

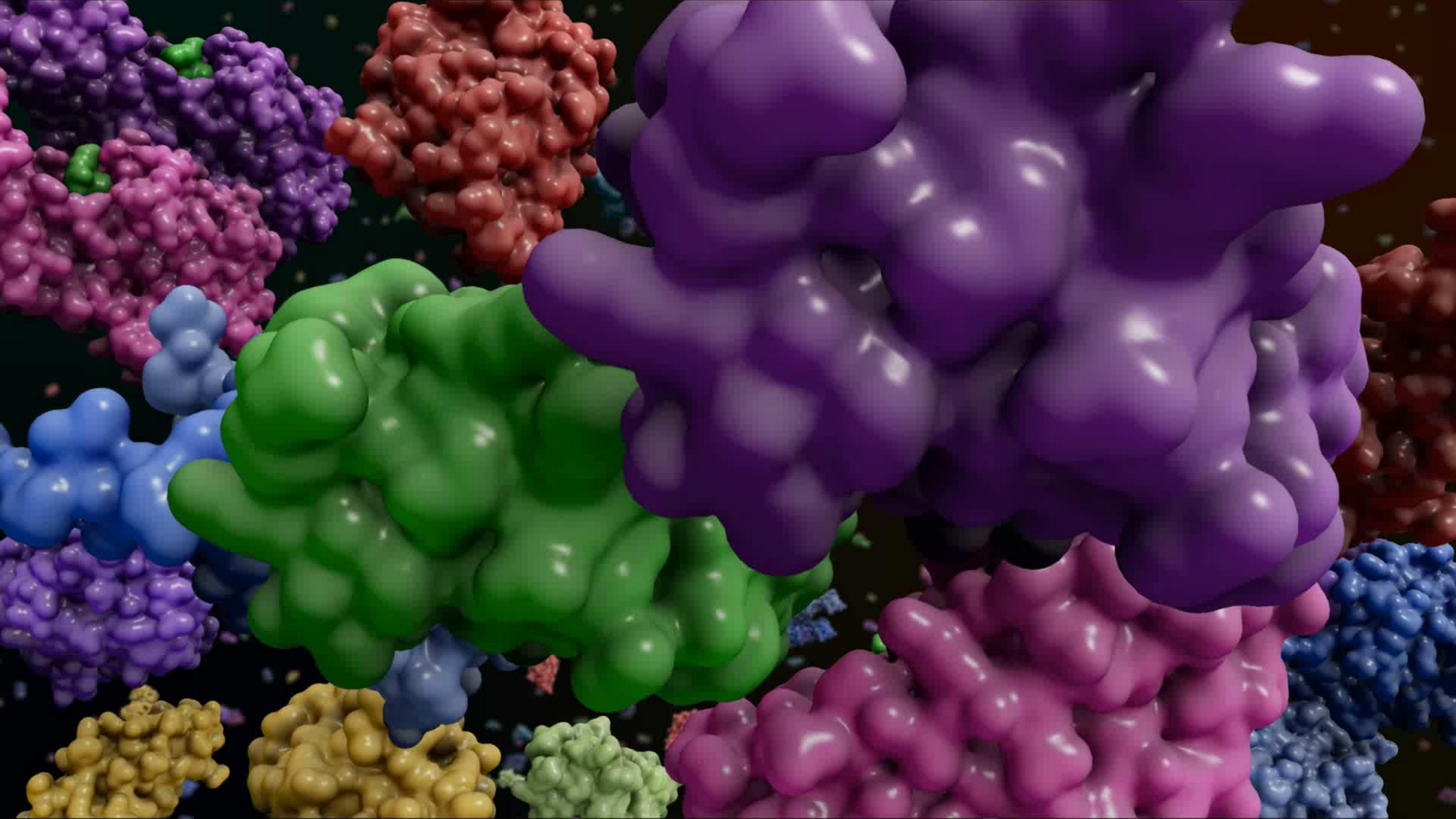
# XXVIII Symposium on Bioinformatics and Computer-Aided Drug Discovery

12:00PM 25 May, 2022  
6:00PM, SEOUL

## **Drug Discovery with Fragment Molecular Orbital (FMO) Method**

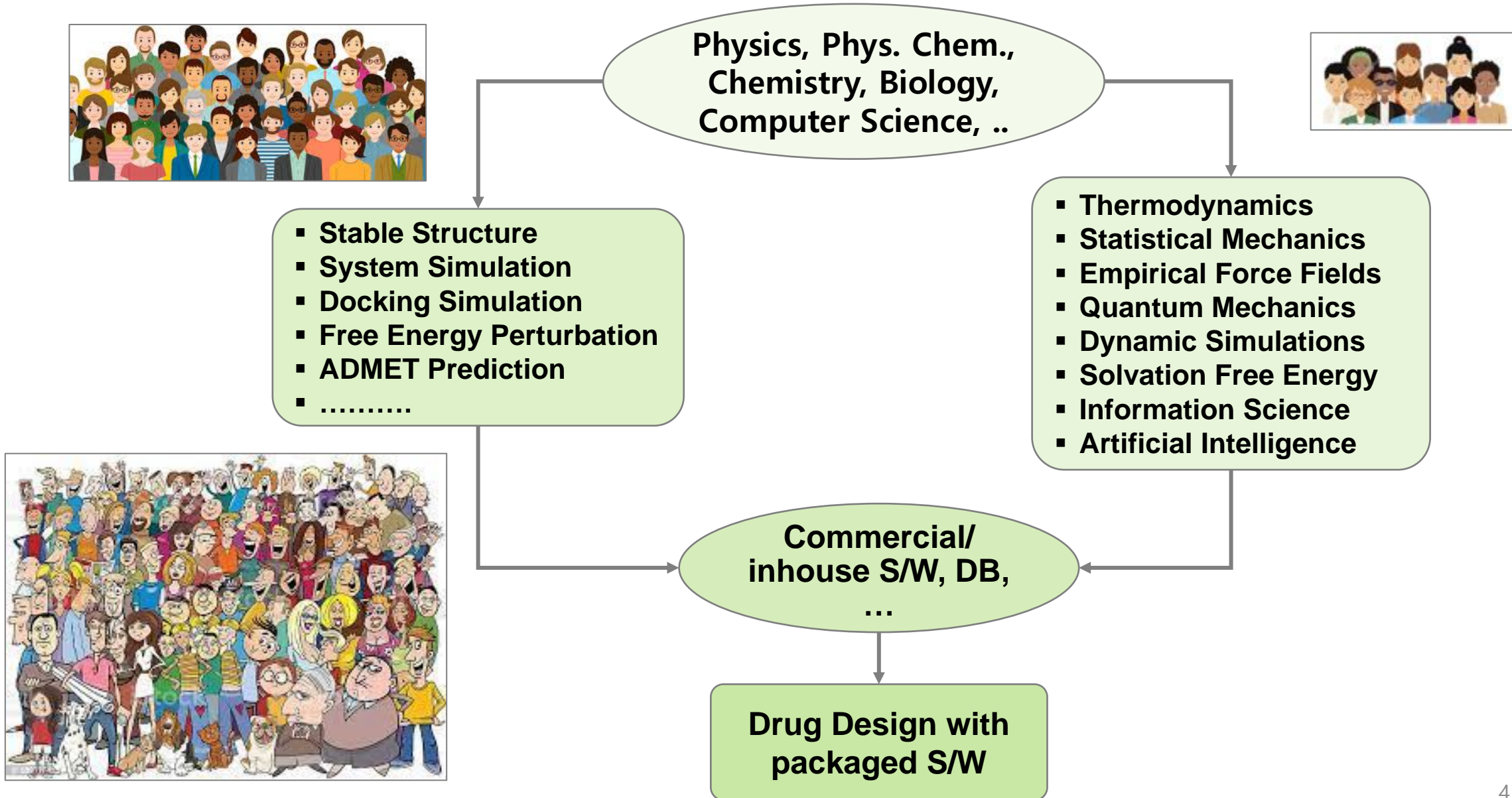
**Bioinformatics & Molecular Design Research Center (BMDRC)  
Yonsei University, Baobab AiBIO Inc.**

**Hocheol Lim, Hyeon-Nae Jeon, Jong Wan Kim, Kyoung Tai No**

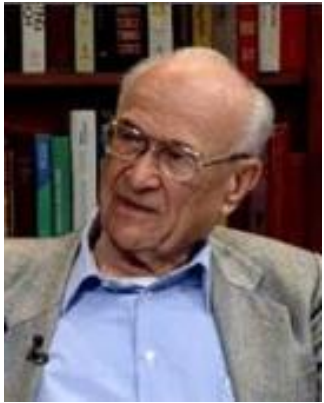


# *Frontiers in Structure Based Drug Discovery*

# CADD From Basic Science to Commercial Design Packages



## Energy – Mechanics Based Design



**Harold Scheraga**

ECEPP/2,3

FF for Protein in  
Torsion space



**Martin Karplus**

CHARMMnn

All intra degree  
of freedom

Noble Prize 2013



**Peter Kollman**

AMBER

Most widely used  
→ open source



**Norman Allinger**

MM/2&3

Intramolecular FF  
For smaller  
molecular structure



**William Jorgensen**

OPLS,..., OPLS3e..

Good for liquid Sim.  
Fit to Free Energy  
Perturbation



**BMDRC**

**PMFF**

Since 1987~2020  
Physics based FF  
parameters  
determination  
First in ASIA

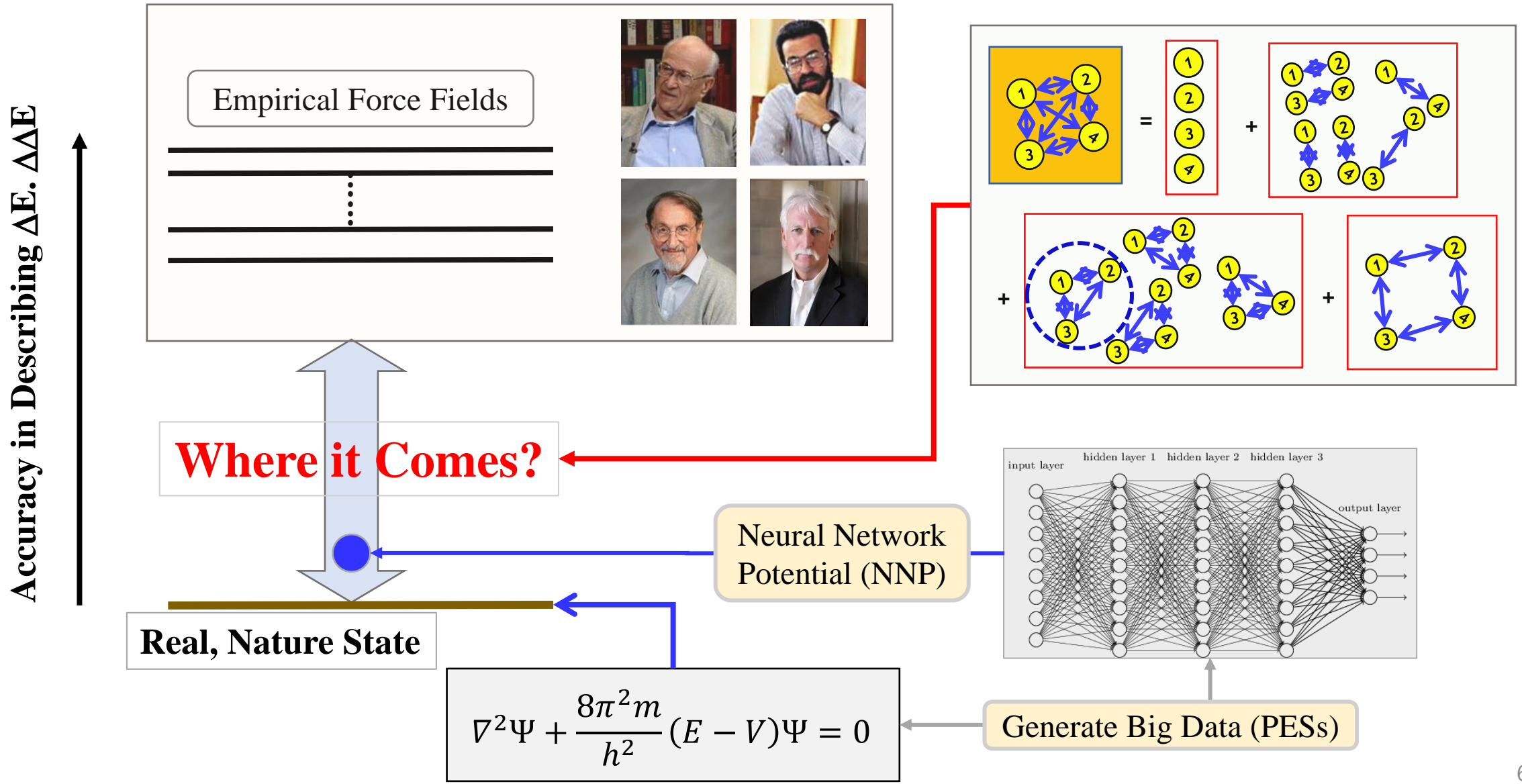


**PMFF: Development of a Physics-Based Molecular Force Field for Protein Simulation and Ligand Docking**

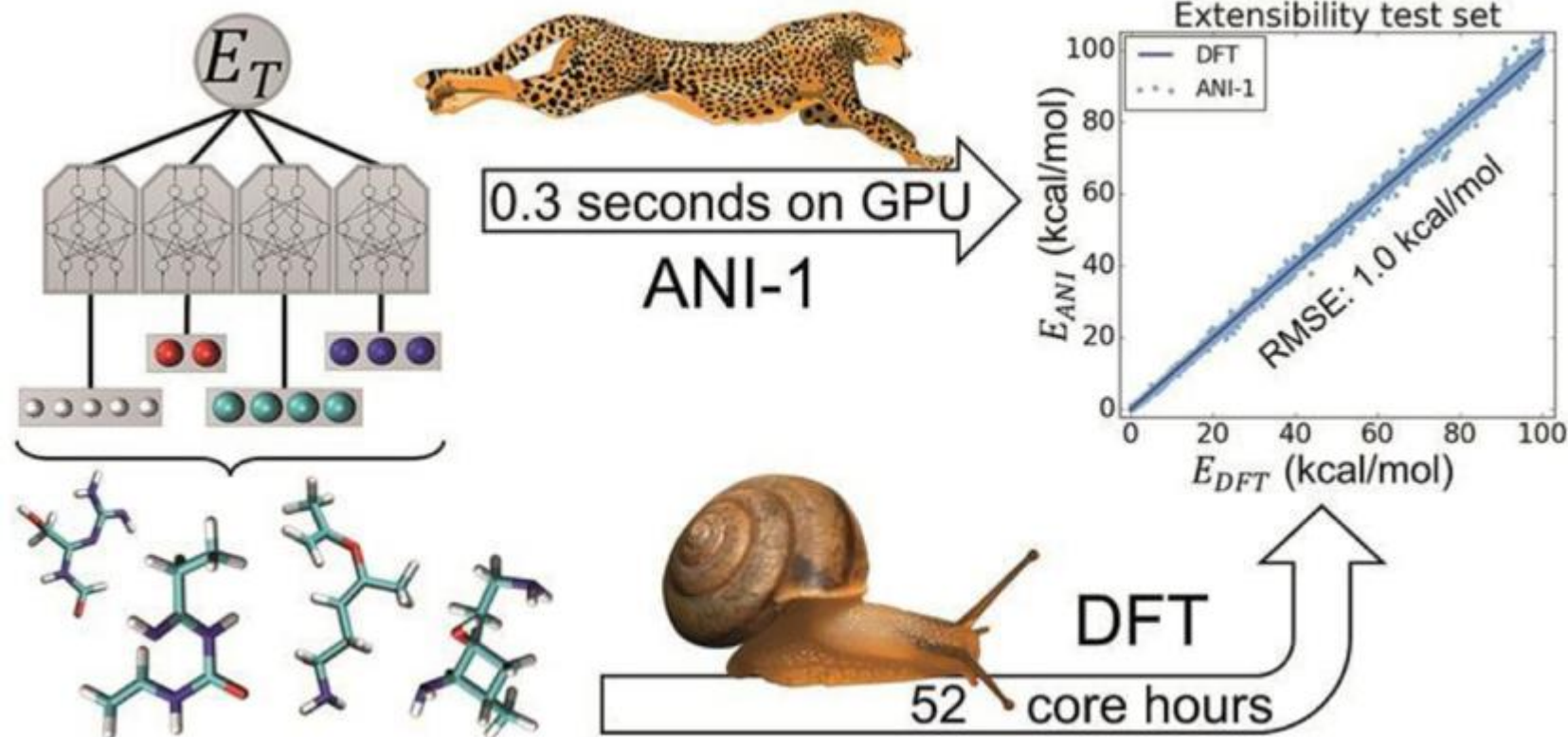
Sung Bo Hwang, Chang Joon Lee, Sehan Lee, Songling Ma, Young-Mook Kang, Kwang Hwi Cho, Su-Yeon Kim, Oh Young Kwon, Chang No Yoon, Young Kee Kang, Jeong Hyeok Yoon, Ky-Youb Nam, Seong-Gon Kim, Youngyong In, Han Ha Chai, William E. Acree, Jr., J. Andrew Grant, Ken D. Gibson, Mu Shik Jhon, Harold A. Scheraga, and Kyoung Tai No\*

SB Hwang, et al., J. Phys. Chem. B (2020)

# Limitation of Empirical FF in Accuracy of Energy Calculation



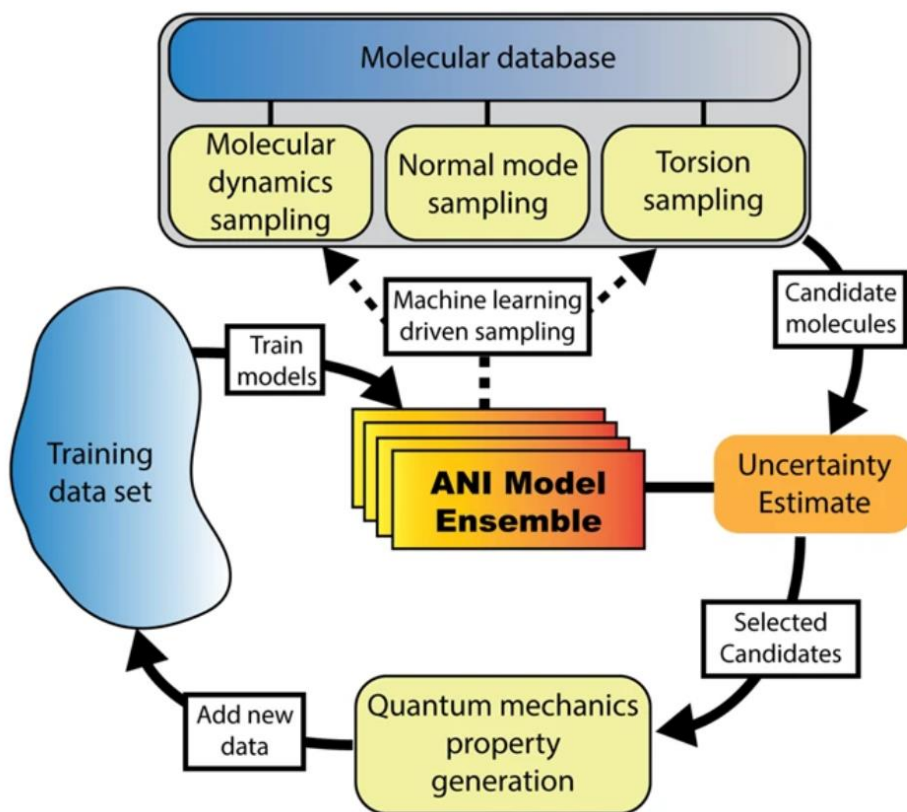
Adrian E. Roitberg



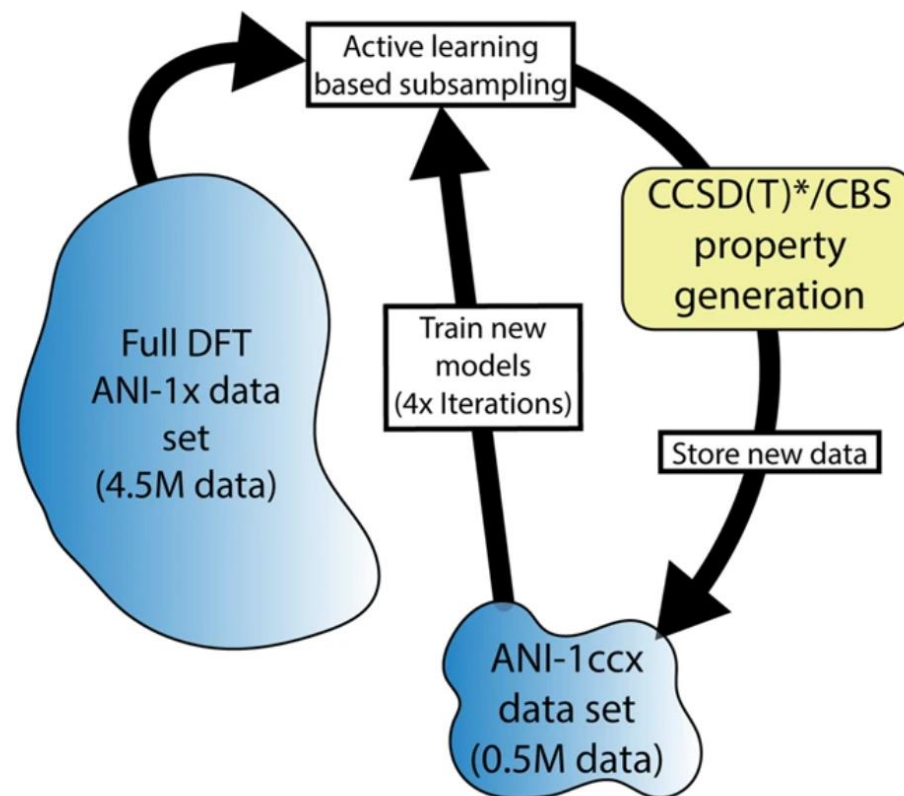
Deep neural network (NN) trained on quantum mechanical (QM) DFT calculations can learn an accurate and transferable potential for organic molecules.

ANAKIN-ME: Accurate Neural network engine for Molecular Energies

a Active learning sampling algorithm



b CCSD(T)\*/CBS ANI-1ccx selection

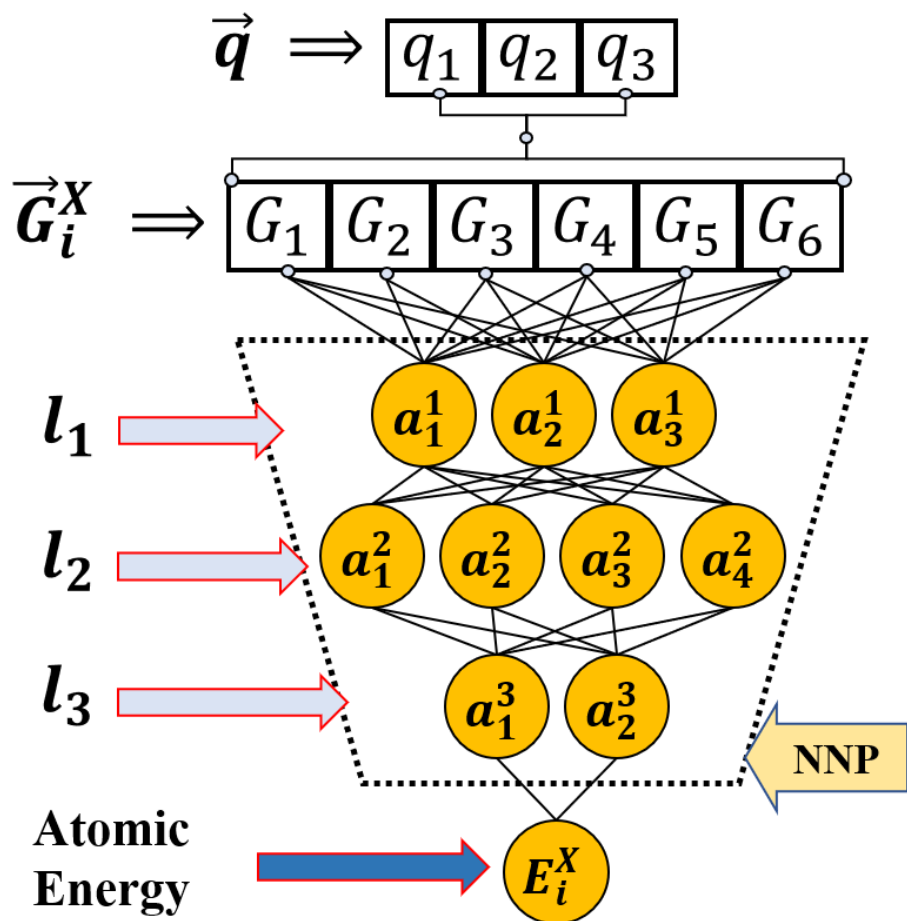


- **ANI-1:** ANI-1: an extensible neural network potential with DFT accuracy at force field computational cost
- **ANI-1x:** Less is more: Sampling chemical space with active learning
- **ANI-1ccx:** Approaching coupled cluster accuracy with a general-purpose NNP through transfer learning
- **ANI-2x:** Extending the Applicability of the ANI Deep Learning Molecular Potential to Sulfur and Halogens

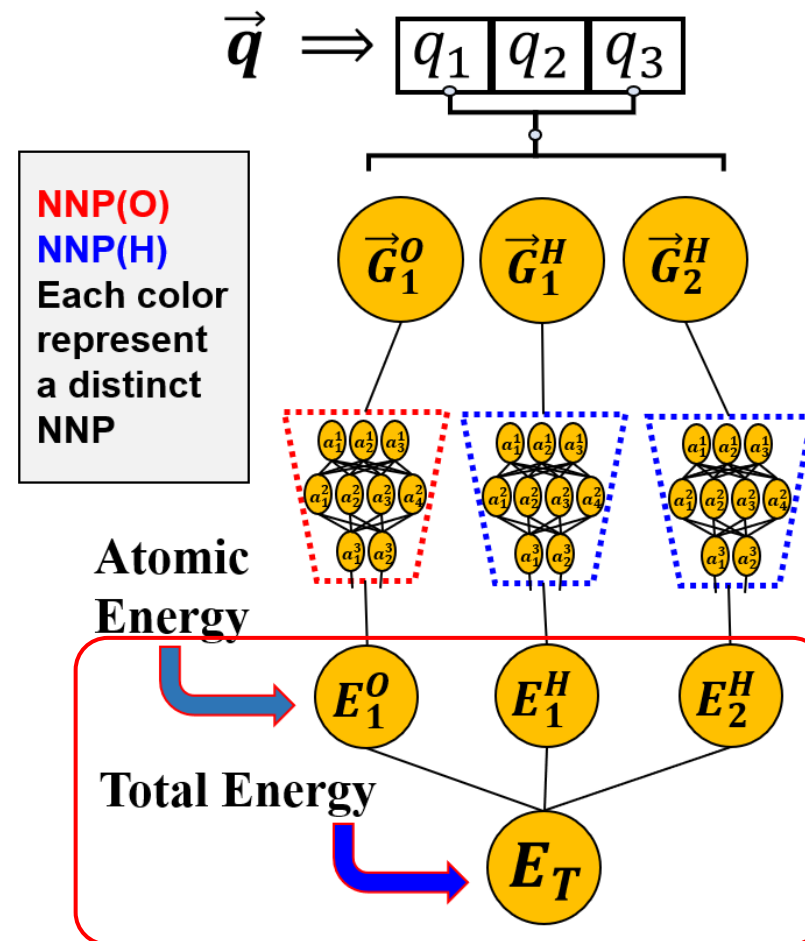


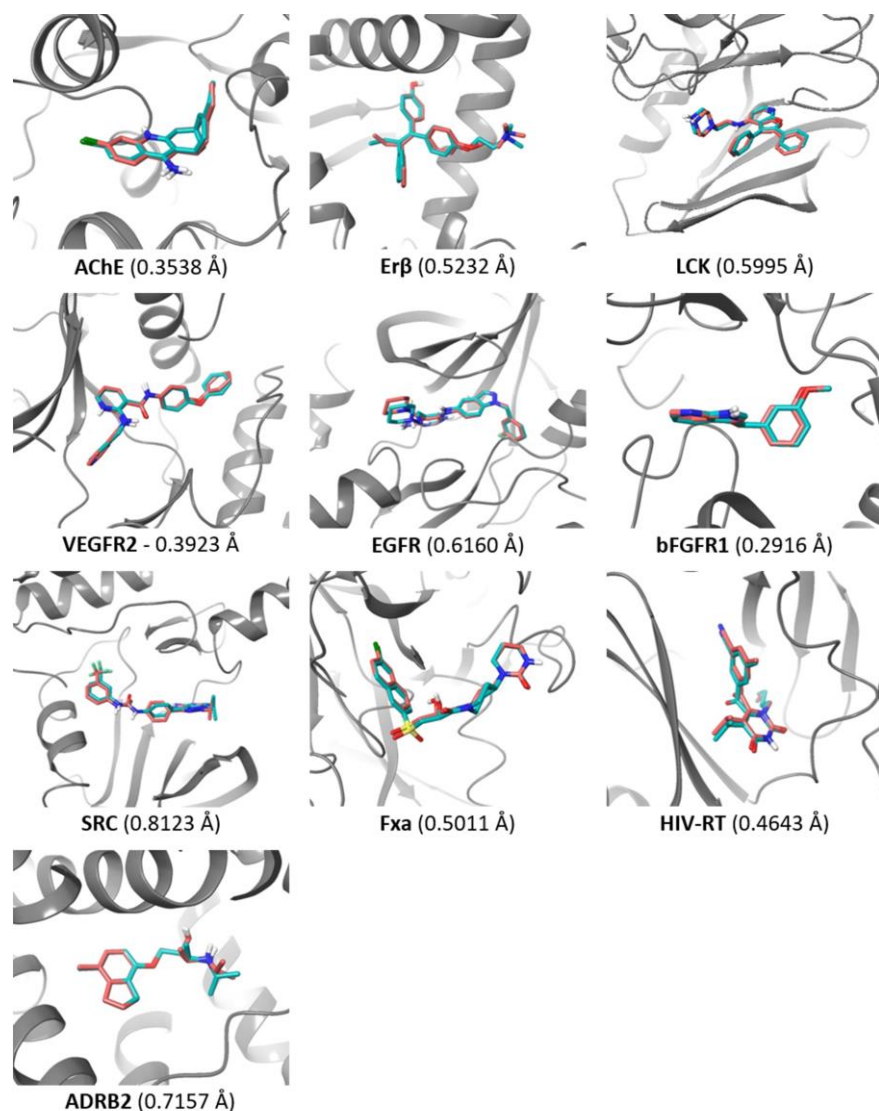
Behler and Parrinello's HDNN or HD-atomic NNP model.

Atomic NNP(X)



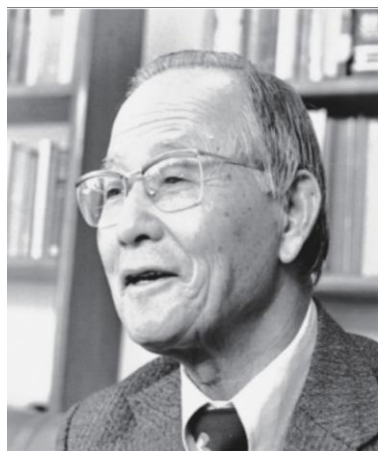
HD-Atomic NNP(H<sub>2</sub>O)





Top ranking of docking poses in 10 X-ray crystal structures					
PDB ID	Generated Poses	Calc. Time (s)	Total Atoms	RMSD (Å) of ANI-2x Top 1	RMSD (Å) of Emodel Top 1
1E66	44	10.23	8247	0.3538	0.3538
2FSZ	512	66.27	3900	0.5232	0.9998
2OF2	133	18.41	4407	0.5995	0.5995
2P2I	333	51.52	4867	0.3923	0.7912
2RGP	955	155.66	5141	0.616	1.4343
3C4F	88	13.35	4871	0.2916	0.2916
3EL8	126	19.25	4462	0.8123	0.8679
3KL6	410	53.65	3688	0.5011	1.2538
3LAN	53	12.74	9120	0.4643	0.4643
3NY8	101	20.68	7180	0.7157	2.511

Neural network potentials have provided accurate results for intra- and intermolecular interactions in protein-ligand complexes. Although ANI-2x was not trained for protein structures and ionic molecules, scoring the docking poses with ANI-2x was reasonable and we showed that ANI-2x can be applied to molecular docking simulations. These methods can be incorporated directly into existing docking scoring methods to select the most favorable binding pose of a ligand. These few applications of NNP would be the start point of how machine learning will create new trends in biosciences.



Prof. Taikyue REE



Prof. Kenichi FUKUI

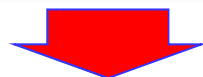


Prof. Keiji MOROKUMA



Prof. Kazuo KITAURA

How to calculate the Energy (Electron density) of Proteins with Quantum Chemical Calculation



Fragment Molecular Orbital (FMO)



分子科學研究所, 岡崎  
Institute of Molecular Science, Okazaki

**Energy Decomposition** (Partitioning): the total dissociation energy  $D_e$  is decomposed into a number of physically meaningful components by dividing the interaction process between two or more fragments  $A$  and  $B$ .

Kitaura–Morokuma or Ziegler–Rauk schemes

$$-D_e = \Delta E_{elec} + \Delta E_{ex} + \Delta E_{pol} + \Delta E_{CT} + \Delta E_{mix}$$

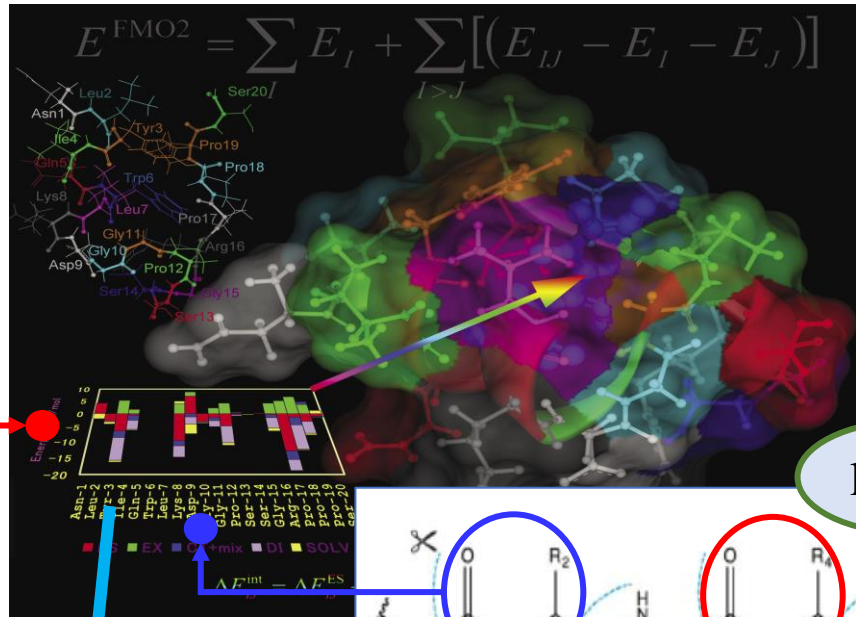
**Structure Fragmentation:** The bond energetics within a molecule is to *decompose* the total energy of the molecule within a given quantum-chemical method into a sum of monoatomic and diatomic contributions (**fragments**) as follows,

$$E = \sum_A E(A) + \sum_{A>B} E(AB) = \sum_A E(A) + \frac{1}{2} \sum_{A \neq B} E(AB)$$

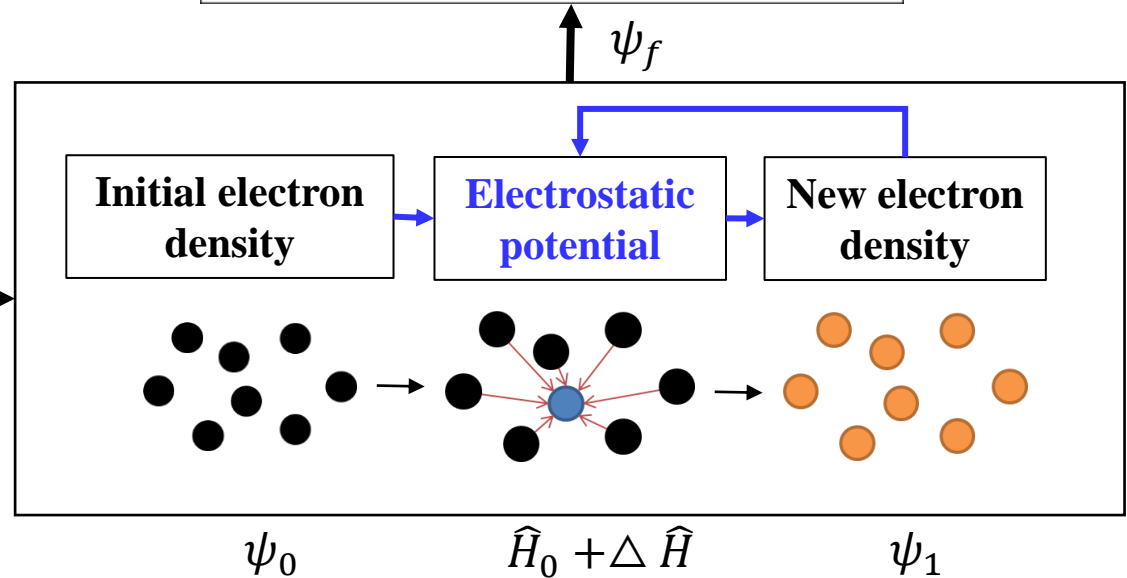
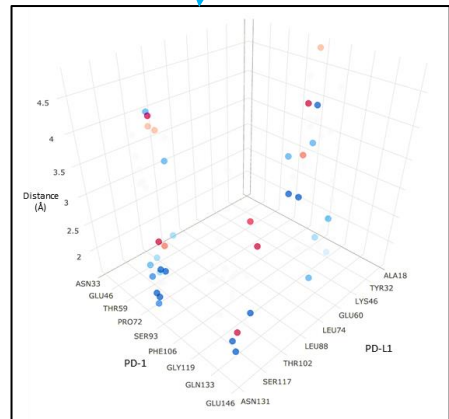
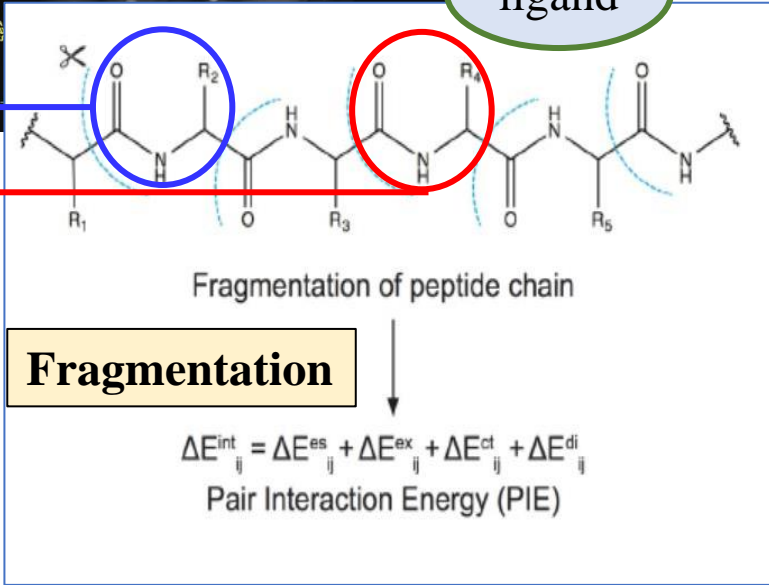
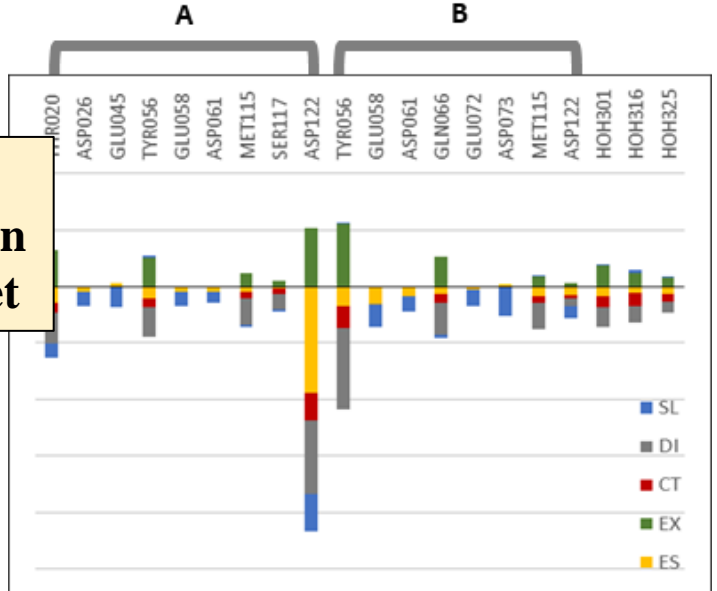
Fragment MO (FMO)

A new energy decomposition scheme for molecular interactions within the Hartree-Fock approximation, Kazuo Kitaura & Keiji Morokuma, Int. J. Quantum Chem., 1976, 10, 325–340  
On the calculation of bonding energies by the Hartree Fock Slater method, Tom Ziegler & Arvi Rauk, Theoretica Chimica Acta, 1977, 46, 1–10

# Structure Fragmentation of Protein

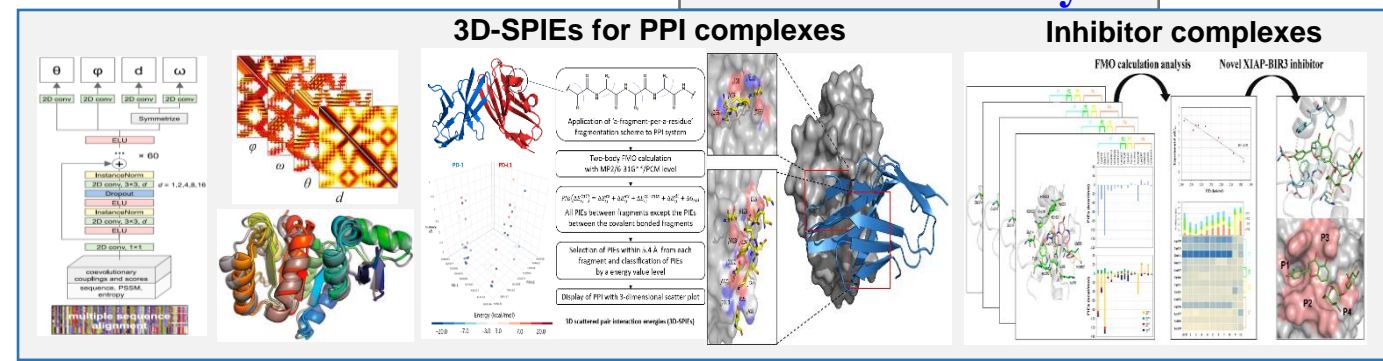
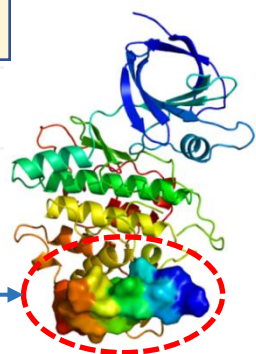
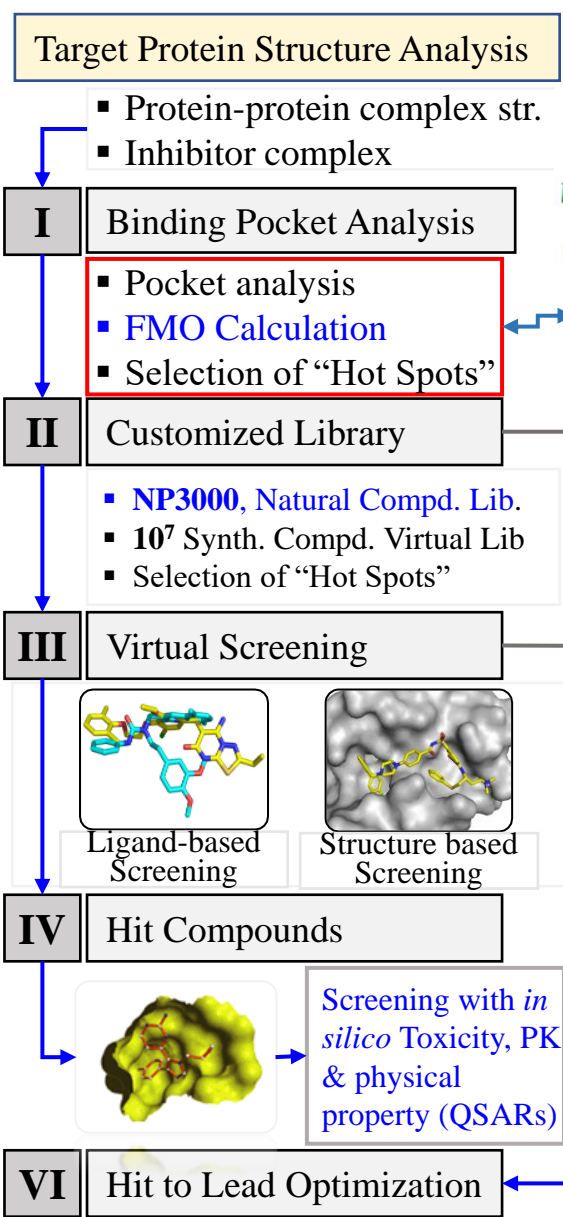


**Pair Interaction E**  
**Energy decomposition**  
**Define binding pocket**



# FMO based Drug Design Platform, AVENGERS

STAGE I  
STAGE II  
STAGE III



**In vitro study – Efficacy**

- Luciferase activity

**In vitro study - Binding**

- Cryo-EM
- SPR assay
- Thermal shift assay
- FRET assay

**A Feature-specific filtering**

- Pharmacophore-based screening
- Shape-based ligand clustering

**B Initial binding pose generation**

- ANI-1-based conformational search (NNPot)
- Docking-based binding pose generation

**C Initial binding pose filtering**

- MM-based pose ranking
- FMO-DFTB3-based pose ranking**

**D Semi-empirical-based pose optimization**

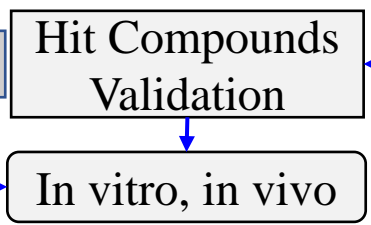
- FMO-DFTB3-based pose optimization**

**E Receptor-specific scoring function**

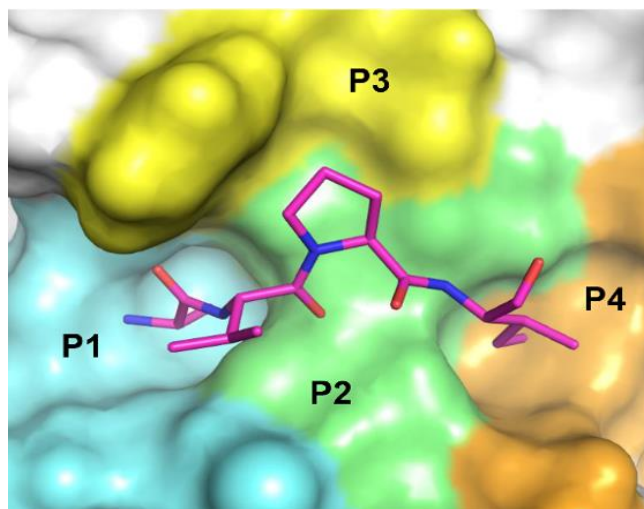
- FMO-PIEDA based enthalpy term
- PCM (MM/GBSA) based solvation term
- Non-polar-SA ( $N_{rot}$ ) based entropy term

**F Hit-based scoring function optimization**

- Classification models (e. g., fluorescence assays)
- Regression models (e. g., binding affinity)



X-linked inhibitor of apoptosis protein (XIAP), inhibits caspases through its (BIR) domains.



Ligand	IC <sub>50</sub> (μM)	PDB (resol/Å)	PIEs
AVPI	0.32	1G73 (2.00)	-246.078
1	>5,000	5C3H (2.65)	-204.792
2	>495	5C7A (2.36)	-217.849
3	5.5	5C7C (2.32)	-220.880
4	0.64	5C84 (2.36)	-257.064
5	0.22	5M6F (2.39)	-241.754
6	0.16	5C83 (2.33)	-247.424
7	0.15	5M6H (2.50)	-246.405
8	0.044	5M6M (2.37)	-246.913

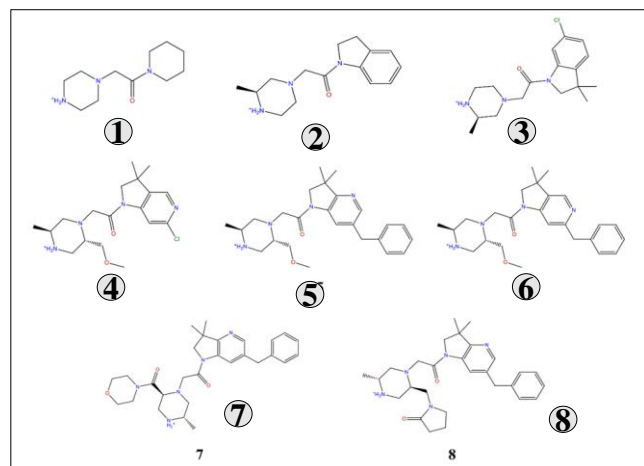
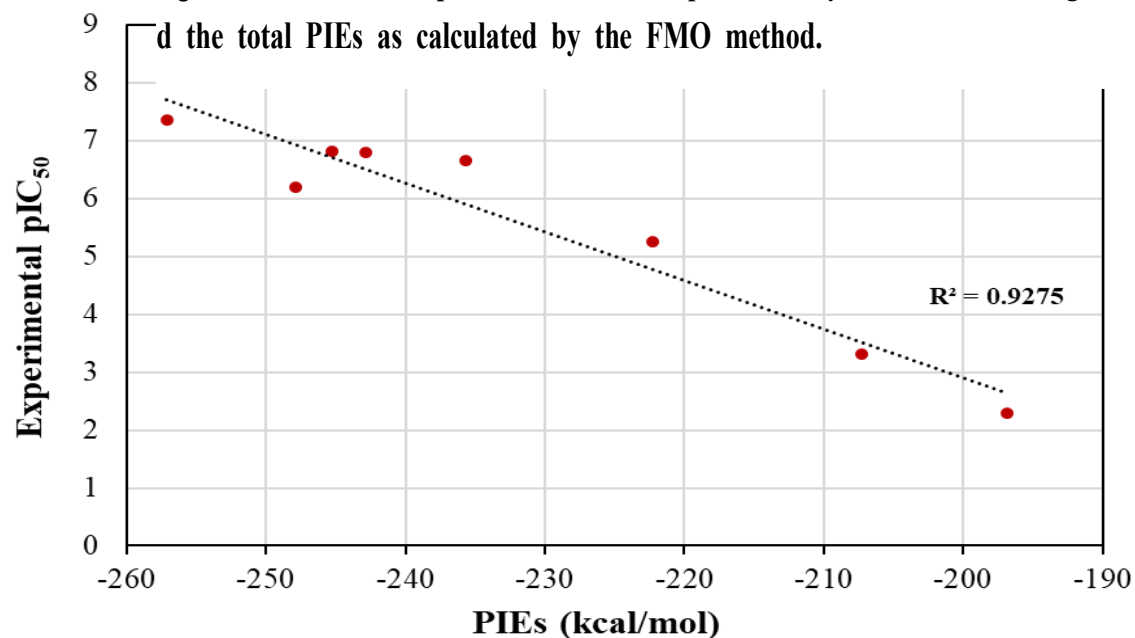
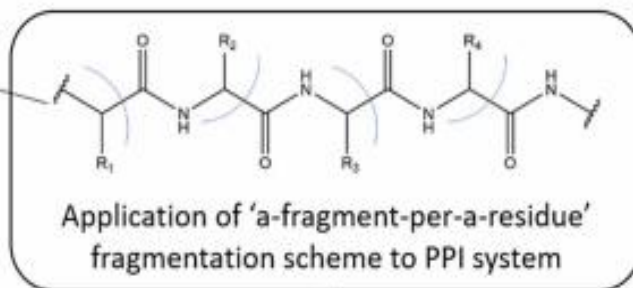
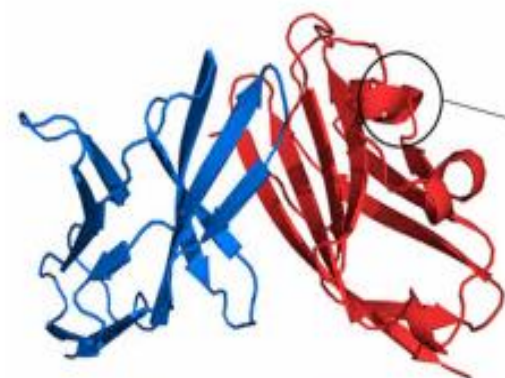


Figure 1. Correlation plot between the experimentally measured binding affinity pIC<sub>50</sub> and the total PIEs as calculated by the FMO method.



# Analysis of PD1-PDL1 Interaction



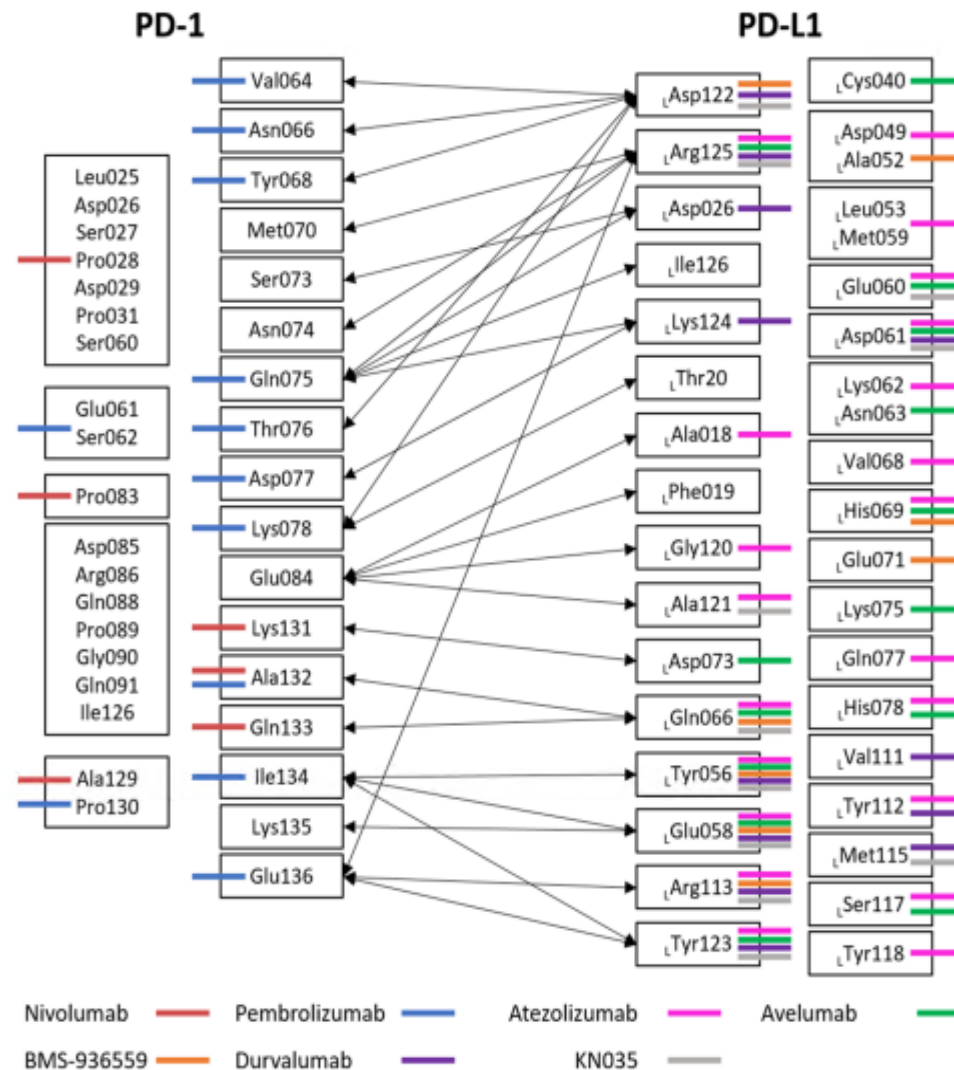
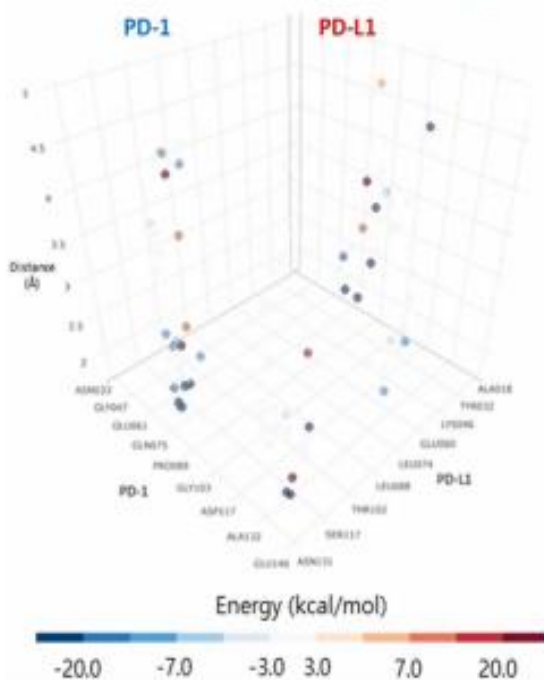
Two-body FMO calculation with MP2/6-31G\*\*/PCM level

$$PIE(\Delta E_{ij}^{int}) = \Delta E_{ij}^{es} + \Delta E_{ij}^{ex} + \Delta E_{ij}^{ct+mix} + \Delta E_{ij}^{di} + \Delta G_{sol}$$

All PIEs between fragments except the PIEs between the covalent bonded fragments

Selection of PIEs within 5.4 Å from each fragment and classification of PIEs by an energy value level

Display of PPI with 3-dimensional scatter plot





# Analysis of SARS-CoV-2 Spike Protein & h-ACE2 Interaction

Jan. 6, 2020

Confirm Coronavirus pathogens with **TEM**

In Jan, 2020

How the virus is transmitted is key to prevent & controlling it

Feb.15, 2020

SAR-CoV2 gene sequence & purified the spike protein

Feb. 19, 2020

Structure: SARS-CoV2 spike protein bound to h-ACE2: **Cryo-EM**

Feb. 21, 2020

Structure, Function, & Antigenicity of the Spike Glycoprotein: **Cryo-EM**

Feb. 26, 2020

spike protein structure from SARS-CoV-2 on PDB

In two months

In Mar., 2020

QM calculation on Spike protein-hACE2 with the structure from PDB

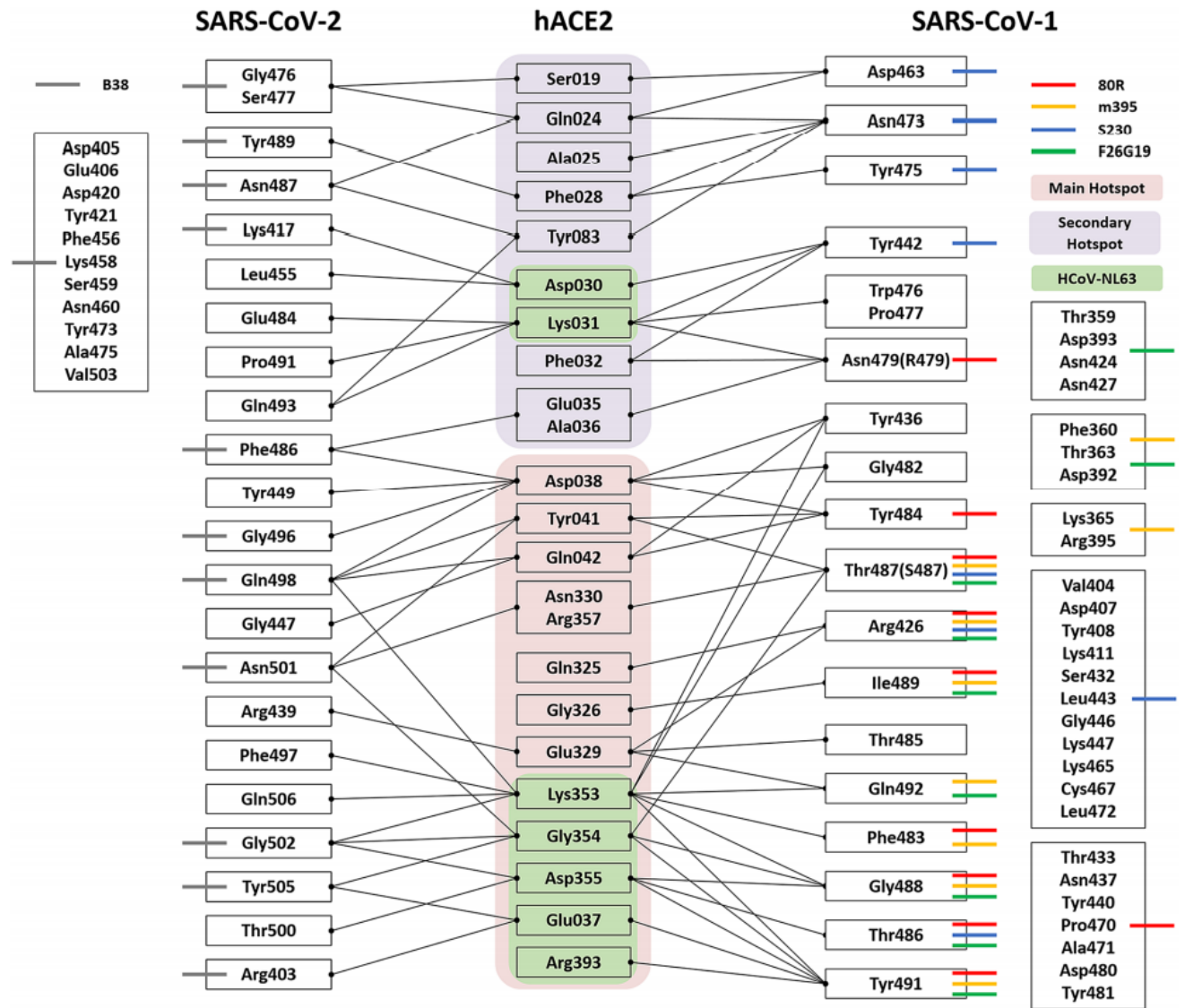
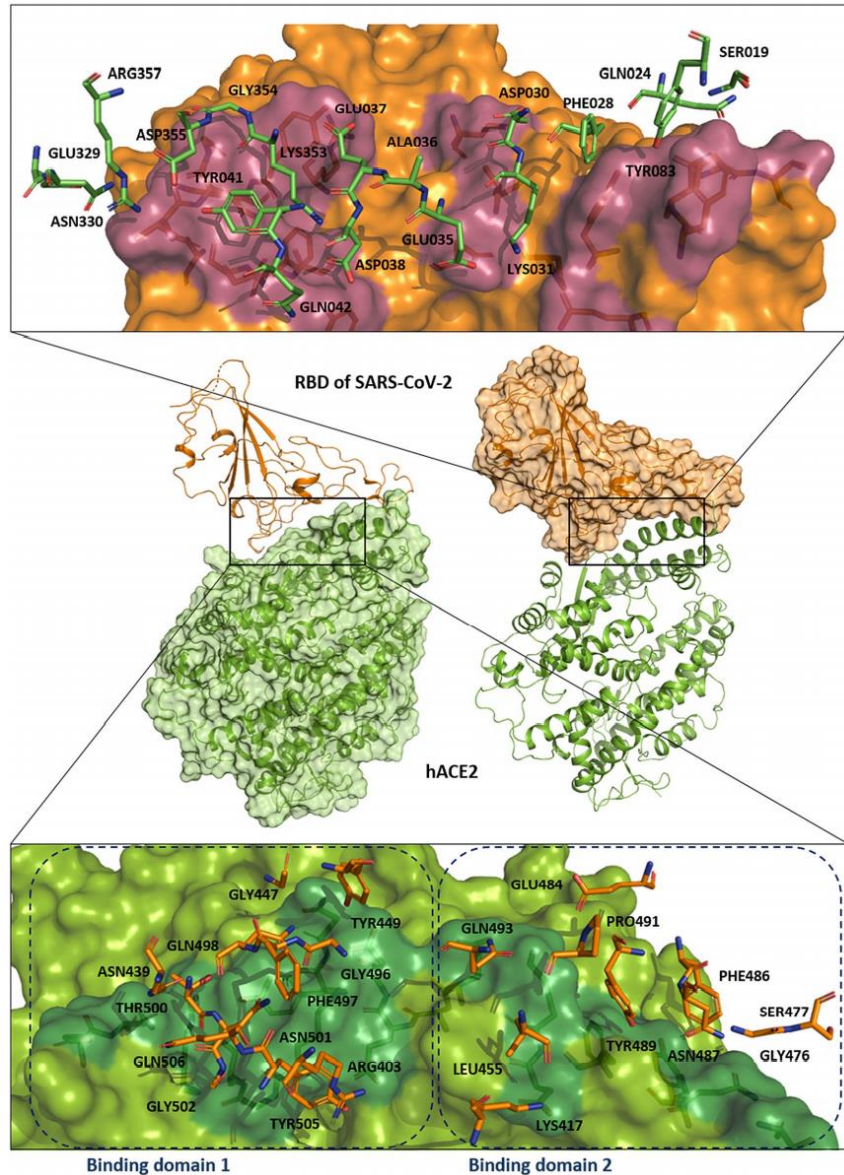
Apr.20 , 2020

Submit information on the import interaction points between Spike protein and h-ACE2 (bioRxiv: April 27): **FMO (QM)**

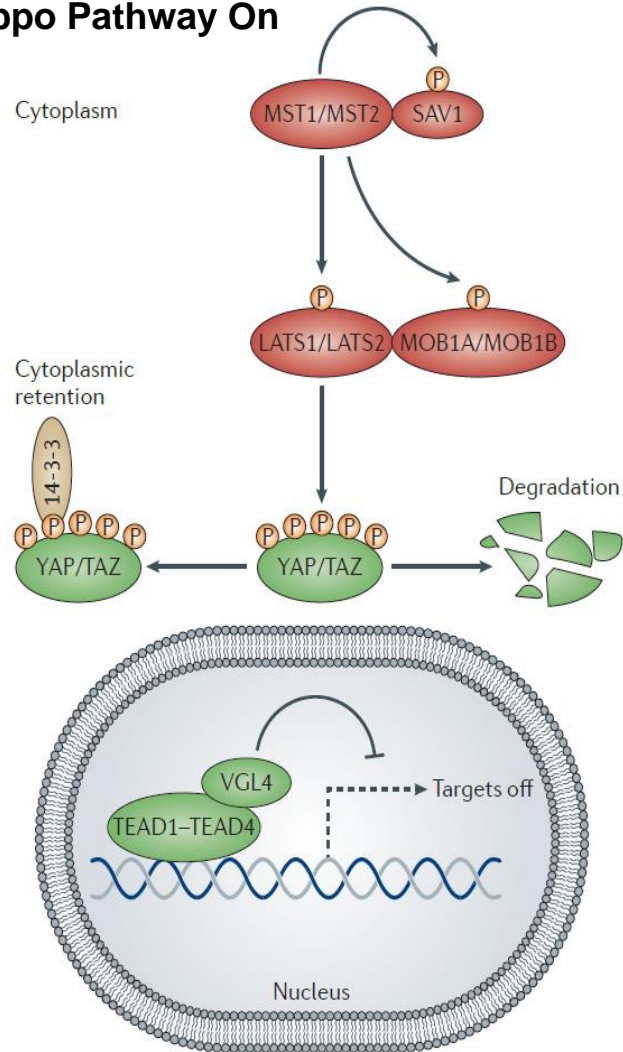
In Apr. , 2020

Virtual Screening for drug repositioning with hot spots: **AVENGERS**

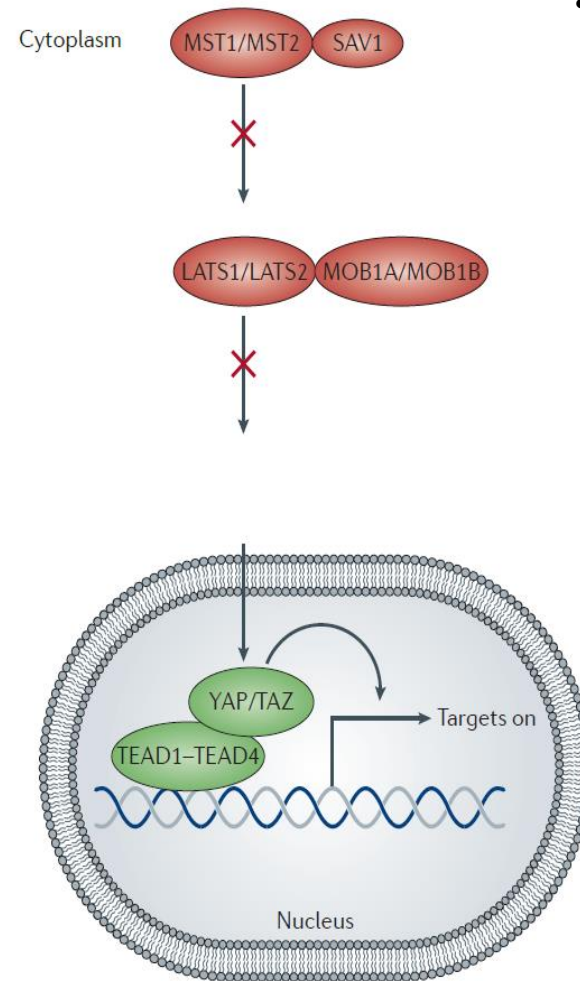
# Analysis of SARS-CoV-2 Spike Protein & h-ACE2 Interaction



## Hippo Pathway On

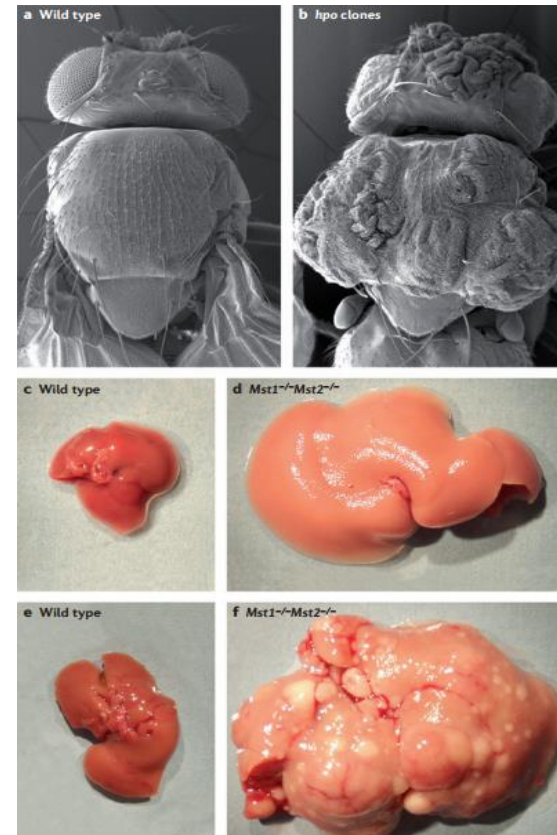


## Hippo Pathway Off

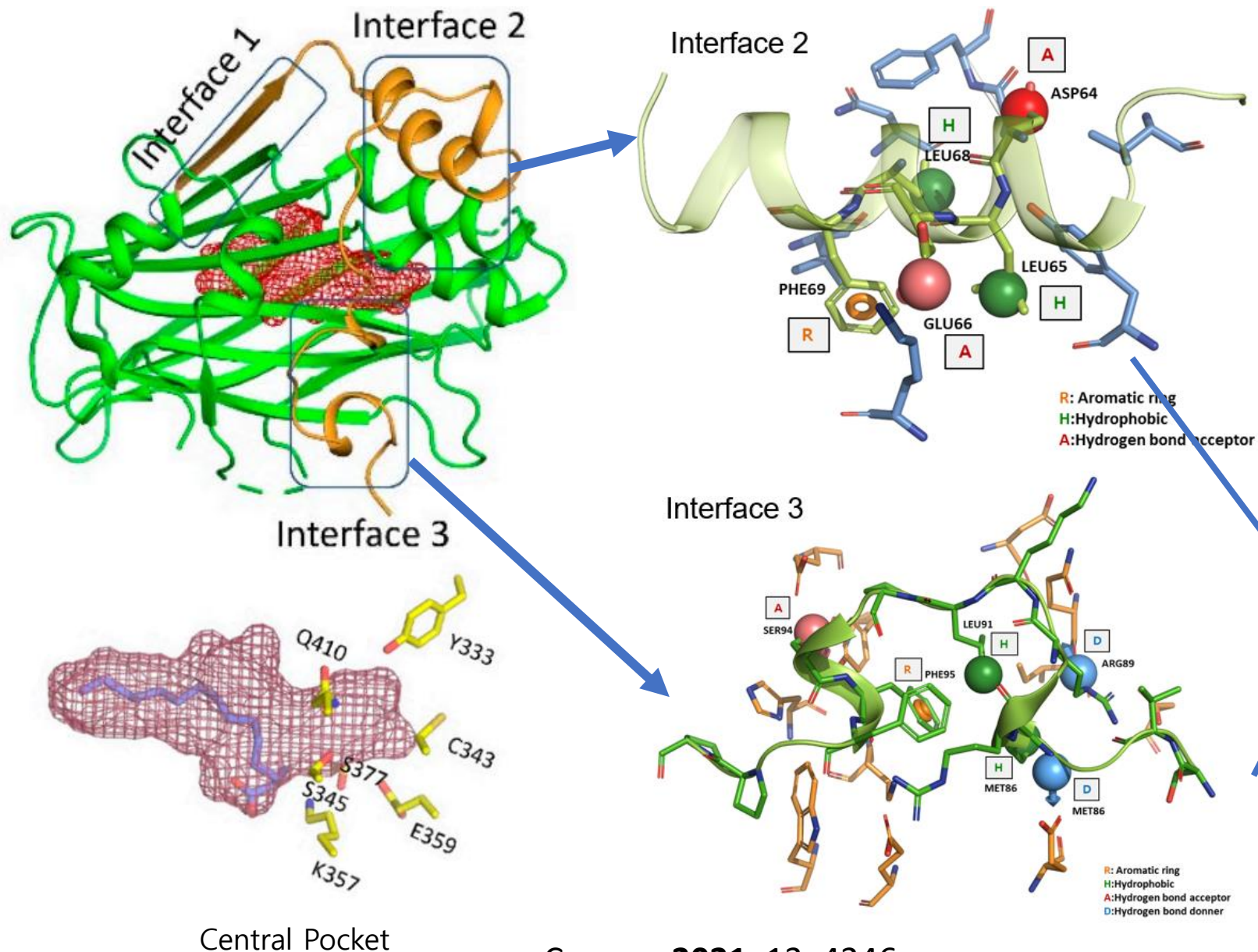


## Growth control pathway

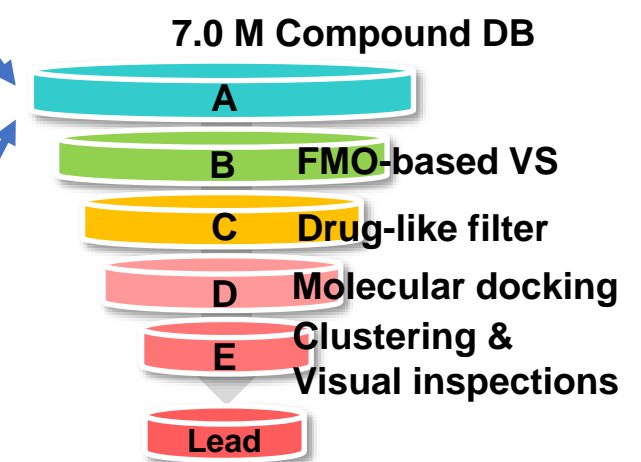
- Organ growth control, stem cell function, regeneration, and tumor suppression
- 2. Deregulated in many cancers → cancer initiation and progression



**“Loss of Hippo signaling and YAP overactivation are observed in many cancer patient”**

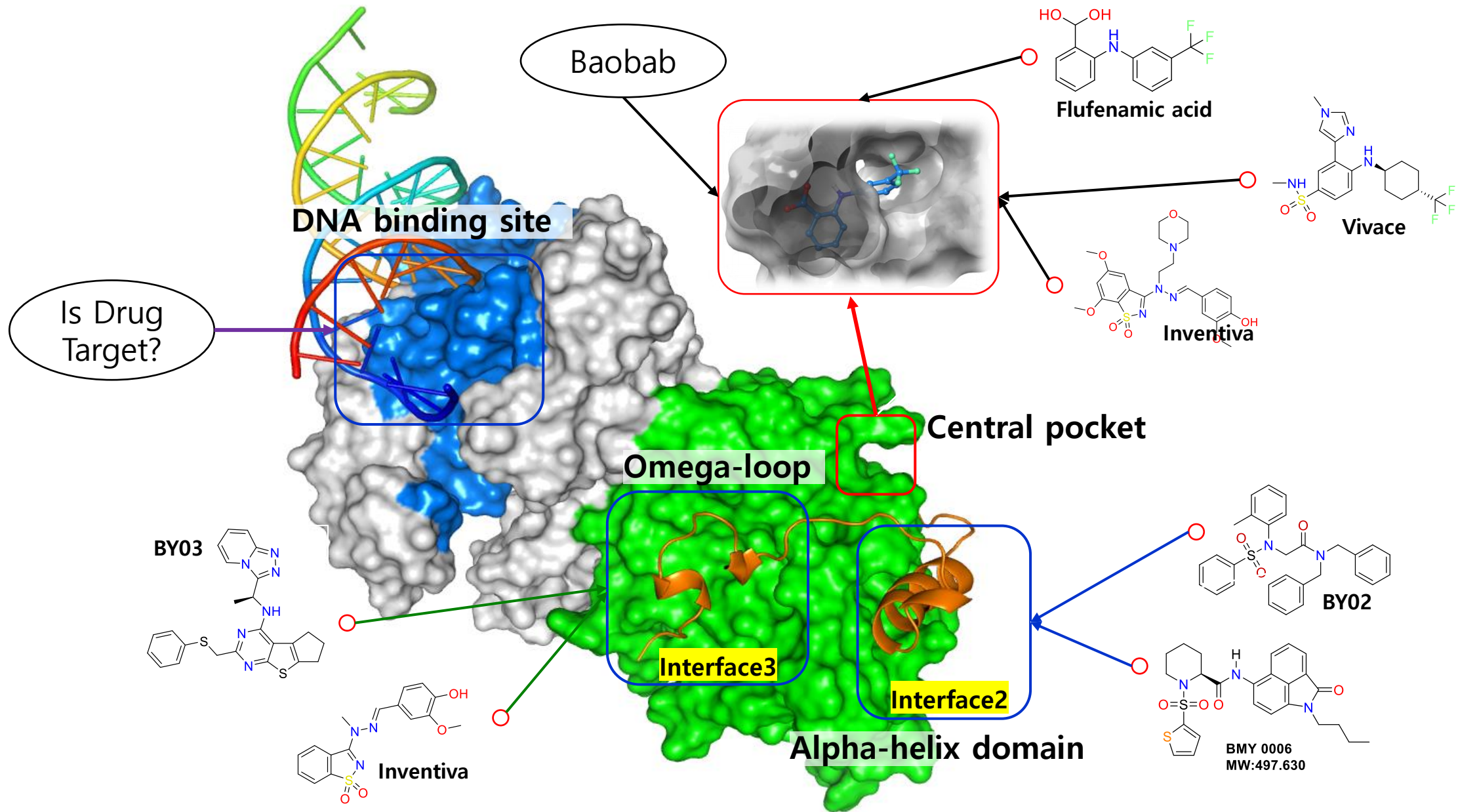


- Features of pharmacophore were generated from hot spot information obtained with FMO calculations
- Features are selected within the surface range that small molecules can cover.
- Then Virtual Screening

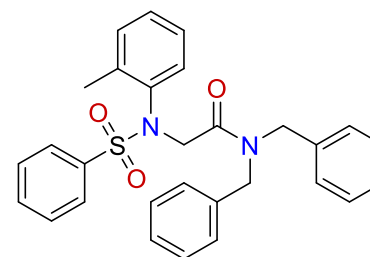
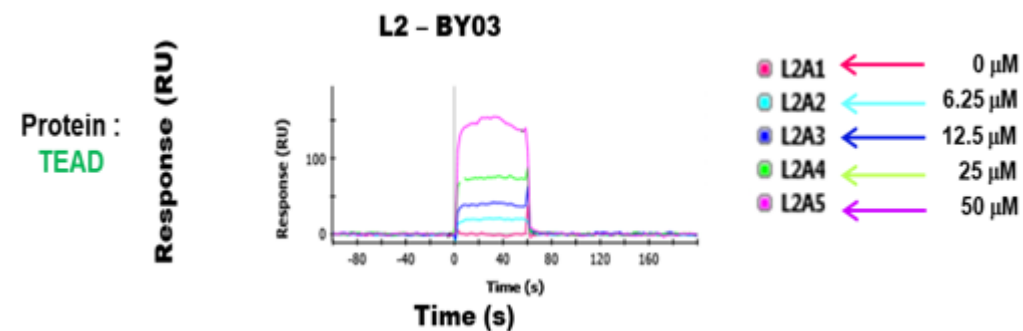
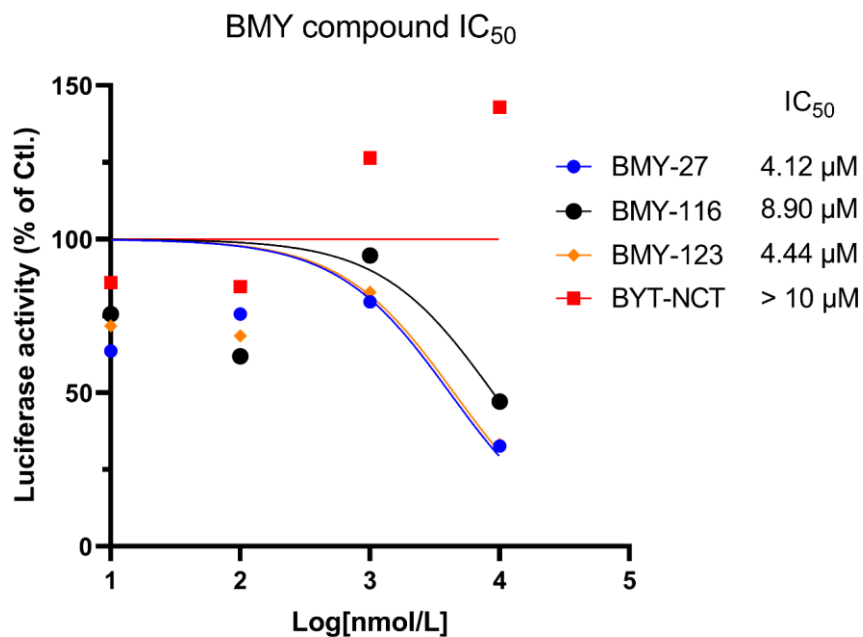
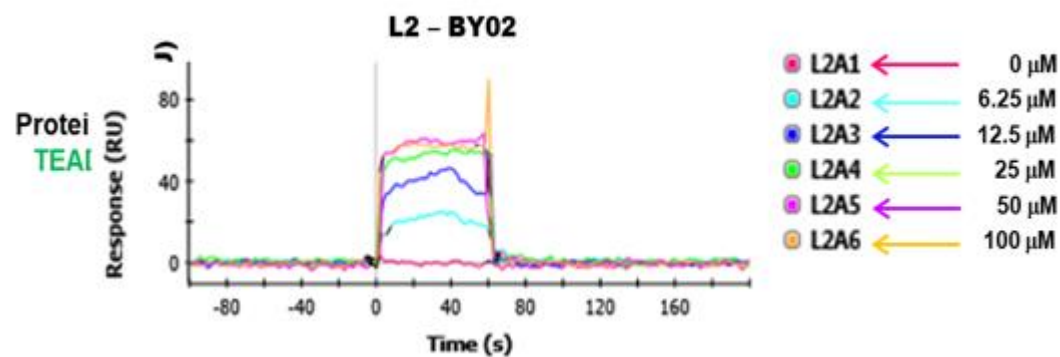
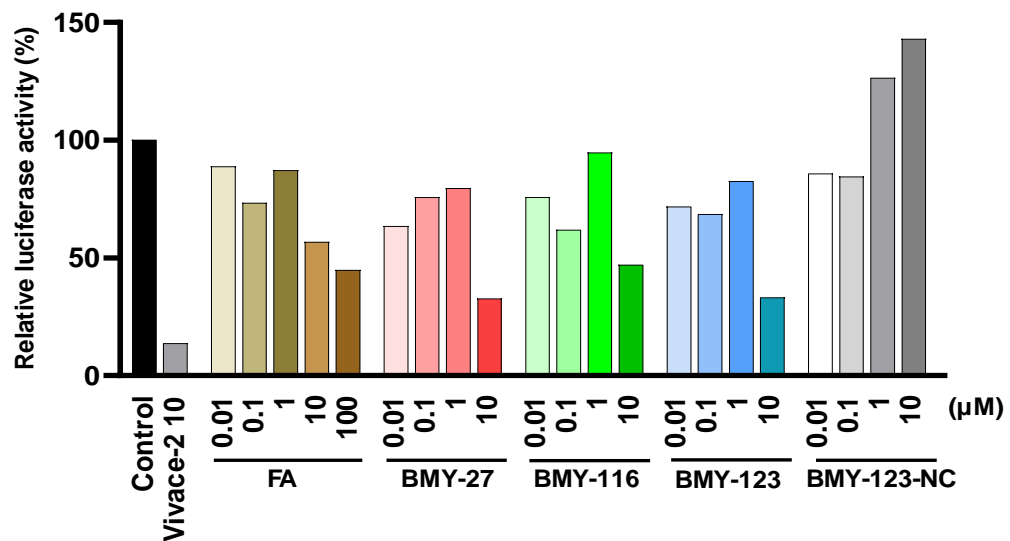


Central Pocket

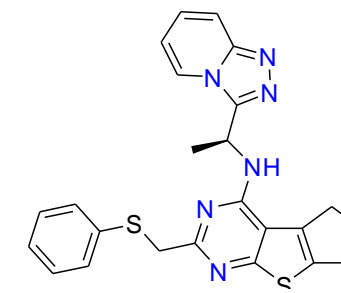
# YAP-TEAD PPI Inhibitor Discovery (TEAD Pharmacophores)



# Measure Activity of BY02, BY03 by Luciferase Report Assay

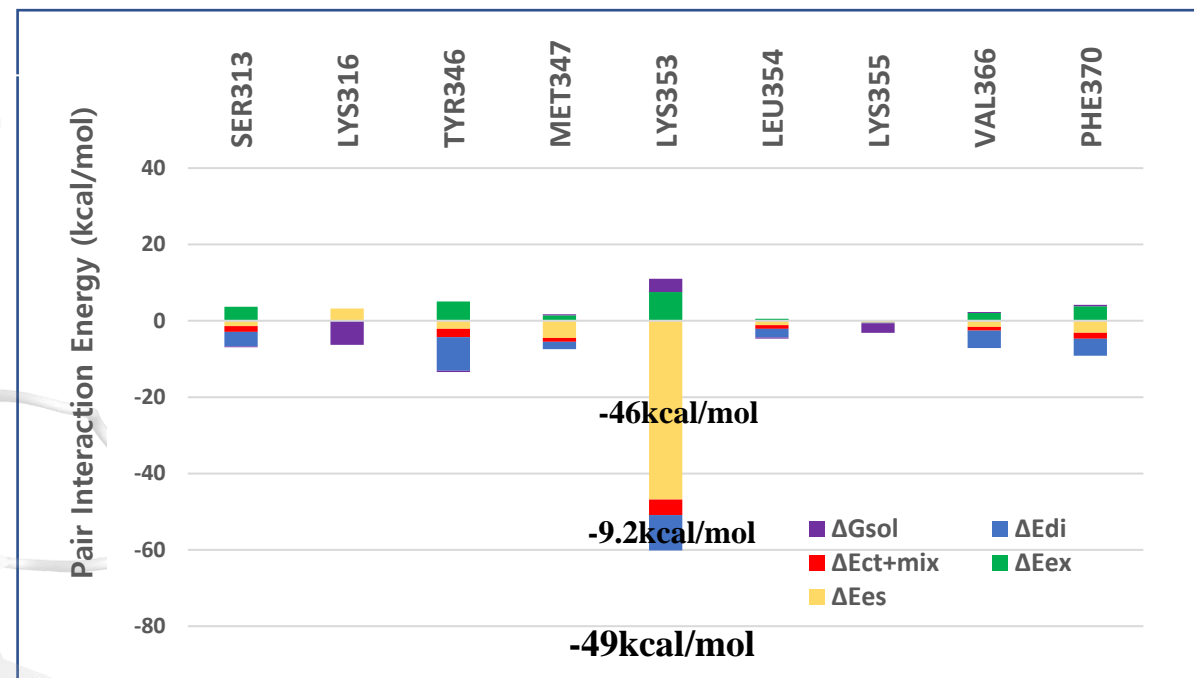
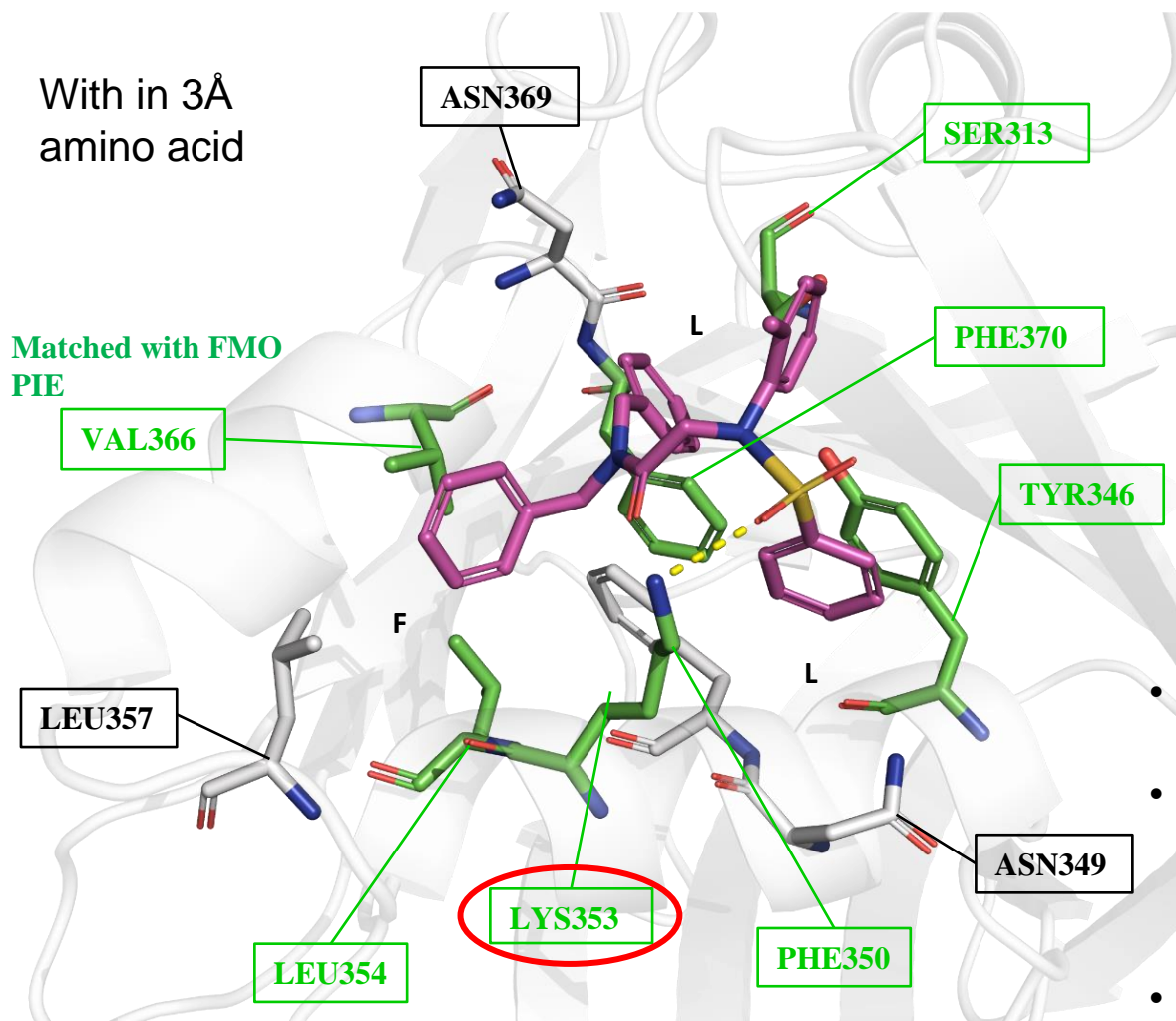


BY-02

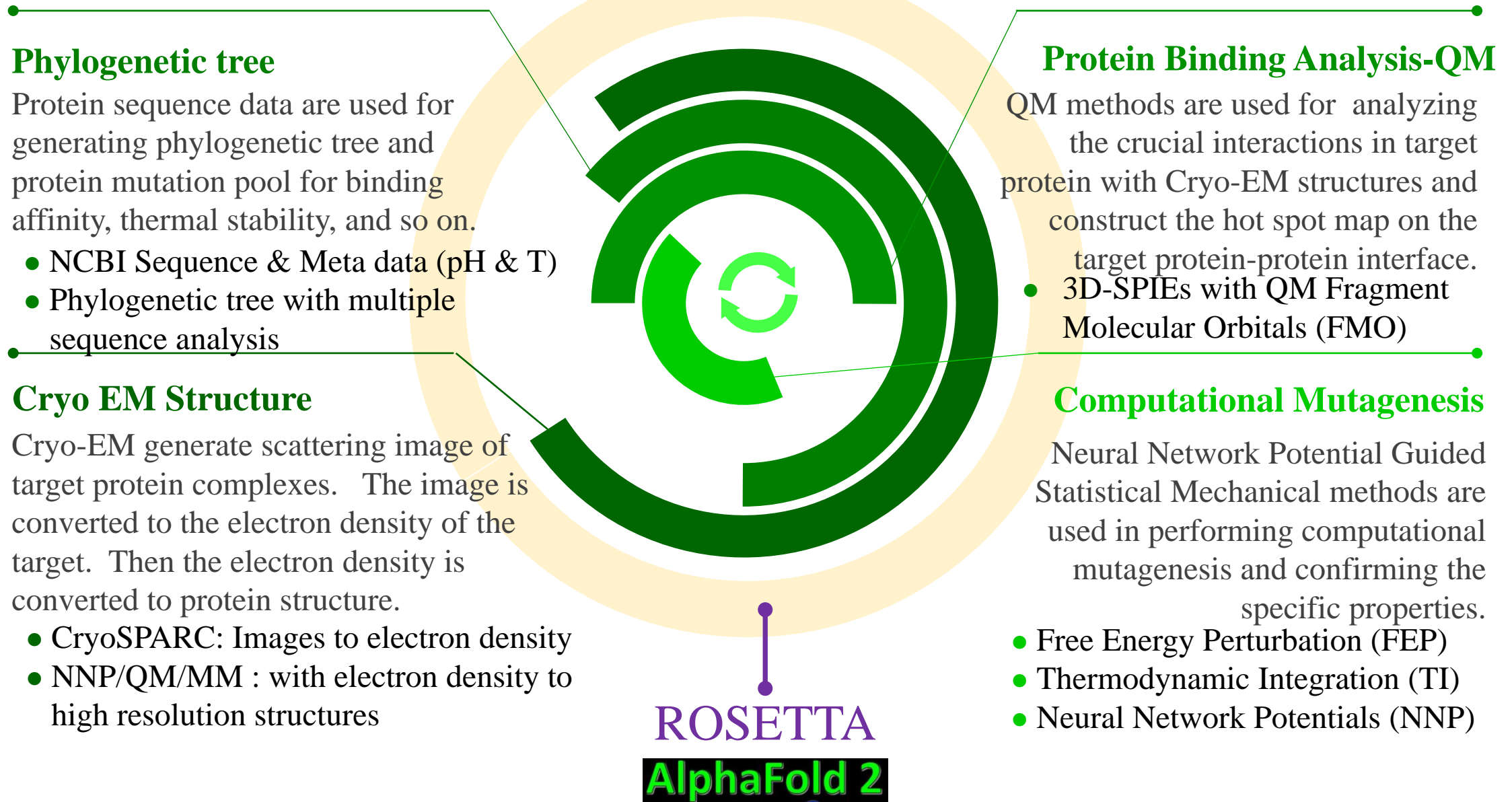


BY-03

# Binding Energy Analysis of BY-02 with FMO PIE

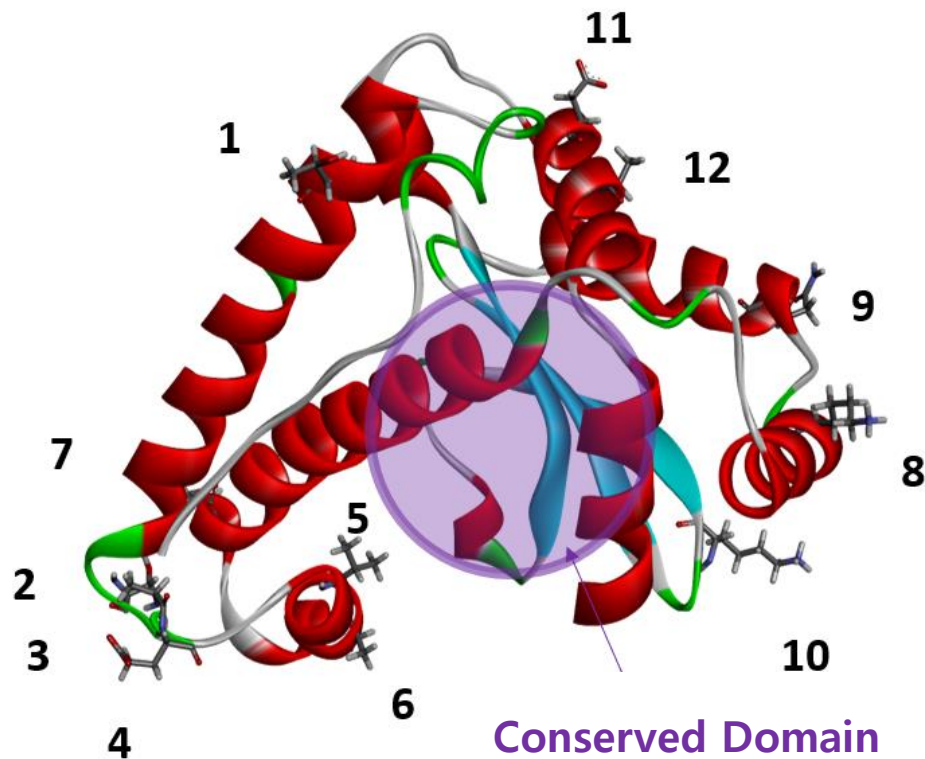


- TEAD's binding amino acids are represented within 3Å from BY02 docking pose.
- BY02 was performed at FMO-DFTB3/D/PCM level with the third order corrected density functional tight-binding (DFTB3) method with 3OB parameter set, UFF-type dispersion correction (D), and polarizable continuum model (PCM).
- In energy minimization, the residues within 10.4 Å from ligand were included and fixed, while only the ligand was fully flexible.

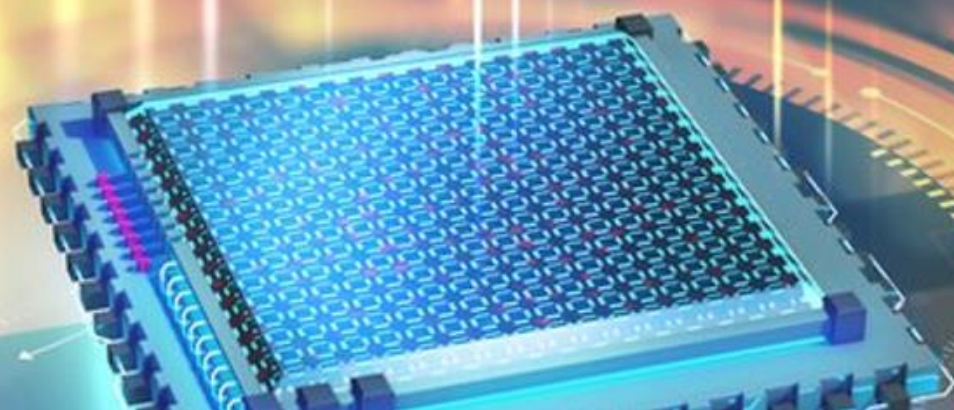
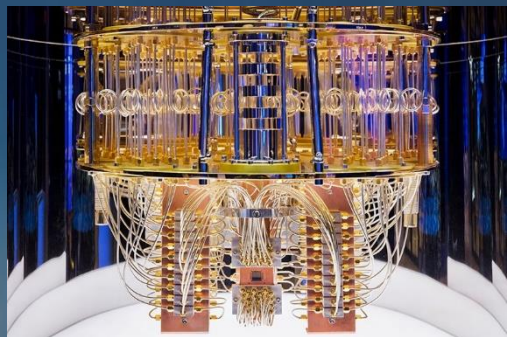




- Propose 12 Variants from 50% Thermophiles
- 12 heat-resistant SOD candidates were cloned
- Purified variants were characterized for:
  - Activity, protein quantification, heat resistance



	Specific Activity (U/mg)	Residual activity (%)	BCM_Tm1 (°C)	Tagg 266 (°C)
wild type	2200	47.5	55	64
1	1708	75	65	38
2	2161	92	66	37
3	1381	86.5	67	57
4	868	89.1	51	39
5	2618	80.8	64	51
6	650	55.5	66	36
7	1641	82.7	44	50
8	1934	50.7	NaN	38
9	1857	56	NaN	56
10	1747	104.2	61	52
11	2124	24.1	63	54
12	1503	45.1	46	56



# Quantum Computing



- Quantum computing's ability to simulate larger, more complex molecules could be game changing. Pharmaceutical companies should reflect on their **strategic stance to this promising new technology now**.
- Pharma & chemical industry will be one of the **first industries to benefit** by the impact of Quantum Computing (QC).
- Given its focus on molecular formations, pharma as an industry is a **natural candidate** for QC.
- Since molecules are actually quantum systems, systems that are based on quantum physics, QC is expected to be able to predict and simulate the structure, properties, and behavior of these molecules **more effectively than conventional computing can**.

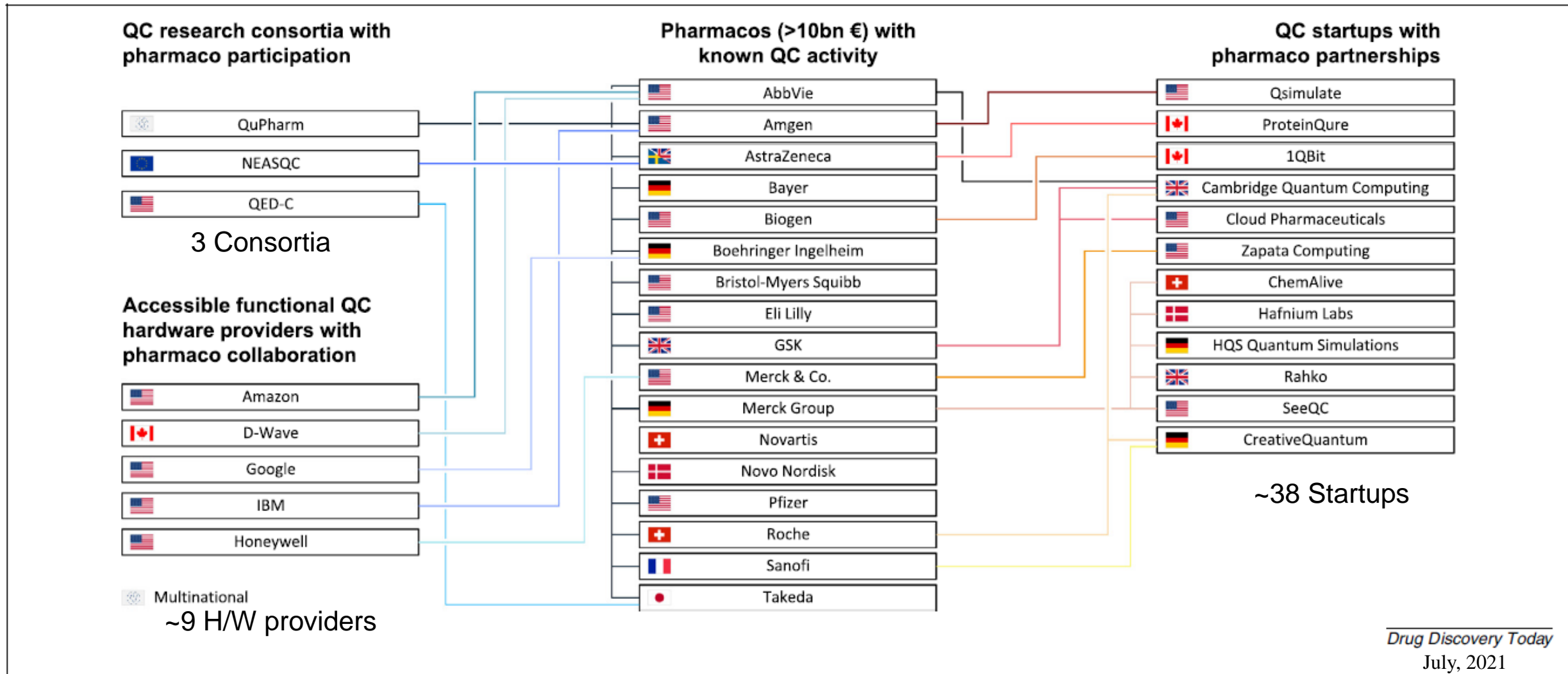
June 2021, McKinsey & Company

# Quantum Computing Ecosystem in Drug Discovery

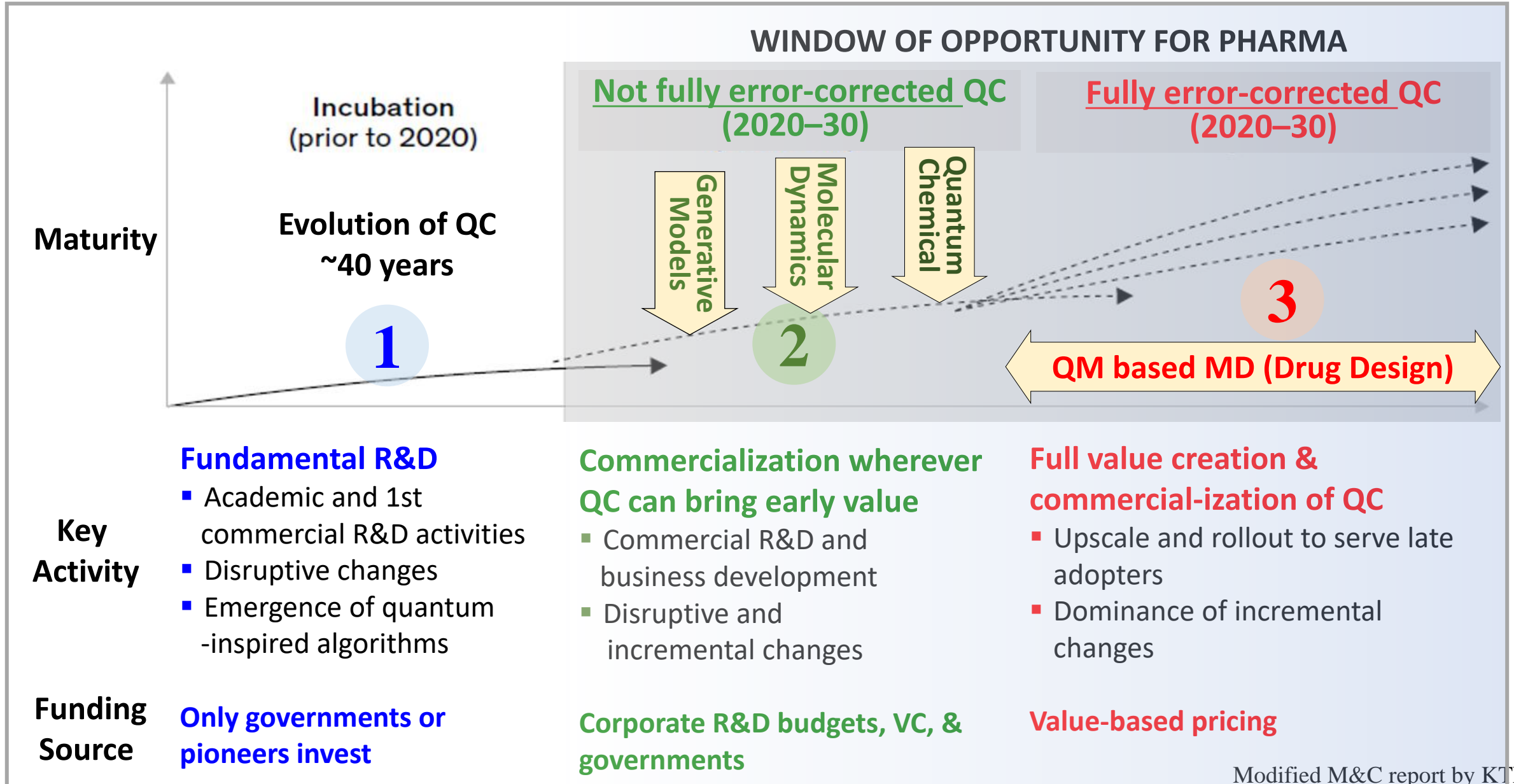
Pharmacos: For Drug Discovery & Development

Startups: Provide Quantum Algorithm for Drug Design

Hardware providers: Quantum Computer & Languages

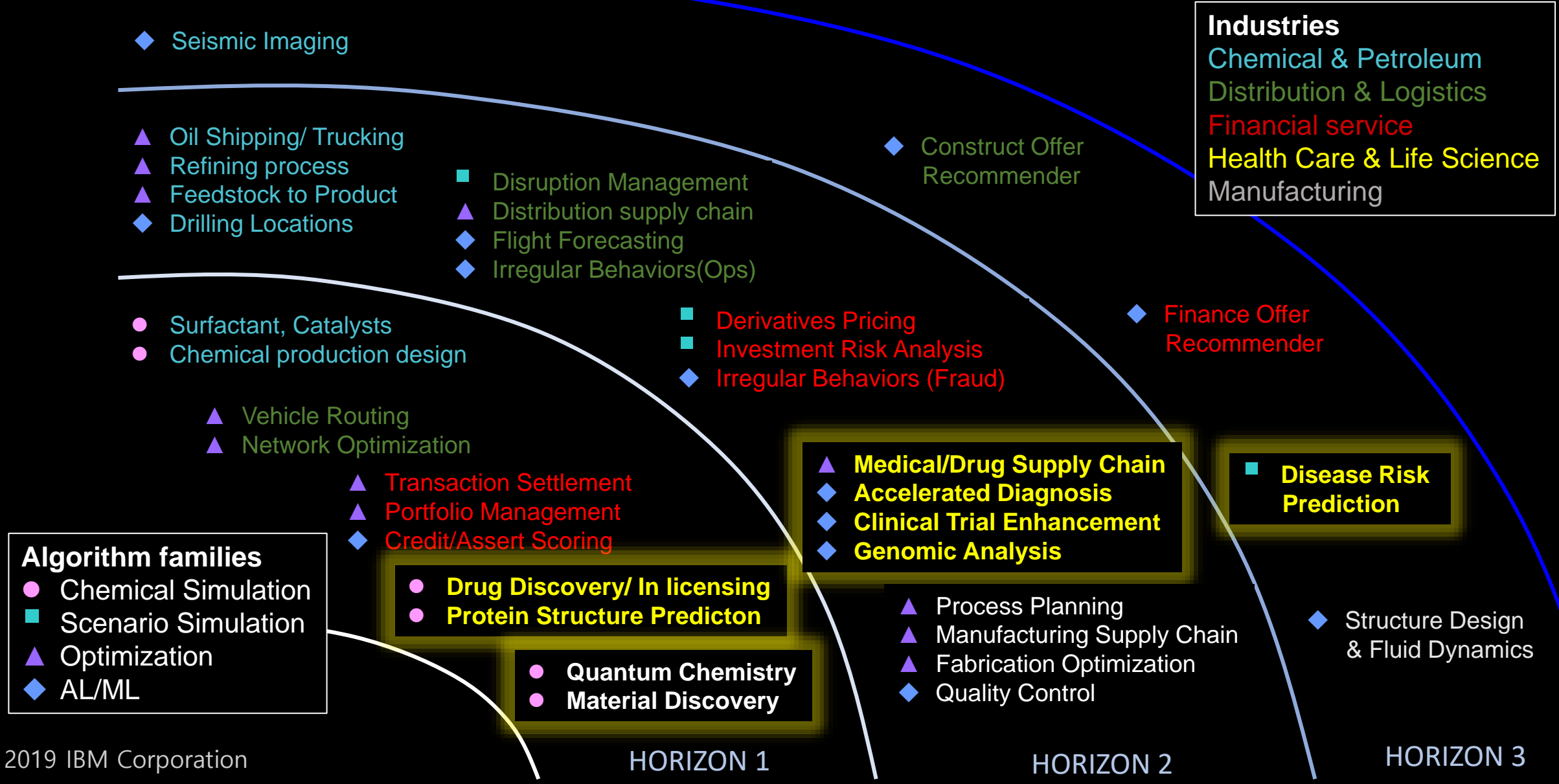


# Value Creation through QC in the Pharmaceutical Industry

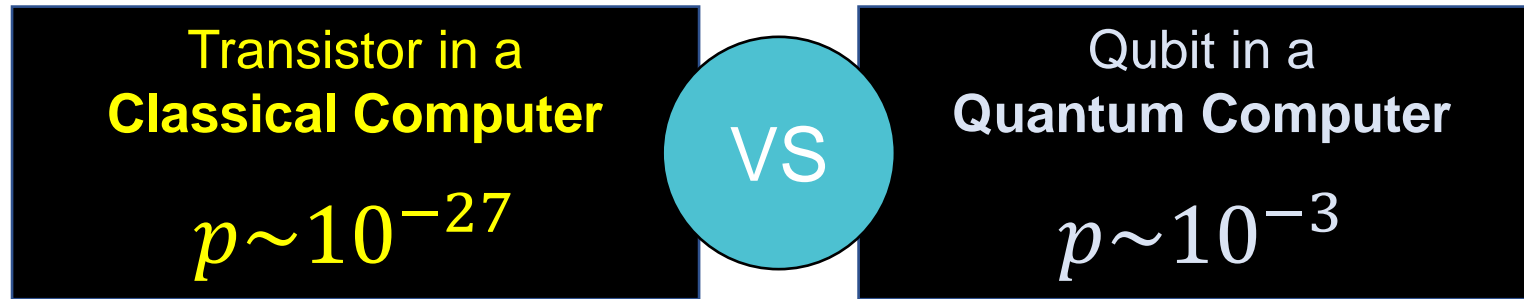




# Quantum Volume and Industrial Application Potential



**Quantum Error:** High Probability of Hardware Error in Quantum Computer  
→ Need Error Correction → Stabilizer



~24 orders of magnitude difference

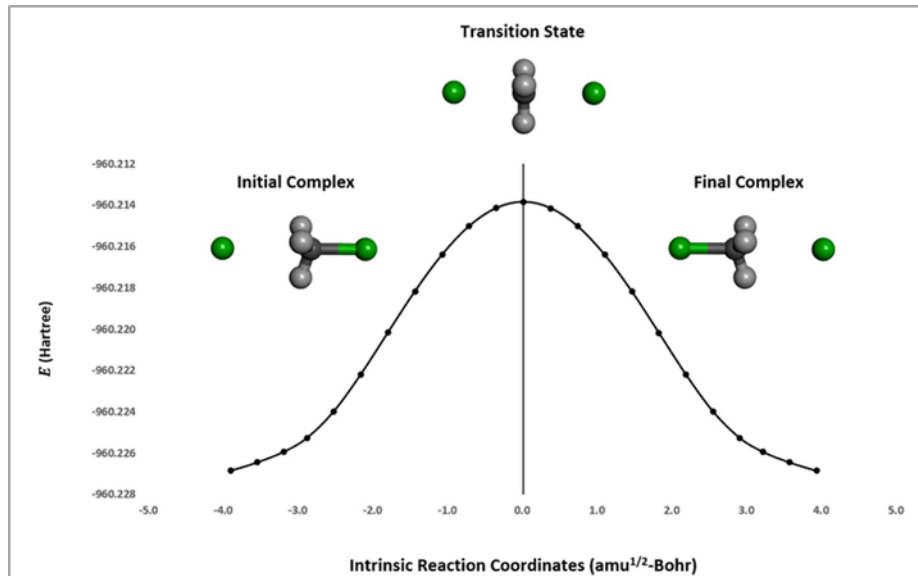
IBM Quantum / © 2021 IBM Corporation

**Quantum volume:** a metric that measures the capabilities and error rates of a [quantum computer](#). It expresses the maximum size of square quantum circuits that can be implemented successfully by the computer.



## Quantum computational study of chloride ion attack on chloromethane for **chemical accuracy** and **quantum noise effects** with UCCSD and k-UpCCGSD ansatzes

- 현재의 Quantum Volume(QV)과 Quantum Error Correction(QEC) 환경에서 가능한 화학 시스템 계산
- QV와 QEC의 개선 후 분자설계 가능성 확인 및 준비
- FMO를 위한 알고리즘의 협력 개발 및 IP 공유
- QC를 사용한 구조기반 모델링 공동 개발 계약
- 국내 최초로 QC를 TS 계산에 적용



Qunova

이준구(KAIST교수)  
전임 연구원 2인  
KAIST 연구실

Quantum Algorithm 개발

- 양자역학 기반 QC
- FMO용 Quantum Algorithm
- Deep Generative Model QA



Baobab AiBIO

오병두, 노경태

전현내  
임호철  
김정훈

QC 이용 신약개발 응용

- QC기반 QM 도입 / 논문 1
- FMO 기본 아이디어 제공
- 자연어 기반 분자생성

**공동사업 협약**

- 바이오 분야
- 양자코드 개발
- 신약개발 적용
- IP 50:50 결정

- **FMO is a very useful tool for calculating the electron density and energy of proteins.**
- **Using FMO, it is possible to calculate the interaction energy between a protein and a ligand, and furthermore, the interaction type can be analyzed with the energy-decomposition tool (PIE).**
- **Compared to QM calculation, NNP has a very short calculation time, but the energy can be obtained even at the CCSD MO level depending on the training data set.**
- **We developed AVENGERS for small molecular drug design and CARPET for protein design based on the FMO method. Also, the usefulness of these two platforms was verified through various experiments.**
- **The introduction of quantum computing in Computer-Aided Drug Discovery will allow CADD to lead the entire process of drug discovery within 10 years.**

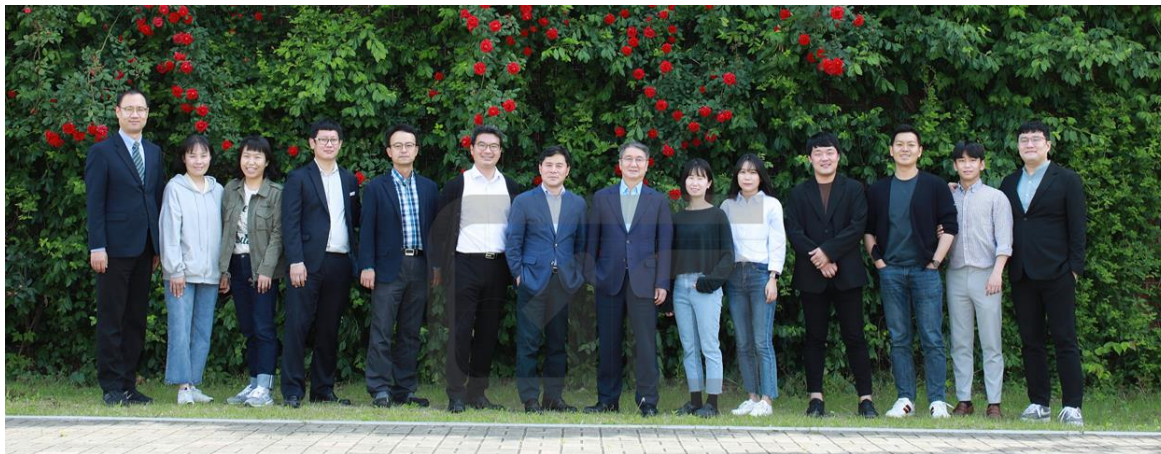


## Bioinformatics & Molecular Design Research Center

- Computer-Aided Drug Design
- CADD Tool Development
- AI & Big Data Analysis



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- Cryo-EM
- Medicinal Chemistry
- Biology



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