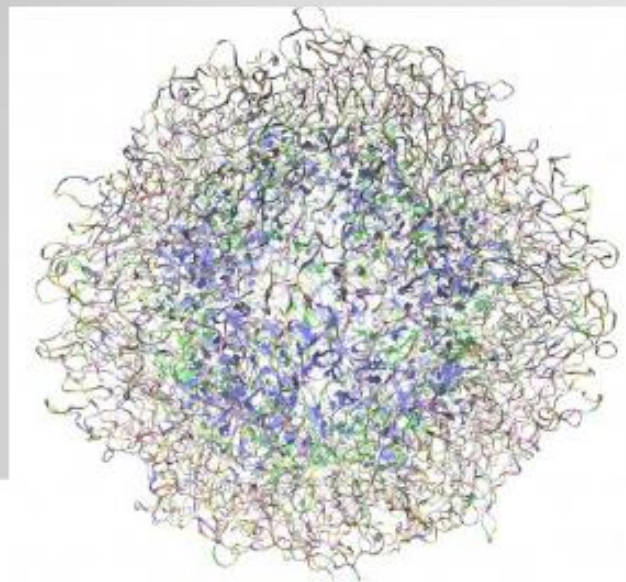
# 이런 기술들을 통해 얻어낸 SIMULATION 성과

## AMOEBA 벤치마크 결과 내역 (Sorbonne Université & Institut Universitaire de France)

2016: TINKER (8 CORES-OPENMP/HASSWELL)  
0.0007 NS/DAY

2018: CINES (Brodwell)  
10000 cores: 0.25 ns/day

2019: IRENE JOLIOT-CURIE (SKYLAKE-AVX)  
10000 CORES MPI : **0.9 NS/DAY**



**2020: SELENE (NVIDIA DGX A100)**  
**1 NODE, 8 GPUS: 4.51 NS/DAY**

**2016-2021: X 6000 ACCELERATION**



S/W 측면 특징점



# GPU 어플리케이션 개발 방법 3가지

Applications

Libraries

“Drop-in”  
Acceleration

OpenACC  
Directives

Easily Accelerate  
Applications

Programming  
Languages

Maximum  
Flexibility

# OpenACC DIRECTIVES EXAMPLE

```
!$acc data copy(A,Anew)
```

```
iter=0  
do while ( err > tol .and. iter < iter_max )
```

```
    iter = iter +1  
    err=0._fp_kind
```

```
!$acc kernels
```

```
    do j=1,m  
      do i=1,n  
        Anew(i,j) = .25_fp_kind *( A(i+1,j) + A(i-1,j) &  
                                   +A(i ,j-1) + A(i ,j+1))
```

```
        err = max( err, Anew(i,j)-A(i,j))  
      end do  
    end do
```

```
!$acc end kernels
```

```
    IF(mod(iter,100)==0 .or. iter == 1)    print *, iter, err  
    A= Anew
```

```
end do
```

```
!$acc end data
```



Copy arrays into GPU memory  
within data region



Parallelize code inside region



Close off parallel region



Close off data region,  
copy data back



```
*laplace2d.c x
43     Anew[j][0] = 1.0;
44 }
45
46 printf("Jacobi relaxation Calculation: %d x %d mesh\n", n, m);
47
48 StartTimer();
49 int iter = 0;
50
51 #pragma acc data copy(A), create(Anew)
52 while ( error > tol && iter < iter_max )
53 {
54     error = 0.0;
55
56     #pragma acc kernels
57     for( int j = 1; j < n-1; j++)
58     {
59         for( int i = 1; i < m-1; i++ )
60         {
61             Anew[j][i] = 0.25 * ( A[j][i+1] + A[j][i-1]
62                                 + A[j-1][i] + A[j+1][i]);
63             error = fmax( error, fabs(Anew[j][i] - A[j][i]));
64         }
65     }
66
67     #pragma acc kernels
68     for( int j = 1; j < n-1; j++)
69     {
70         for( int i = 1; i < m-1; i++ )
71         {
72             A[j][i] = Anew[j][i];
73         }
74     }
75
76     if(iter % 100 == 0) printf("%5d, %0.6f\n", iter, error);
77 }
```

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```
700, 0.000345
800, 0.000302
900, 0.000269
total: 183.593622 s
mebersole@desktop:~/code/openacc/jacobi$ pgcc -acc -Minfo=accel -o laplace2d_acc laplace2d.c
main:
  51, Generating create(Anew[0:][0:])
    Generating copy(A[0:][0:])
  56, Generating present_or_create(Anew[0:][0:])
    Generating present_or_copy(A[0:][0:])
    Generating NVIDIA code
    Generating compute capability 1.3 binary
    Generating compute capability 2.0 binary
    Generating compute capability 3.0 binary
  57, Loop is parallelizable
  59, Loop is parallelizable
    Accelerator kernel generated
    57, #pragma acc loop gang /* blockIdx.y */
      Cached references to size [3x(x+2)] block of 'A'
    59, #pragma acc loop gang, vector(128) /* blockIdx.x threadIdx.x */
  63, Max reduction generated for error
  67, Generating present_or_create(Anew[0:][0:])
    Generating present_or_copy(A[0:][0:])
    Generating NVIDIA code
    Generating compute capability 1.3 binary
    Generating compute capability 2.0 binary
    Generating compute capability 3.0 binary
  68, Loop is parallelizable
  70, Loop is parallelizable
    Accelerator kernel generated
    68, #pragma acc loop gang /* blockIdx.y */
    70, #pragma acc loop gang, vector(128) /* blockIdx.x threadIdx.x */
mebersole@desktop:~/code/openacc/jacobi$
```





mebersole@desktop: ~/code/openacc/jacobi

```
Generating compute capability 3.0 binary
57, Loop is parallelizable
59, Loop is parallelizable
Accelerator kernel generated
57, #pragma acc loop gang /* blockIdx.y */
    Cached references to size [3x(x+2)] block of 'A'
59, #pragma acc loop gang, vector(128) /* blockIdx.x threadIdx.x */
63, Max reduction generated for error
67, Generating present_or_create(Anew[0:][0:])
Generating present_or_copy(A[0:][0:])
Generating NVIDIA code
Generating compute capability 1.3 binary
Generating compute capability 2.0 binary
Generating compute capability 3.0 binary
68, Loop is parallelizable
70, Loop is parallelizable
Accelerator kernel generated
68, #pragma acc loop gang /* blockIdx.y */
70, #pragma acc loop gang, vector(128) /* blockIdx.x threadIdx.x */
```

mebersole@desktop:~/code/openacc/jacobi\$ **./laplace2d\_acc**

Jacobi relaxation Calculation: 4096 x 4096 mesh

```
0, 0.250000
100, 0.002397
200, 0.001204
300, 0.000804
400, 0.000603
500, 0.000483
600, 0.000403
700, 0.000345
800, 0.000302
900, 0.000269
```

**total: 6.023778 s**

mebersole@desktop:~/code/openacc/jacobi\$



# VASP ON GPU

- ▶ VASP has organically grown over more than 25 years (450k+ lines of Fortran code)
- ▶ Previous VASP5.4.4 release: some features were ported with CUDA C
- ▶ Current VASP6.1.X releases: re-reported to GPU using OpenACC
- ▶ The OpenACC port is more complete already than the CUDA port.



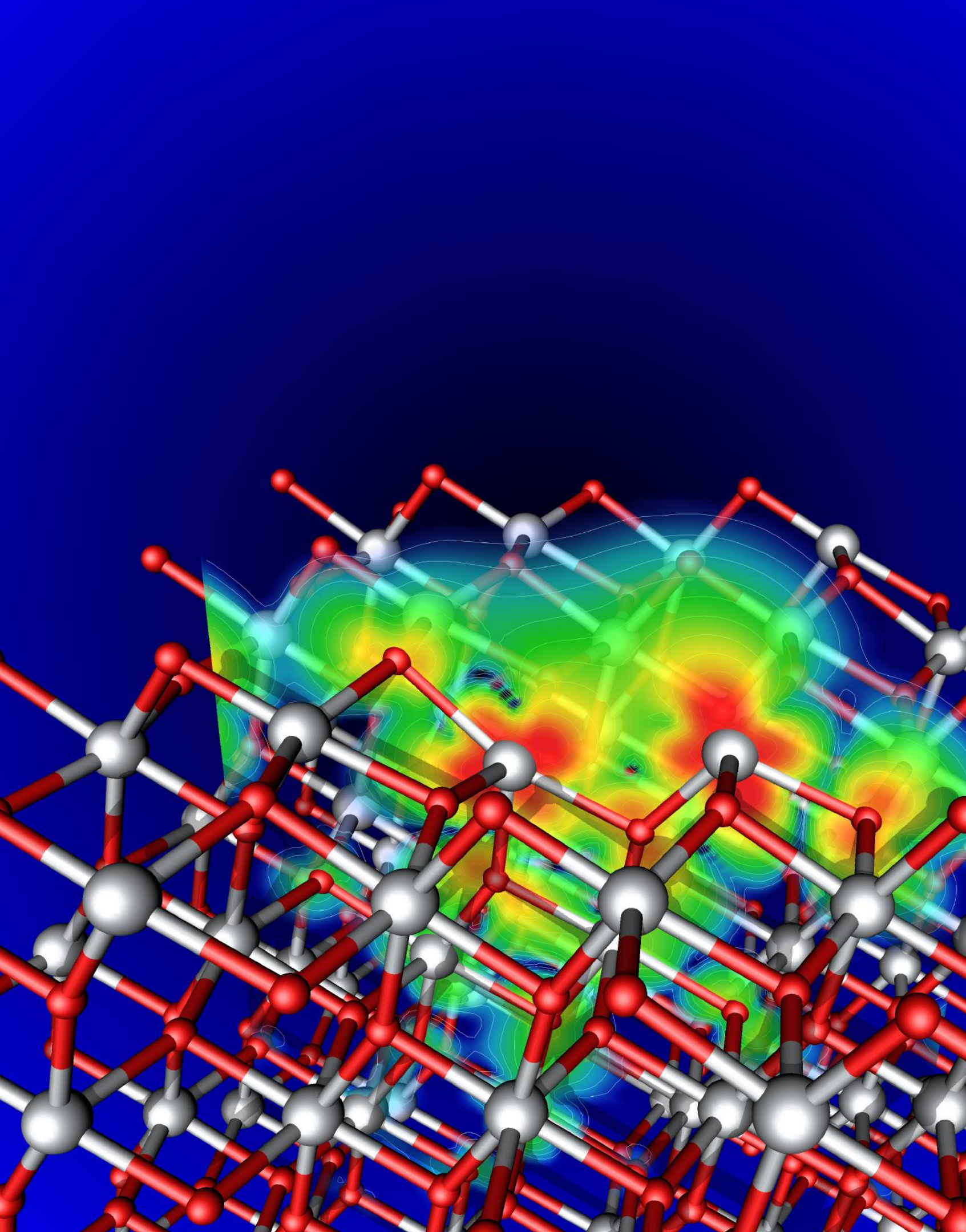
# VASP



Prof. Georg Kresse  
Computational Materials Physics  
University of Vienna

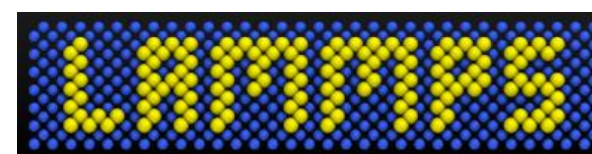


For VASP, OpenACC is *the* way forward for GPU acceleration. Performance is similar and in some cases better than CUDA C, and OpenACC dramatically decreases GPU development and maintenance efforts. We're excited to collaborate with NVIDIA and PGI as an early adopter of CUDA Unified Memory.





# NVIDIA ACCELERATES COMPUTATIONAL CHEMISTRY







이를 위해 탄생한  
CAMBRIDGE-1

# ANNOUNCING CAMBRIDGE-1 AI SUPERCOMPUTER



80 NVIDIA DGX A100 | 400 PETAFLIPS AI COMPUTE | 20 TERABYTES/SEC INFINIBAND | 2PB NVME | 500KW

HEALTHCARE &  
LIFE SCIENCE RESEARCH

LARGE-SCALE AI &  
DATA SCIENCE RESEARCH

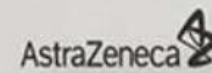
COLLABORATION WITH UK INDUSTRY,  
UNIVERSITIES, STARTUPS

EDUCATE FUTURE  
AI PRACTITIONERS





# CAMBRIDGE-1 POWERING THE FUTURE OF HEALTHCARE WITH AI



Lindsay Edwards  
Head of AI, Respiratory & Immunology



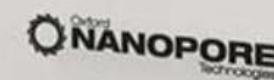
Steve Crossan  
VP, AI and Machine Learning



Sebastien Ourselin  
Professor of Healthcare Engineering



Nadine Hachach-Haram  
Clinical Innovation Lead



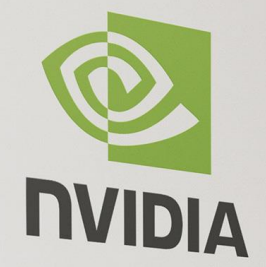
Rosemary Sinclair Dokos  
VP, Product & Programme Management



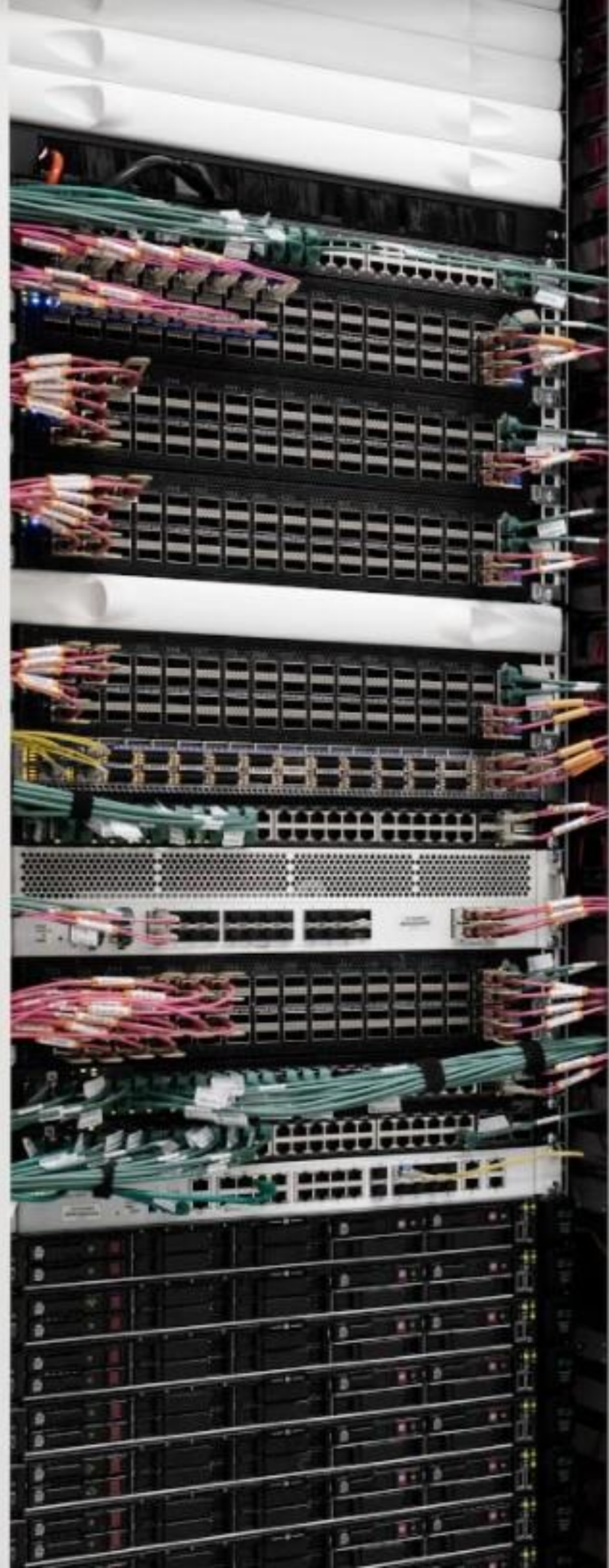
David Hogan  
VP, Enterprise EMEA

07.07.2021















# COMPUTATIONAL DRUG DISCOVERY CALCULATOR

Sizing DGX A100 Infrastructure

## Mix Traditional HPC + New AI Workloads

## Specify Experiment Turn Around Time

## Customize AI Models per Project

## Plan for Future Compute Needs

Summary End-to-End Needs for Drug Development					TOTALS
Domain (row titles, right) Phase (column, below)	Genomics DGX A100	CryoEM DGX A100	AI / ML / QSAR DGX A100	CADD DGX A100	DGX A100
Phase 1: Target Identification	TBD	TBD	1	-	1
Phase 2: Structure Determination	-	3	1	TBD	4
Phase 3: Computer-Aided Drug Design	-	-	14	26	40
Phase 4: HTScreening / Bioimaging	-	-	2	-	2
TOTALS	0	3	18	26	47

Phase 4: HTScreening / Biomaging		
TOTALS		
Target Identification		
	Turn-Around-Time	Num. of DGX A100
Sequencing	2	TBD
Genomics Analyses	2	TBD

Genomics Analyses		
Structure Determination		
	Turn-Around-Time	Num. of DGX A100
Cryogenic EM	2	3
Physics-Based Structure Prediction	1	TBD
Homology Modeling	1	TBD

Computer-Aided Drug Design		
	Turn-Around-Time	Num. of DGX A100
Docking	1	15
Free Energy Methods	5	9
Molecular Dynamics	5	2
Quantum	3	

AI model training			
	Number of Models (per project)	Turn-Around-Time	Num. of DGX A100
Phase 1: Target Identification models	1	5	1
Phase 2: Protein structure prediction models	1	5	1
Phase 3: AI-accelerated MD models	2	3	4
Phase 3: Generative models for lead discovery	2	3	4
Phase 3: Ligand binding score models	2	3	4
Phase 3: ADMET models	2	5	2
Phase 4: Bioimaging models	1	3	2

	1	3	2
Phase 1: Biomining models	1	3	3
Phase 2: ADME/ET models	3	2	3
Phase 3: Binding prediction models	3	3	4
Phase 3: Generative models for lead discovery	3	3	4
Phase 3: AI-accelerated QD models	3	3	4
Phase 3: Protein structure prediction	1	2	1
Phase 4: Target identification models			

Contact NVIDIA Account Executive





# INDUSTRIAL HPC AT THE TIPPING POINT

