

MD Simulation in Pose Refinement and Scoring Using AMBER Workflows

Yuan Hu (*On behalf of Merck D3R Team*)

D3R Grand Challenge 2 Webinar

Department of Chemistry, Modeling & Informatics

Merck Research Laboratories, Merck & Co., Inc.

March 27, 2017

Outline

- ▶ **Overview of the D3R Predictions from Merck**
 - *Today just the Stage 1 results*
 - *Merck Team & Result Ranking*

- ▶ **Overall Pose Prediction and Scoring Approach**
 - *Structure Preparation & Docking*
 - *AMBER Workflows for Pose Refinement & Ranking*

- ▶ **Case Study & Lessons Learned**
 - *Ranking with Ensemble-based MD-MMGBSA*
 - *Pose Exploration with MD*

Acknowledgement

Merck D3R Team

► Modeling

- Ying-Duo Gao
- Xavier Fradera
- Yuan Hu
- Andreas Verras
- Deping Wang
- Hongwu Wang
- James Fells
- Kira Armacost
- Alejandro Crespo
- Brad Sherborne

► Informatics

- Huijun Wang
- Zhengwei Peng
- Robert Sheridan

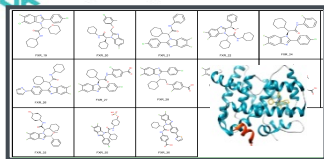
Motivation

- To refine and share our best practices
- To be engaged in the scientific community
- To better understand the capability of sciences in industry & academia

Overall Approach for Stage 1

Step 1: preparation as a team

Drug Design Data Resource



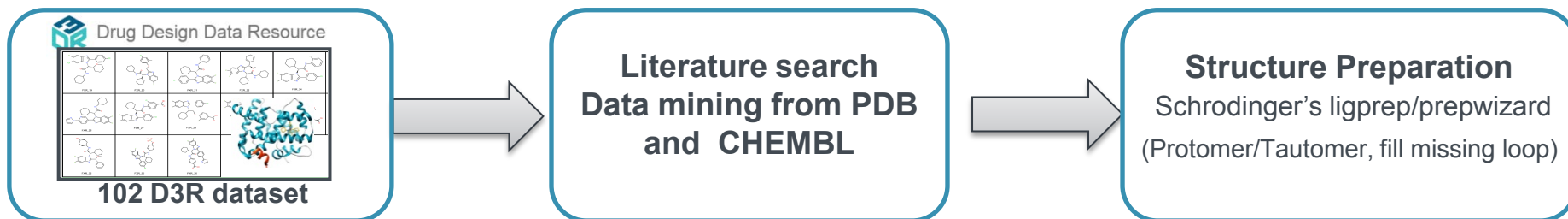
102 D3R dataset

Literature search
Data mining from PDB
and ChEMBL

Structure Preparation
Schrodinger's ligprep/prepwizard
(Protomer/Tautomer, fill missing loop)

Overall Approach for Stage 1

Step 1: preparation as a team



Step 2: docking experiments

Glide Ensemble Docking
Submission A

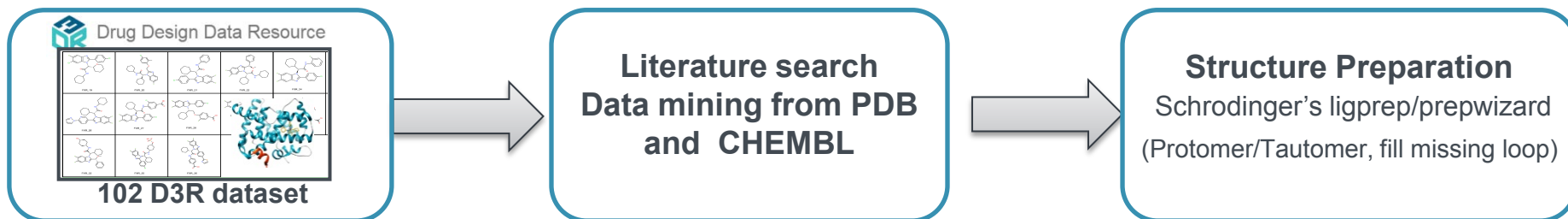
Colony Entropy Docking
Submission B

Glide+Gold Docking
Submission C

Visual Inspection (A+C)
Submission E

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Glide Ensemble Docking
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Step 3: MD-MMGBSA

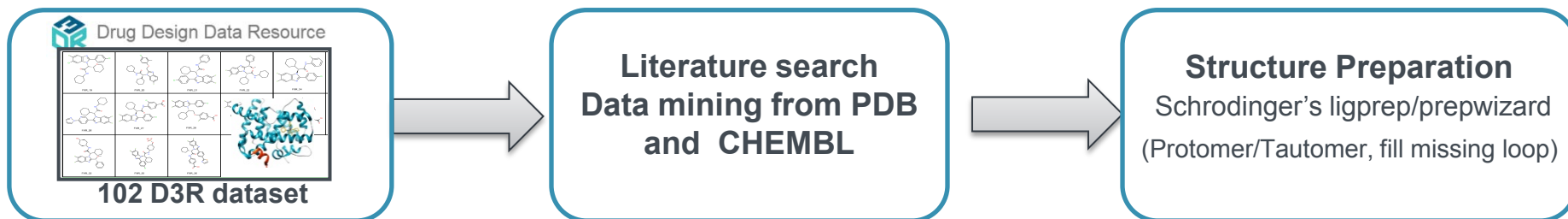
MD simulations using
multiple replicates

MD pose refinement
Submission D

Ensemble-based
MMGBSA ranking

Overall Approach for Stage 1

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Glide Ensemble Docking
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Step 3: MD-MMGBSA

- *Can MD be used to refine docking pose?*
- *How does MD-MMGBSA perform in ranking?*

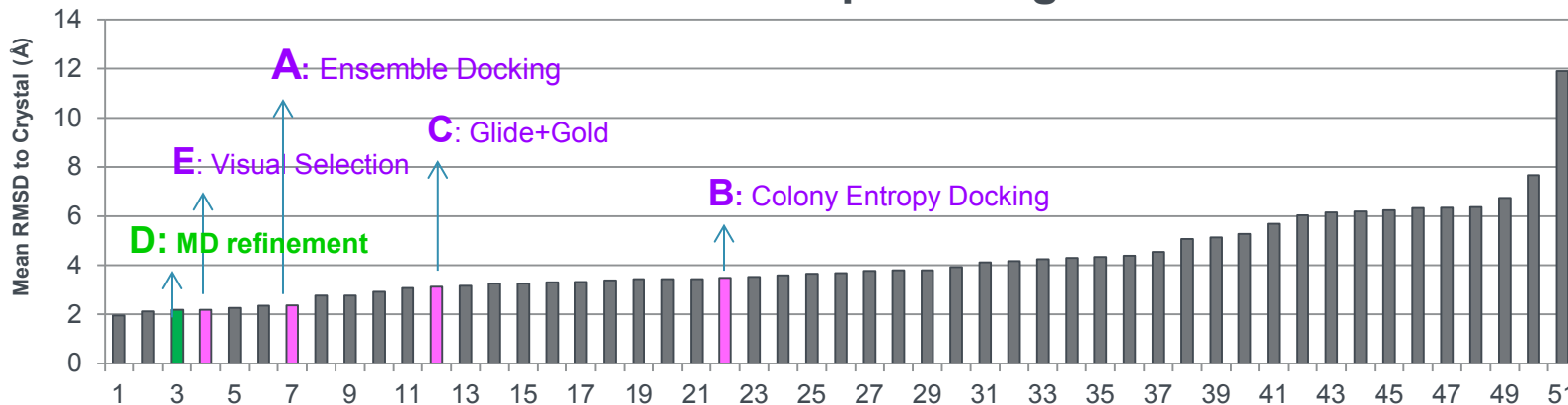
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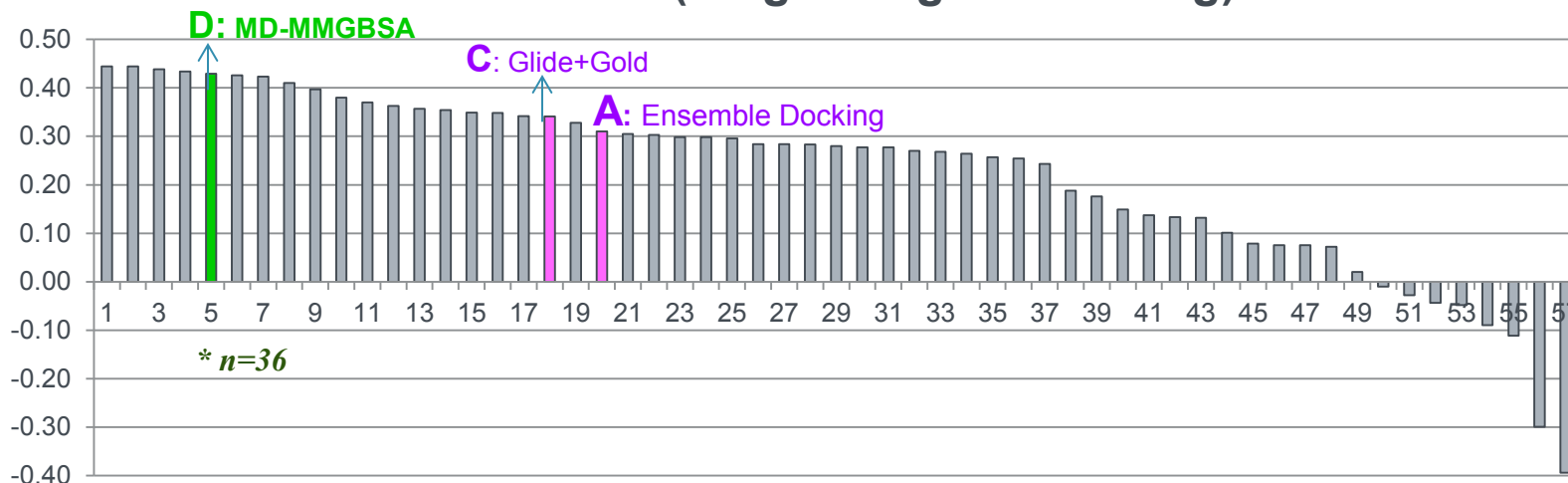
Ensemble-based
MMGBSA ranking

Overall conclusion: MD improves pose prediction and ranking

Mean RMSD of Top Scoring Poses

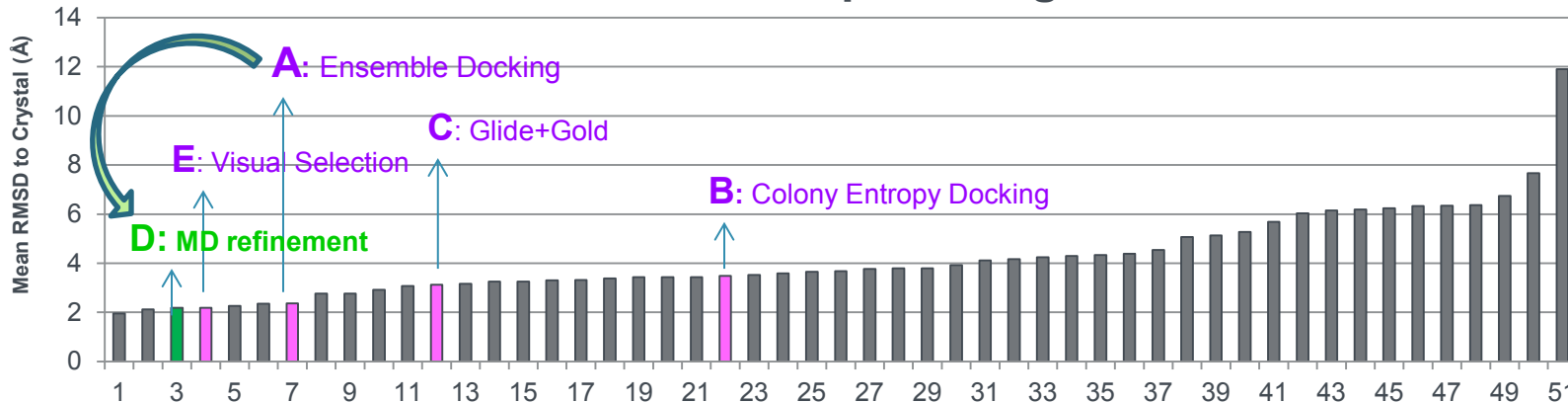


Kendalls Tau (Stage 1-Ligand Scoring)

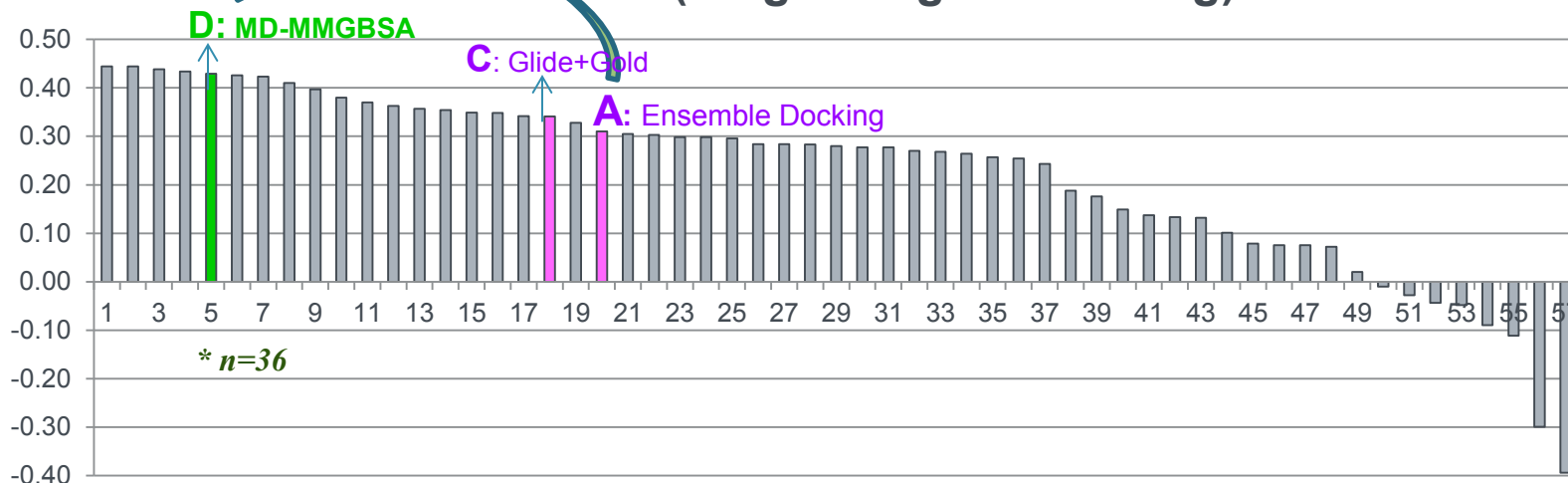


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Mean RMSD of Top Scoring Poses



Kendalls Tau (Stage 1-Ligand Scoring)



Glide Ensemble Docking & AMBER workflows

Completely automated

Ensemble Docking

Ligand/Protein Structure Preparation

Glide XP Ensemble Docking
36 ligands x40 templates =1,440

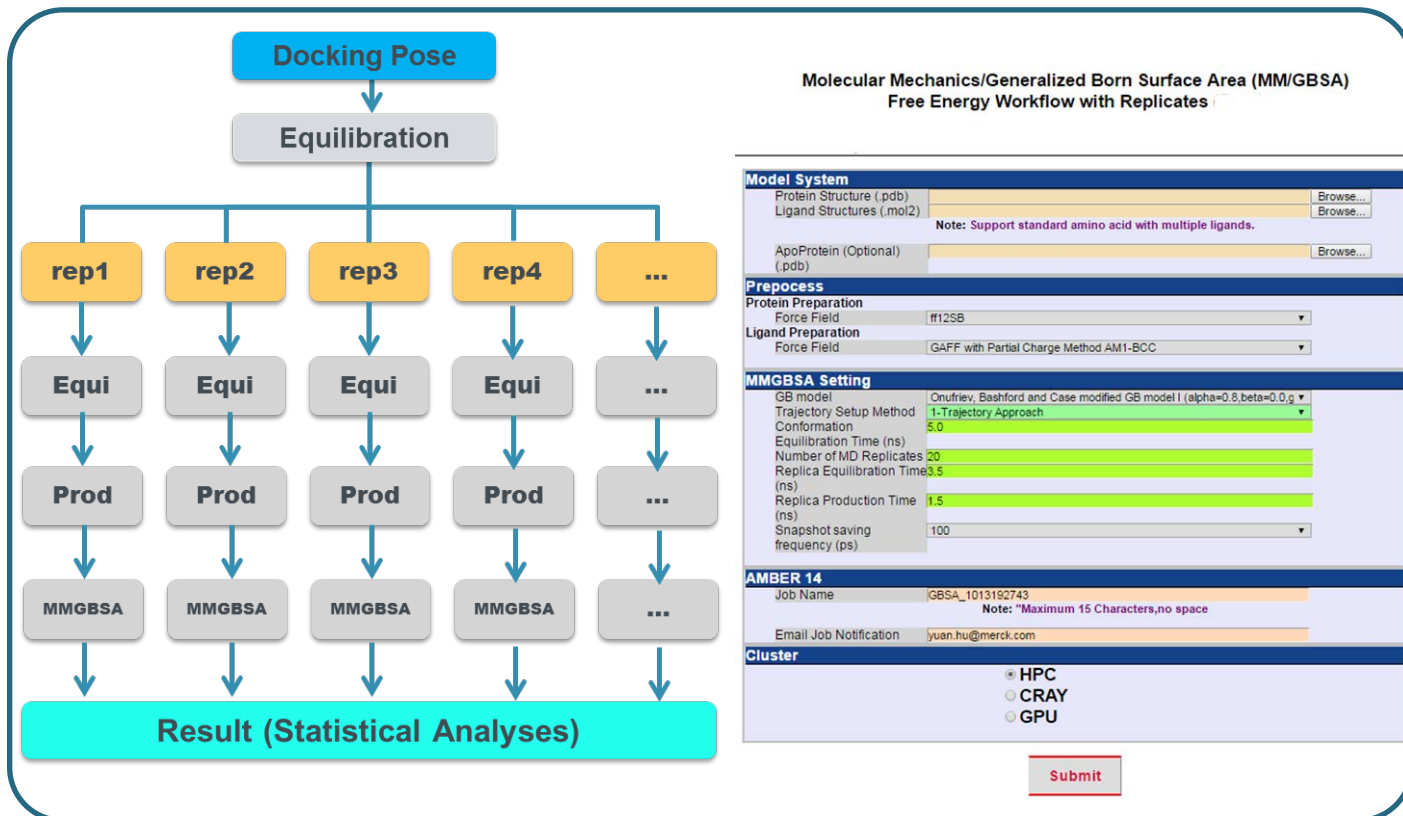
Pose selection

- Rank by score
- rmsd ≥ 1.0 A to previously selected pose to ensure diversity

Top Scoring Pose

**Workflow was validated before on 40 native ligands*

AMBER MD-MMGBSA workflows



**Workflow was validated in large data sets.*

Y. Hu, B. Sherborne, Z. Guo, et al. "How to Obtain Reliable and Reproducible MMGBSA Results?" manuscript in preparation.

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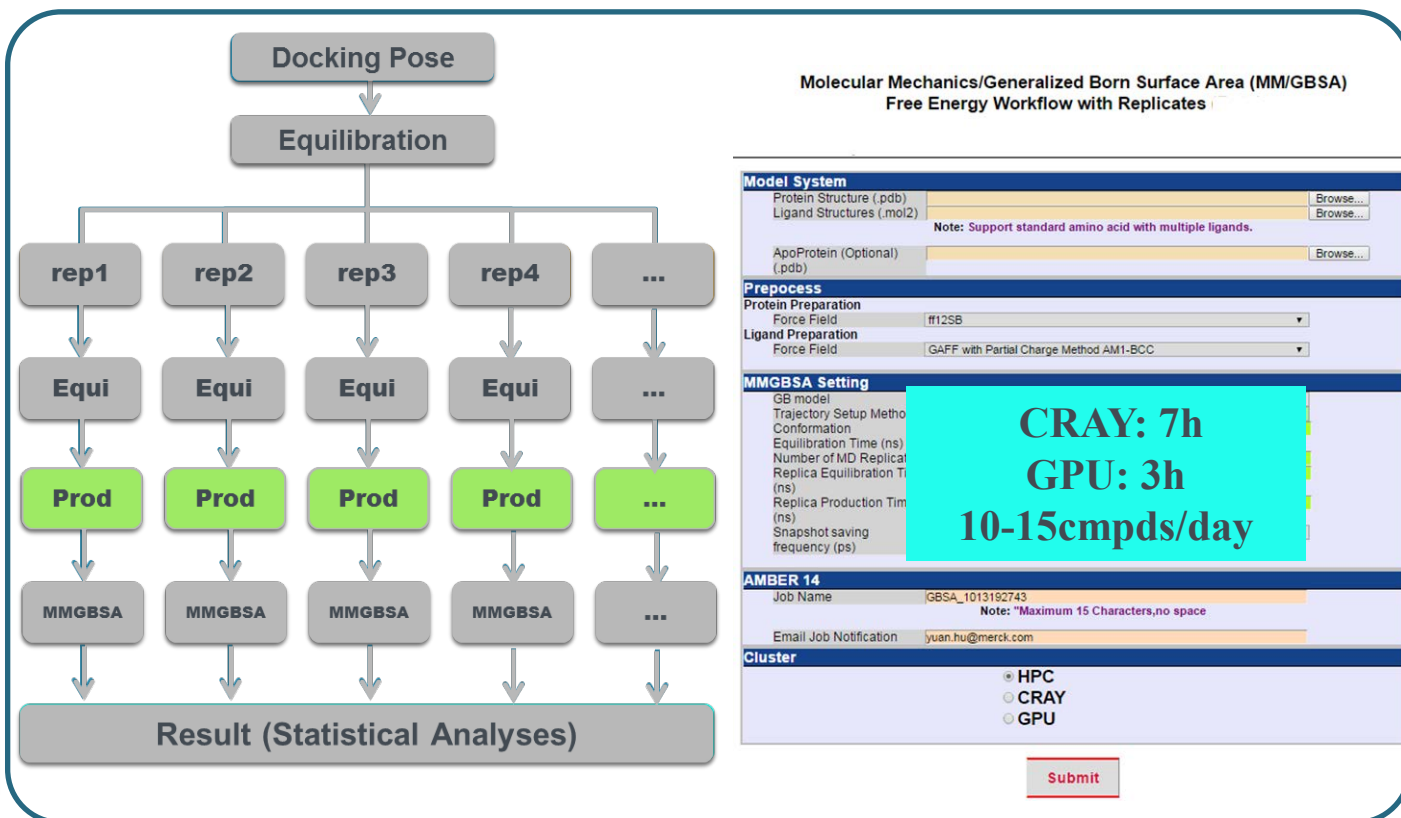
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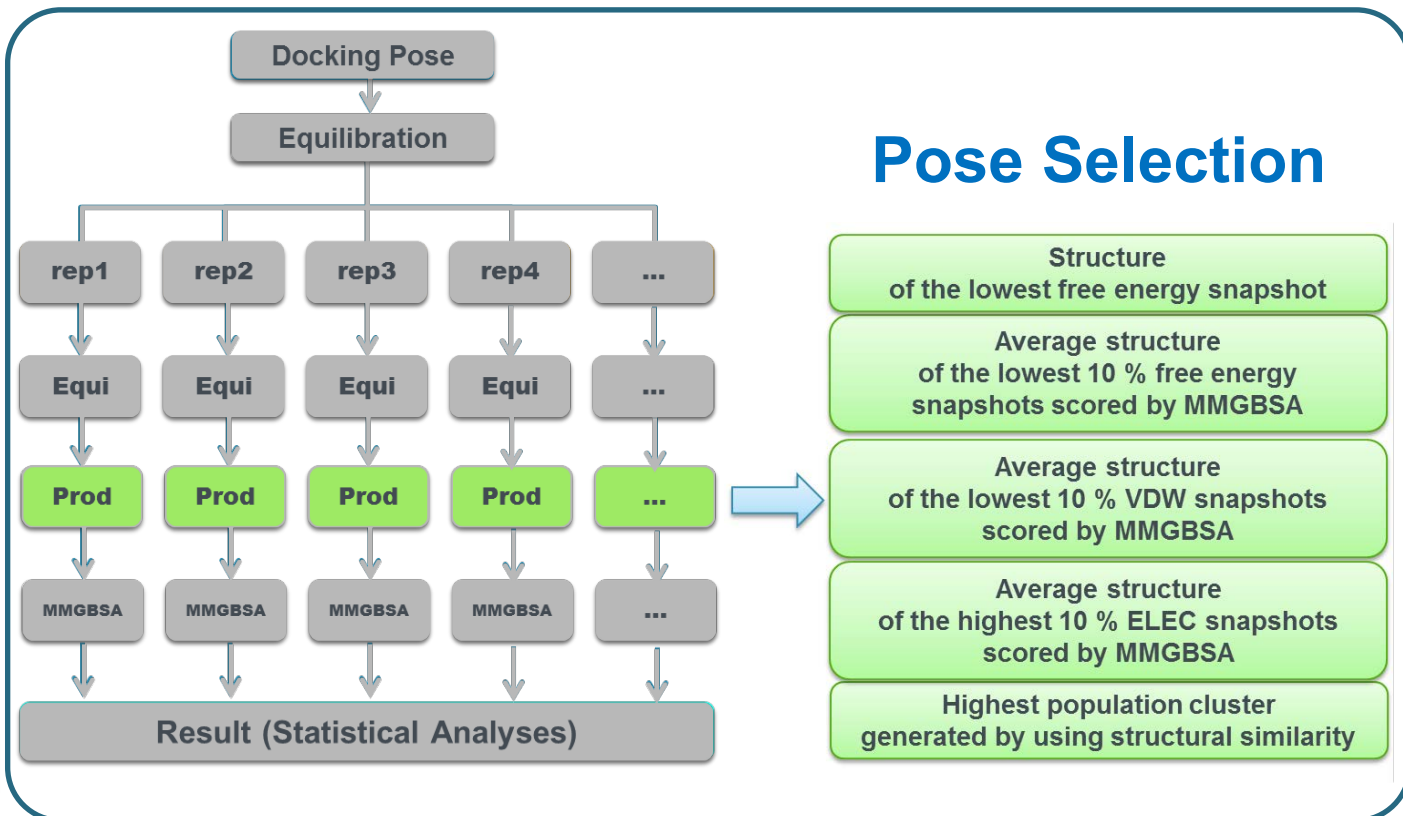
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Ensemble Docking
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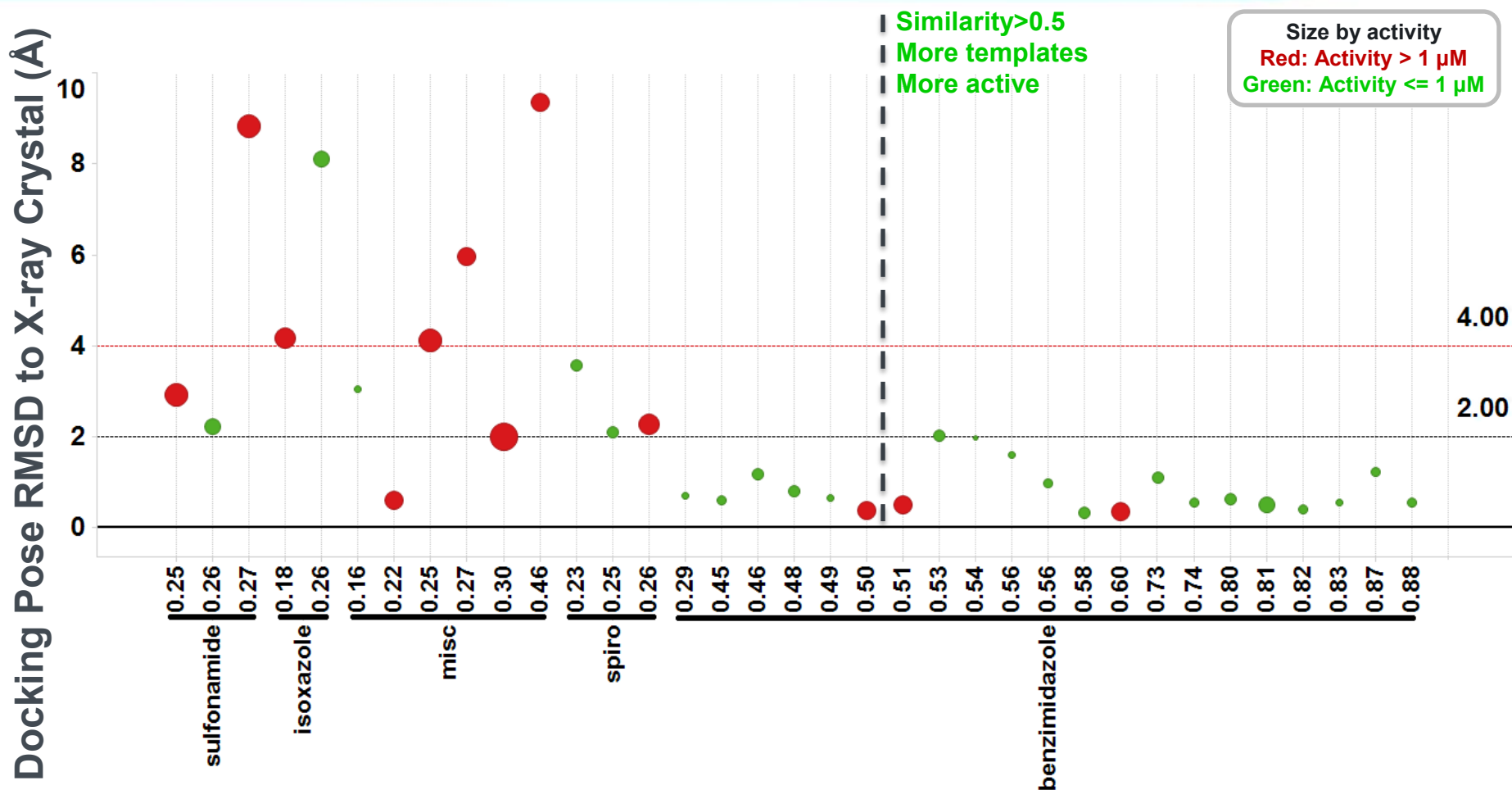
AMBER MD-MMGBSA workflows



**Workflow was validated in large data sets.*

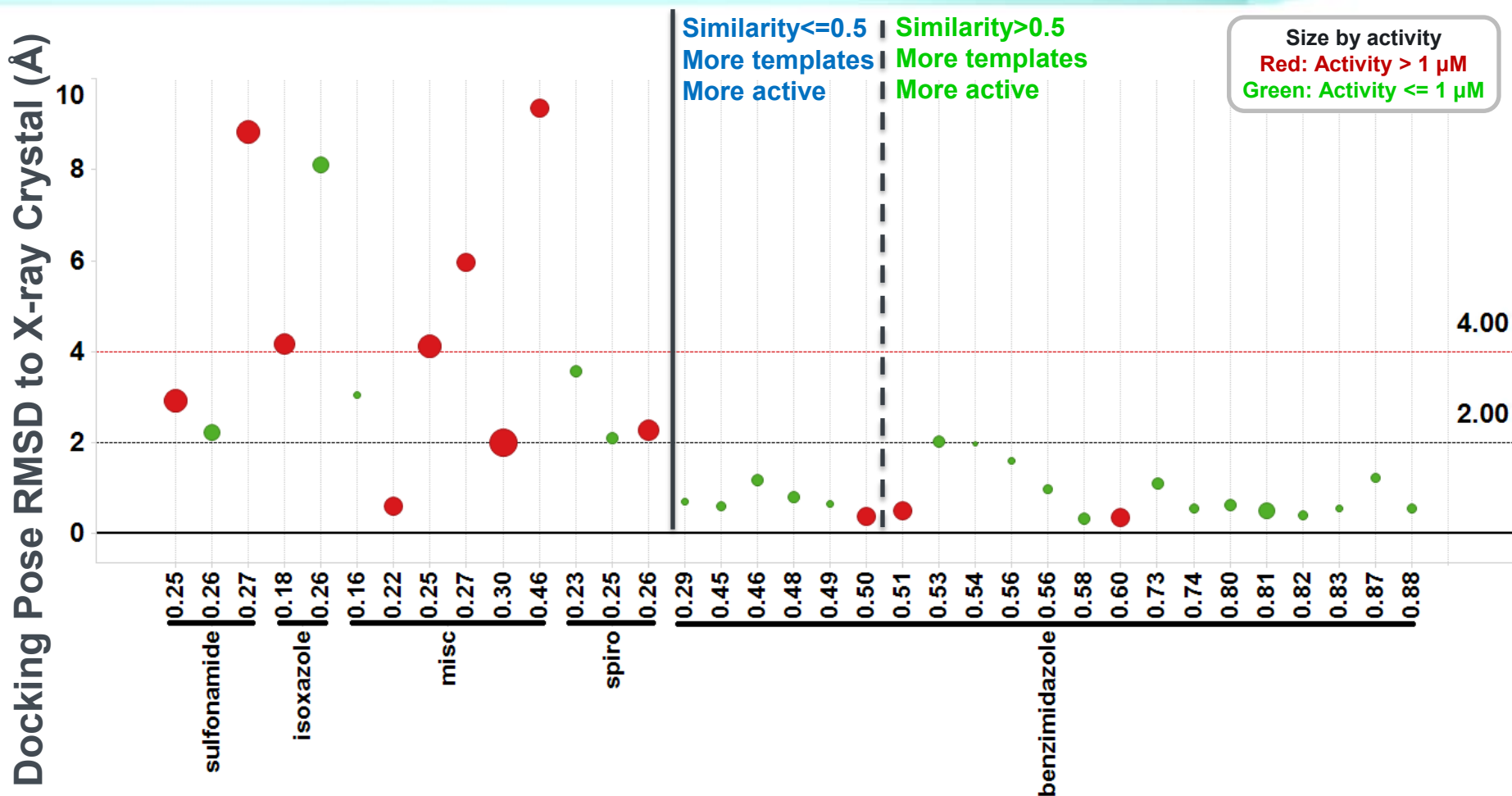
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Good template is important for docking... Similarity matters



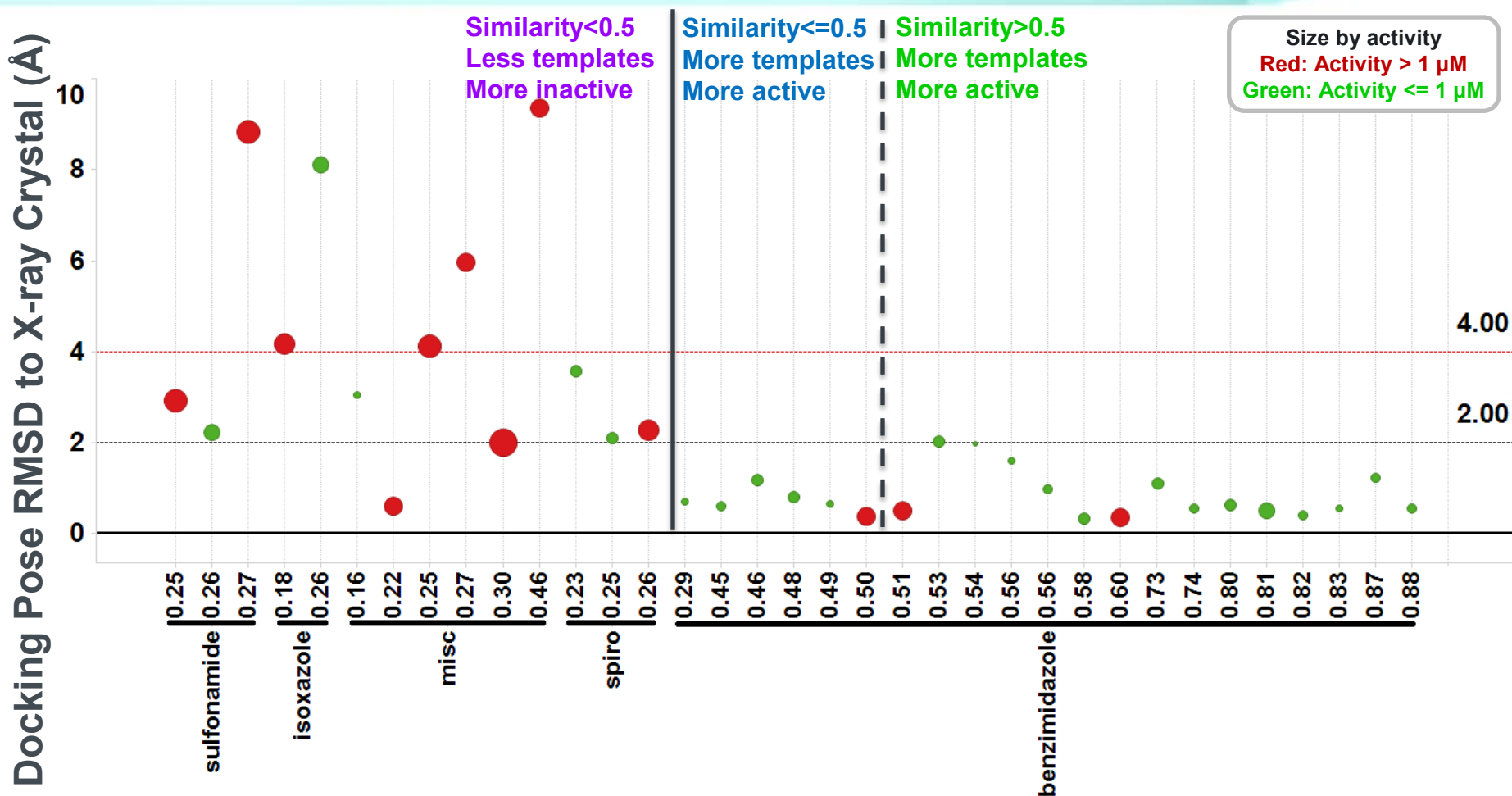
2D Similarity of closest template ligand in ensemble of complexes
(descriptor: ECFP6)

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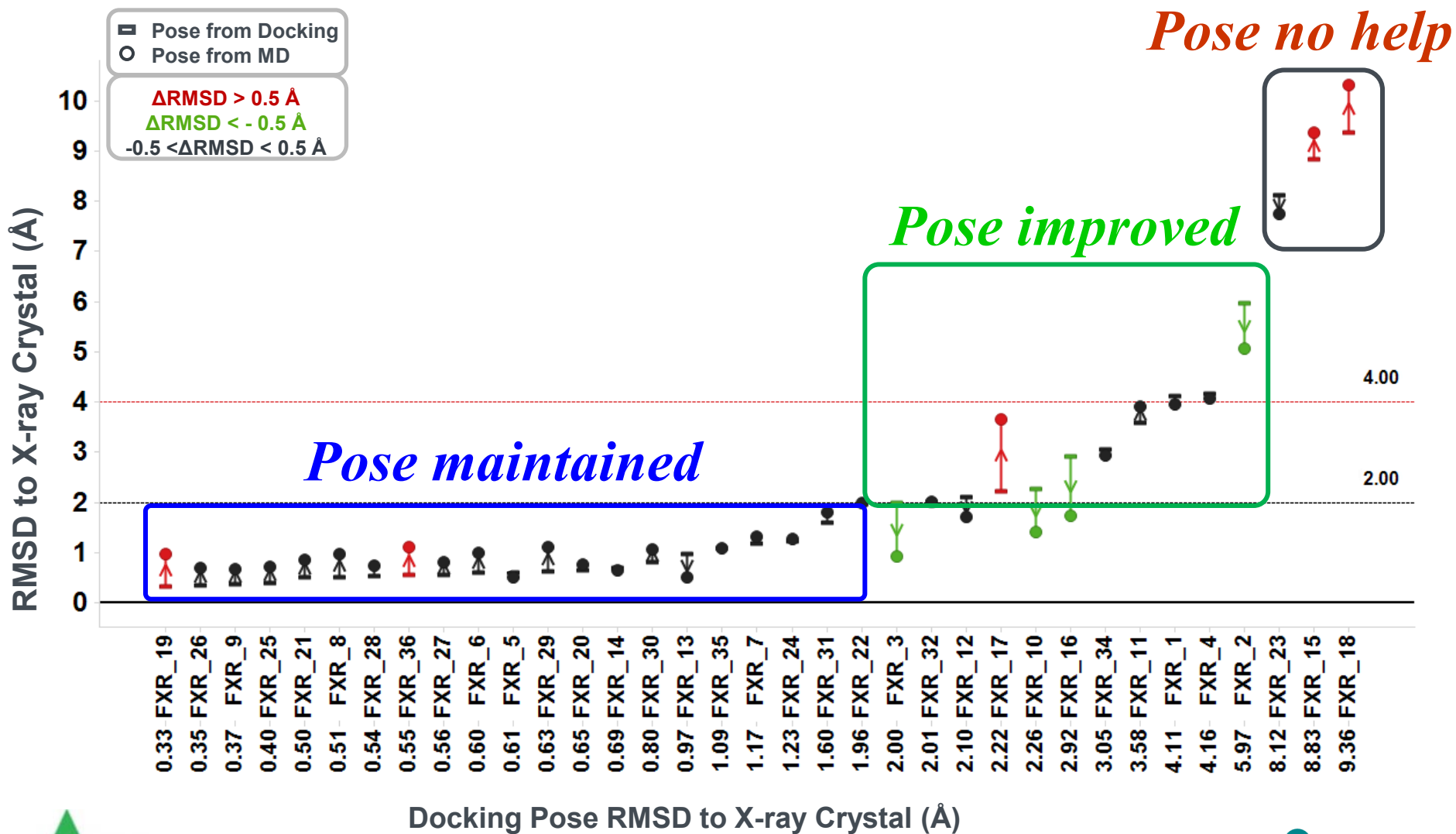


2D Similarity of closest template ligand in ensemble of complexes
(descriptor: ECFP6)

Question 1

Can MD be used to refine docking pose?

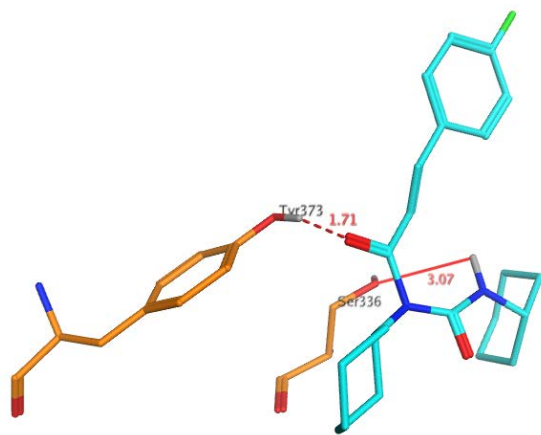
Pose refinement with MD



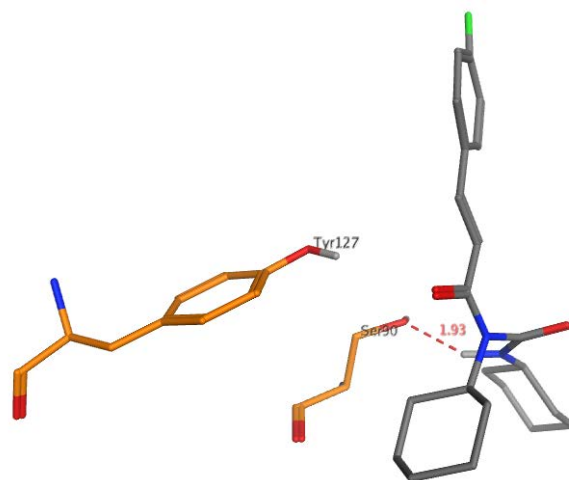
Case Study-success: FXR_3

Ligand interactions optimized through MD

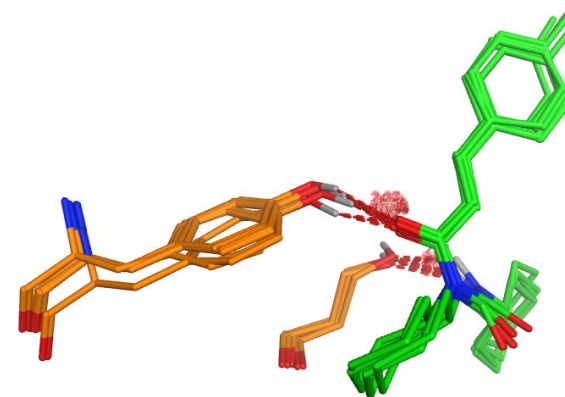
- ▶ Ligand moves to create stable H-bond



Crystal Structure



Docking Pose
RMSD 2.00 Å



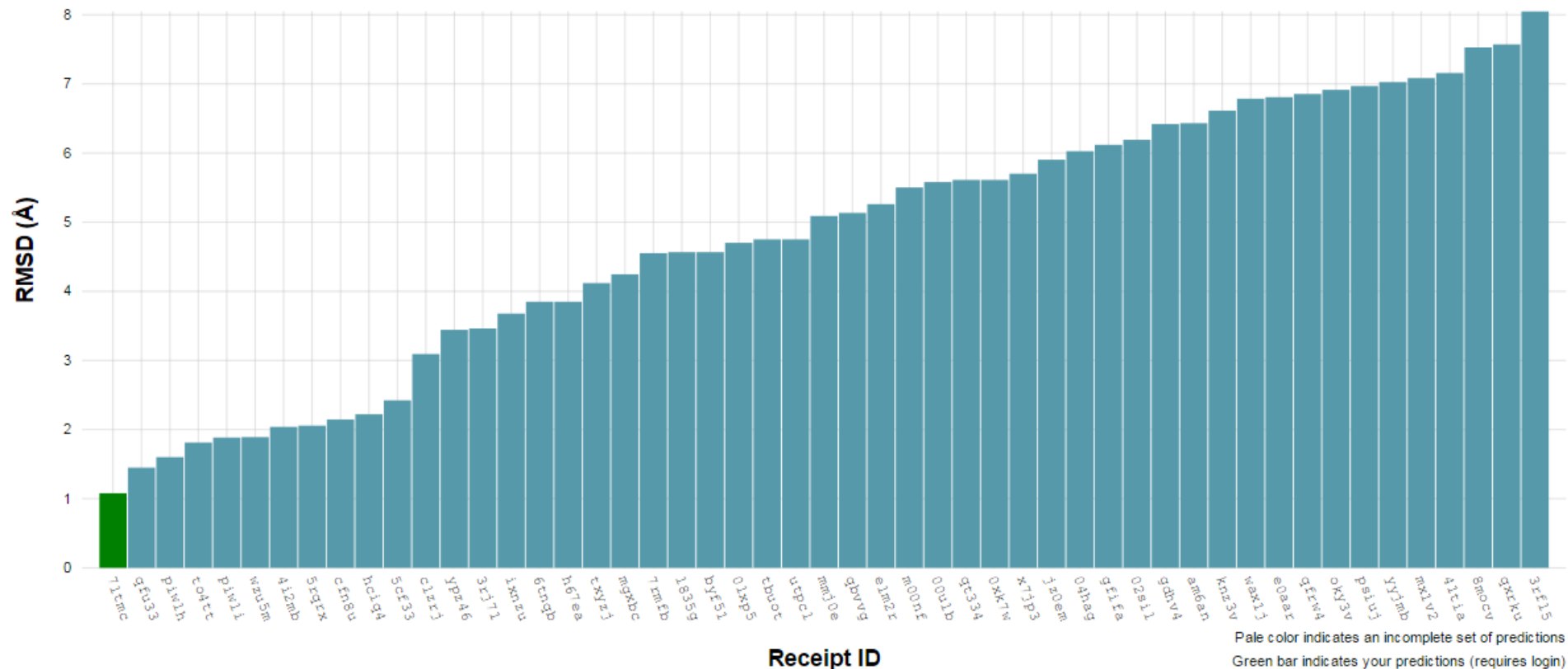
MD refinement
RMSD 0.92 Å

Case Study-success: FXR_3

Ligand interactions optimized through MD

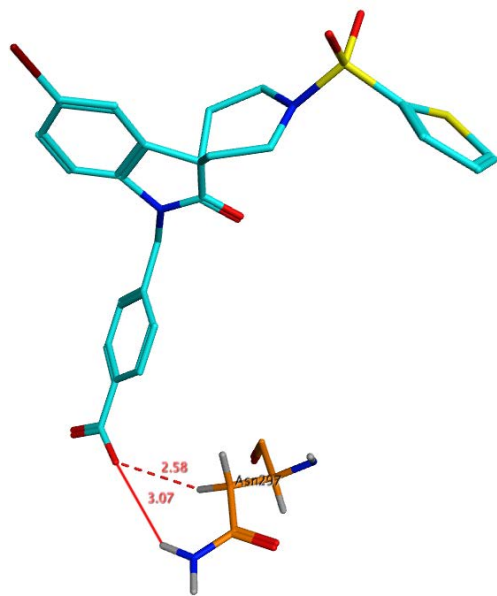
Pose - RMSD - Compound: FXR_3 - Best

Compound:

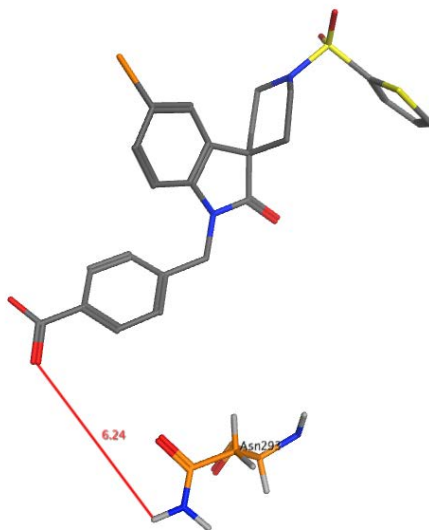


Case Study-success: FXR_10 Protein optimized through MD

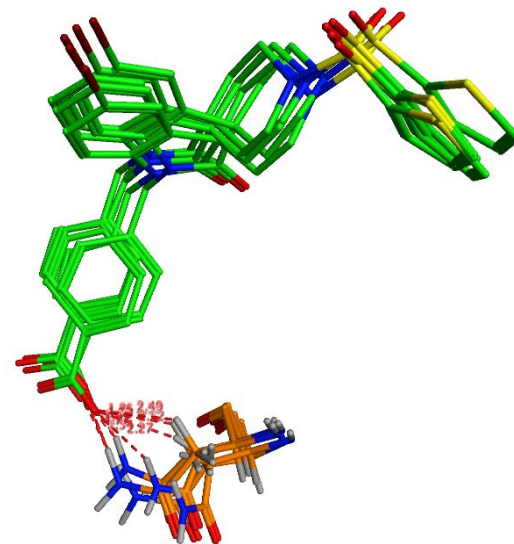
- ▶ MD reorients the Asn to make H-bond contact



Crystal Structure



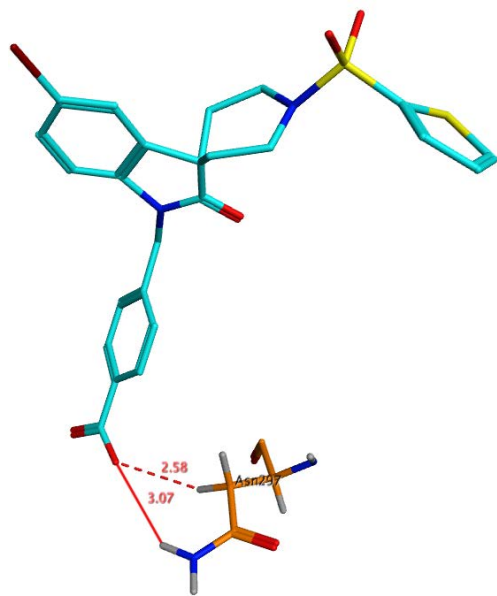
Docking Pose
RMSD 2.26 Å



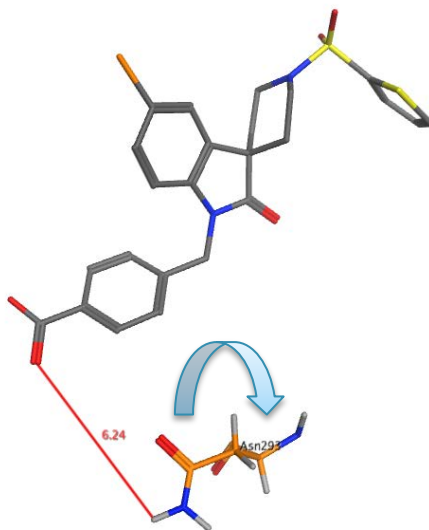
MD refinement
RMSD 1.41 Å

Case Study-success: FXR_10 Protein optimized through MD

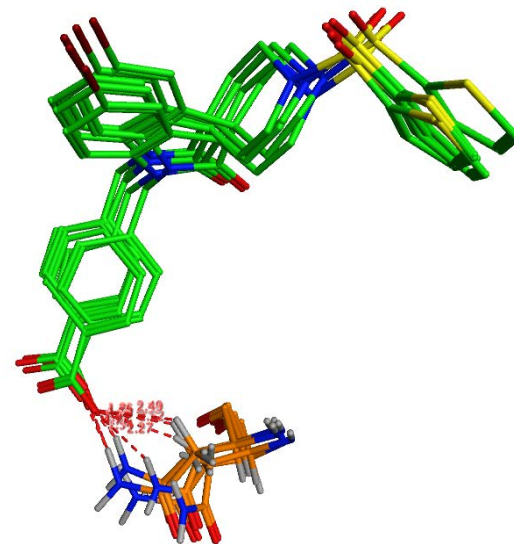
- ▶ MD reorients the Asn to make H-bond contact



Crystal Structure



Docking Pose
RMSD 2.26 Å

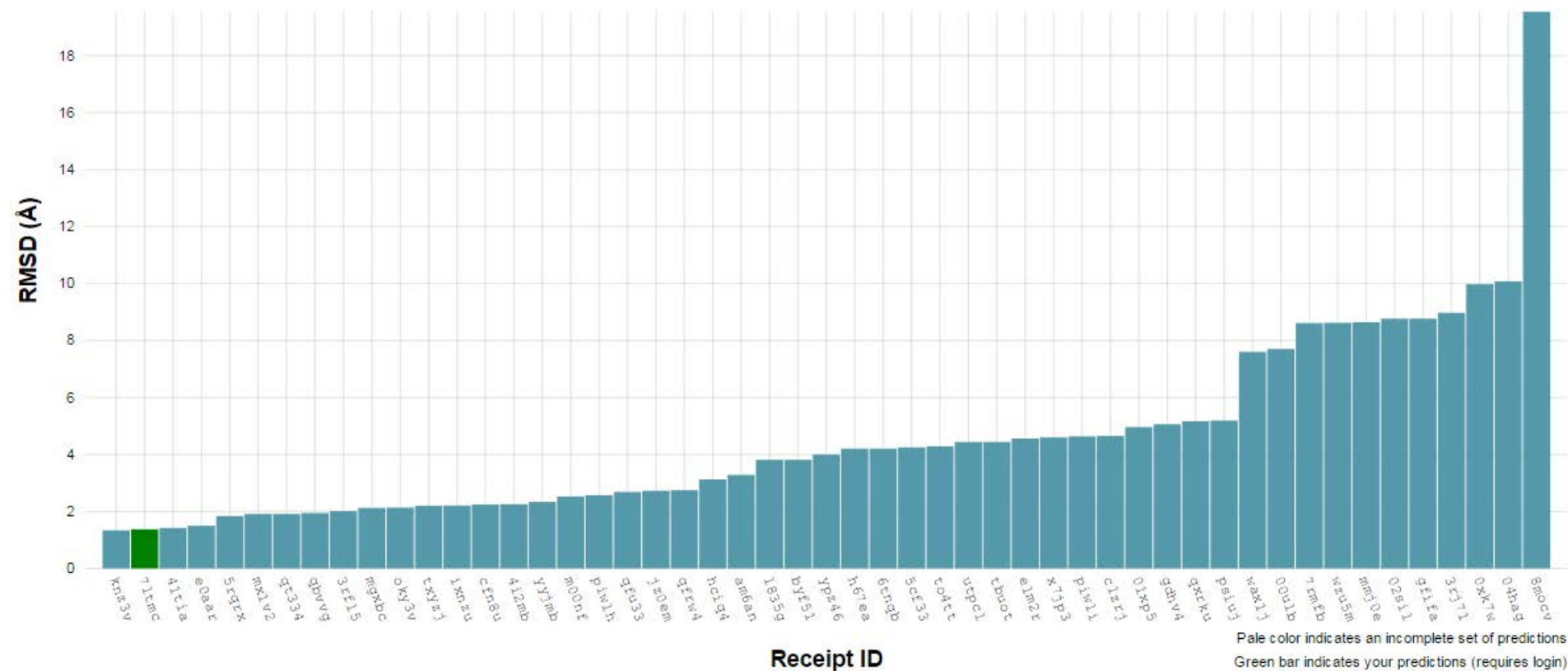


MD refinement
RMSD 1.41 Å

Case Study-success: FXR_10 Protein optimized through MD

Pose - RMSD - Compound: FXR_10 - Best

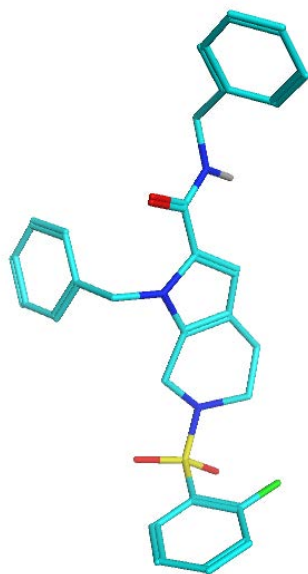
Compound:



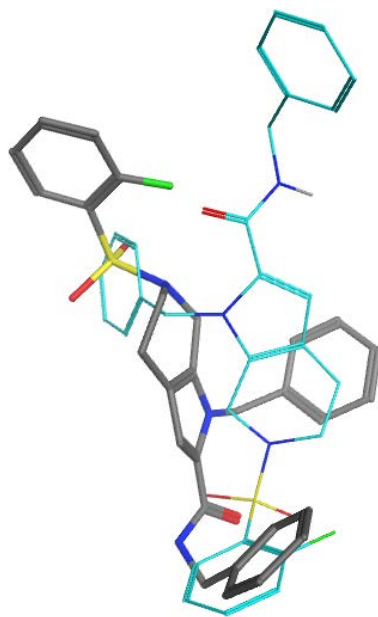
Case Study-failure: FXR_15

MD workflow can't rescue reversed pose

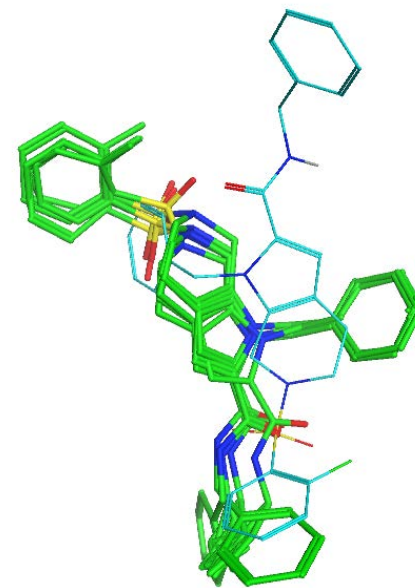
- ▶ The docked pose has a reverse direction comparing to x-ray
- ▶ Hard to refine the structure with MD...



Crystal Structure



Docking Pose
RMSD 8.83 Å



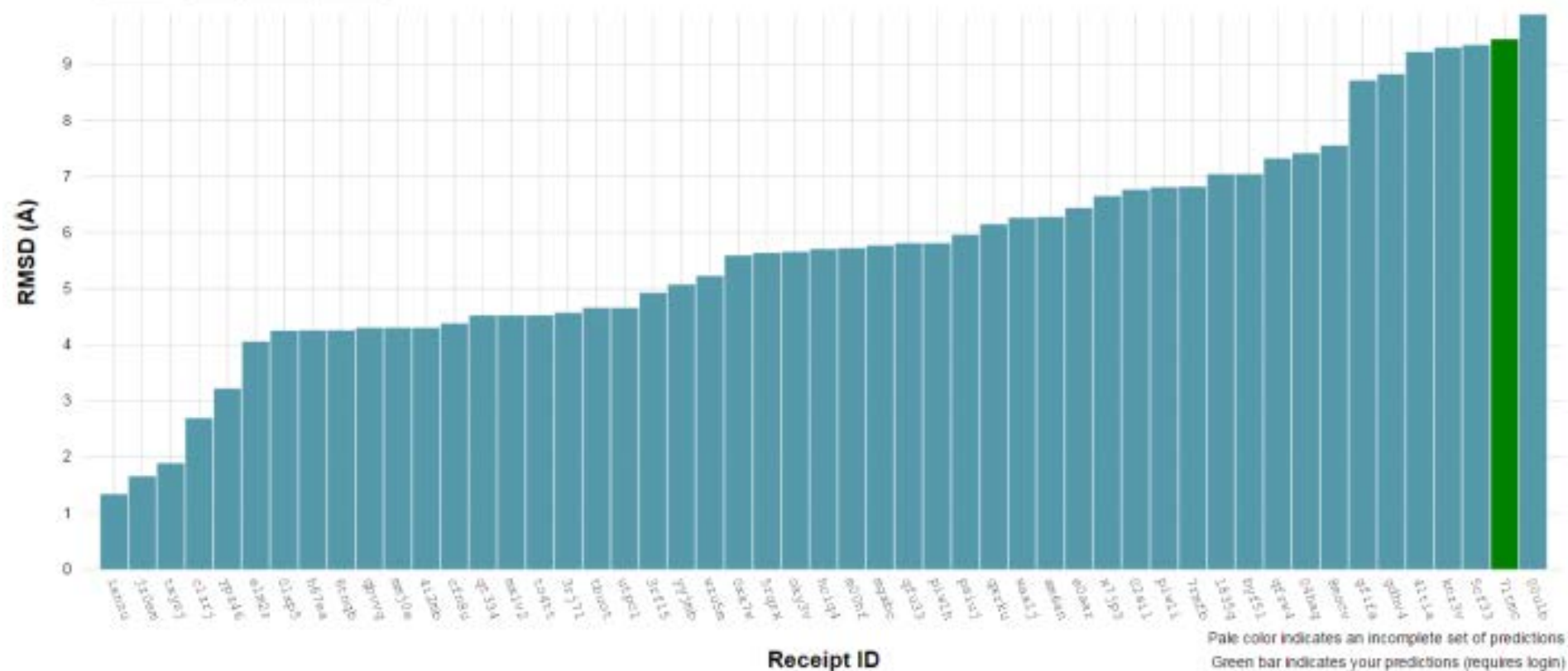
MD refinement
RMSD 9.37 Å

Case Study-failure: FXR_15

MD workflow can't rescue reversed pose

Pose - RMSD - Compound: FXR_15 - Best

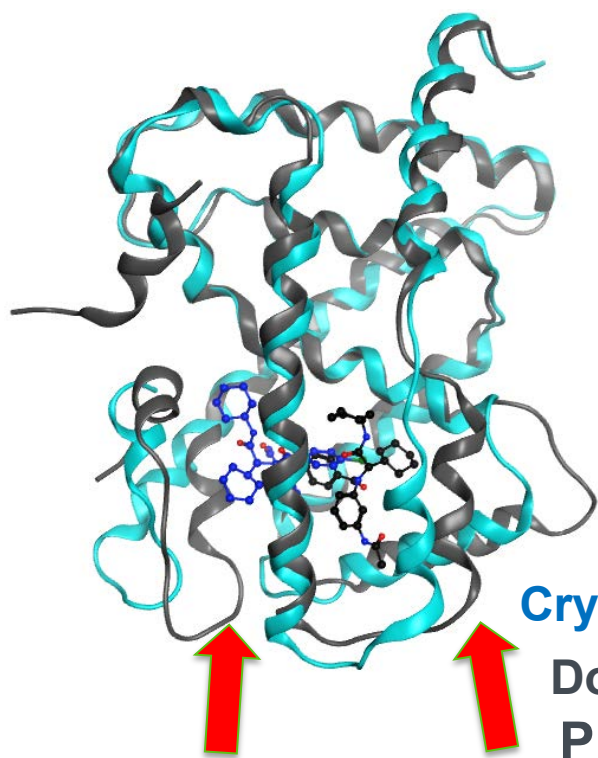
Compound: FXR_15 ▾ Best Average Pose 1



Case Study-failure: FXR_18

MD workflow can't address very large protein movements

- ▶ Protein conformation change



Crystal Structure

Docking Template

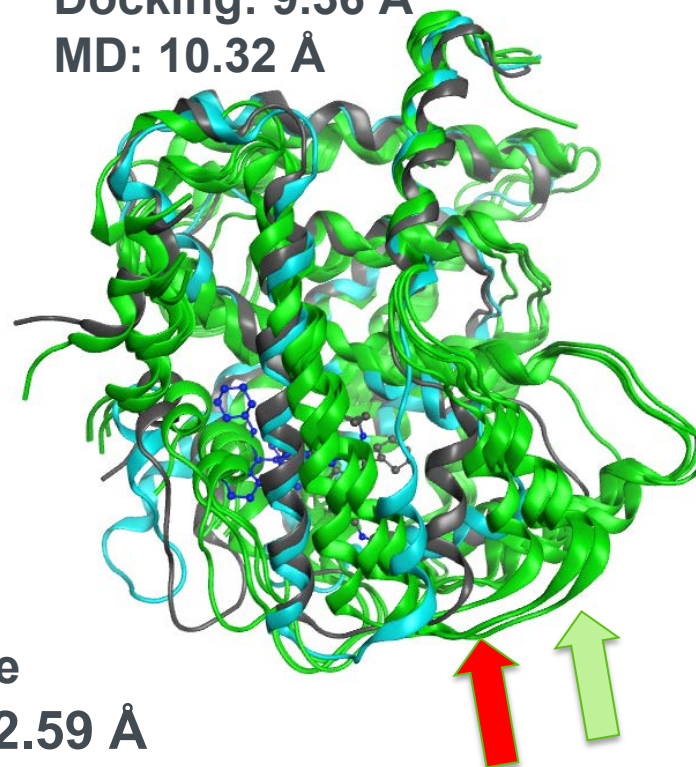
Protein RMSD 2.59 Å

Chain opened up in template

Ligand RMSD to X-ray

Docking: 9.36 Å

MD: 10.32 Å



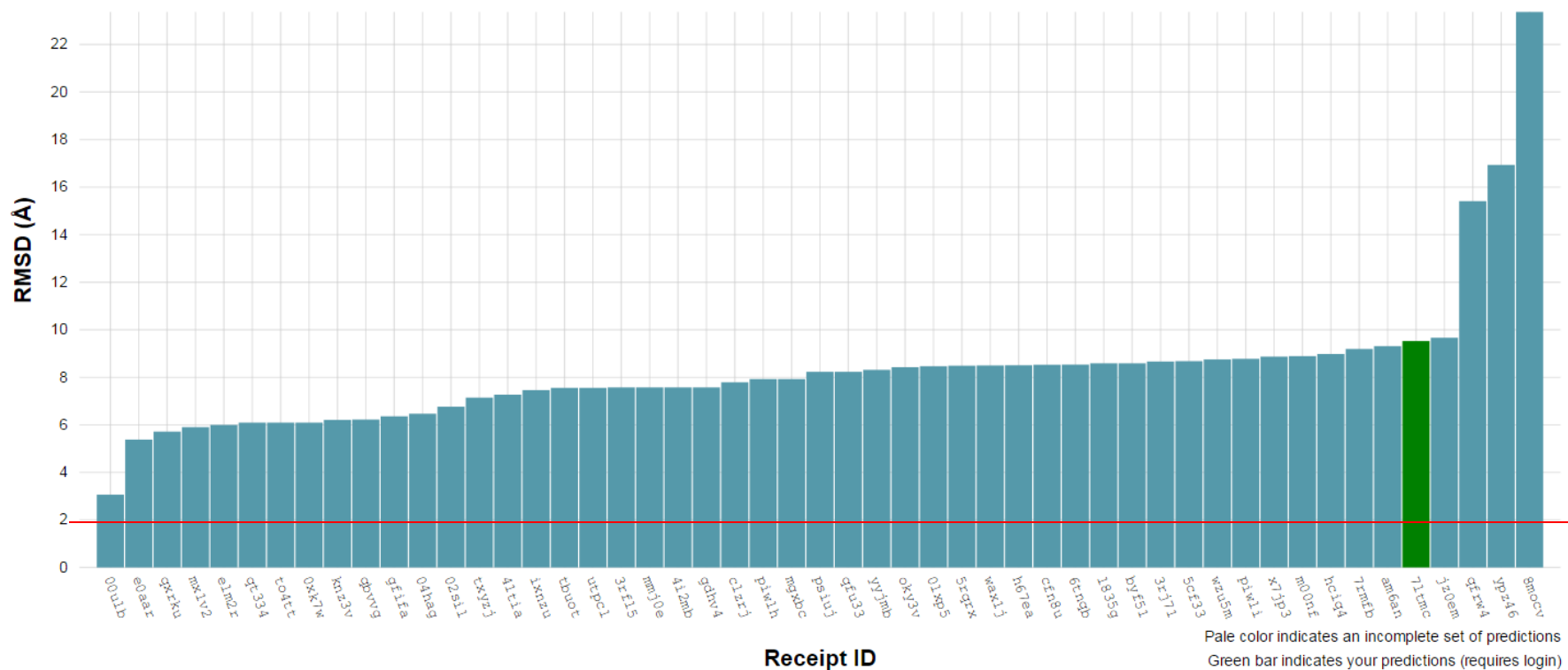
MD refinement

Case Study-failure: FXR_18

MD workflow can't address very large protein movements

Pose - RMSD - Compound: FXR_18 - Best

Compound:



Lesson learned from previous D3R challenge:
“Explicit solvent free energy methods have not yet outperformed faster scoring methods in blinded protein-ligand affinity predictions.”

-D3R website (Posted October 11, 2016)

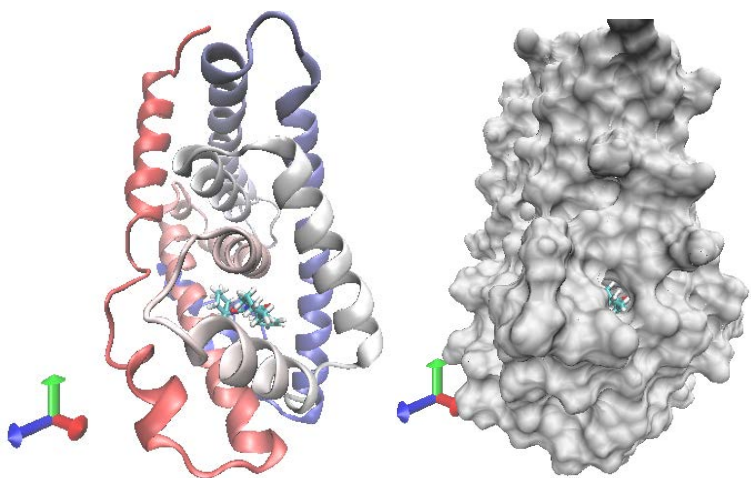
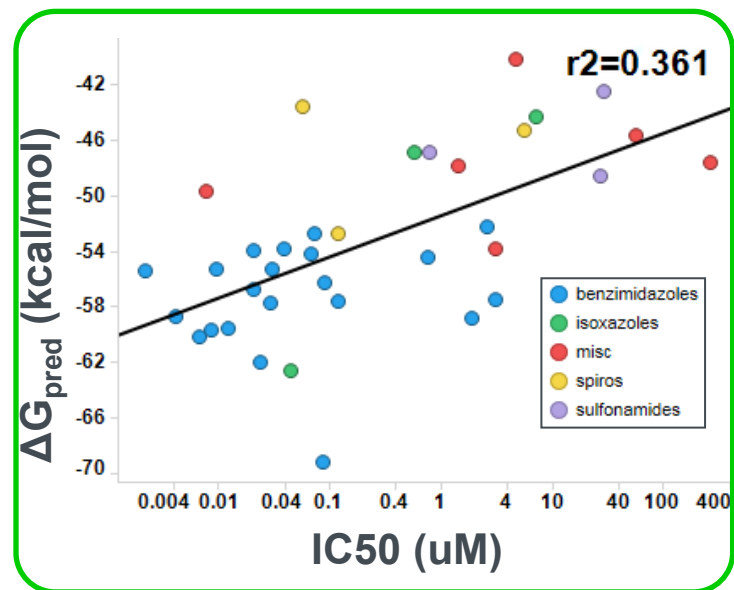
<https://drugdesigndata.org/about/what-we-have-learned>

Question 2

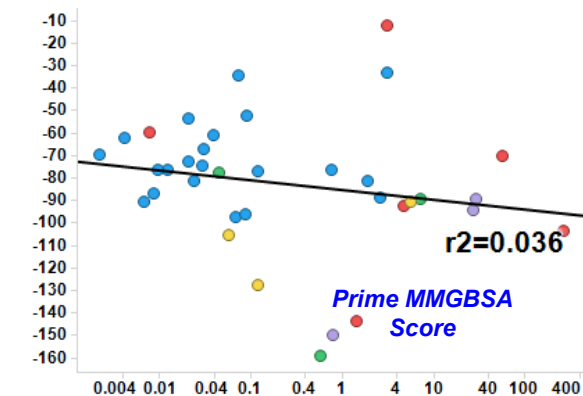
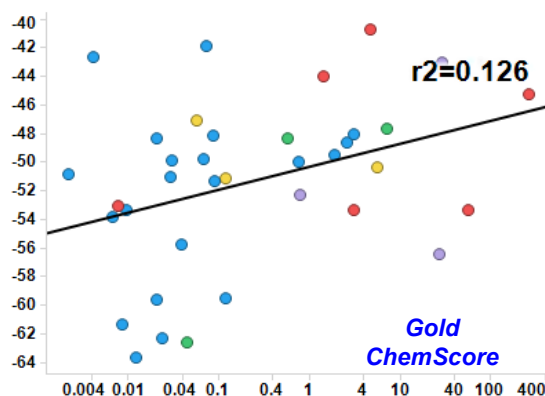
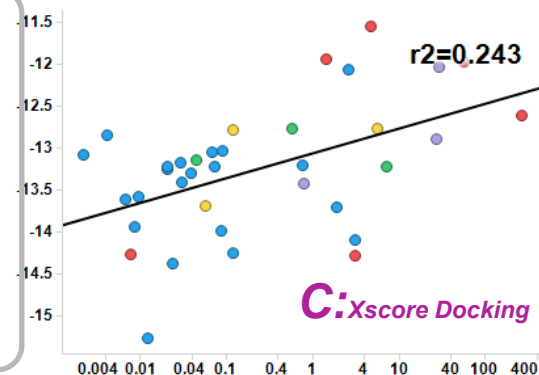
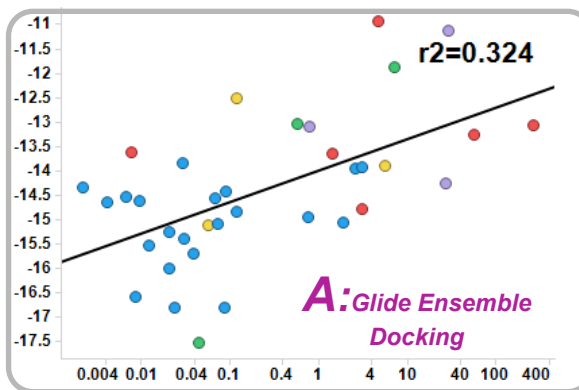
How does MD-MMGBSA perform in ligand scoring?

MD-MMGBSA improves on docking scores

D: MD-MMGBSA



Docking Methods



*binding pocket is deep inside
challenge data set for implicit model (MMGBSA)*

Stage1: 36cmpds

Summary

▶ Lessons

- Ensemble docking performs well in pose prediction & ranking, if there are suitably close protein complexes available
- MD maintains or refines docking poses (protein and ligand) and extends the limit of prediction
 - MD can't refine challenging poses
- Ensemble-based MD-MMGBSA ranking improves on docking scores
- Teamwork broke the challenge down to manageable portions

▶ Next

- AMBER MD-MMGBSA to AMBER TI
- CPU to GPU

The Free Energy Race



8-core CPU: 1 ns/day

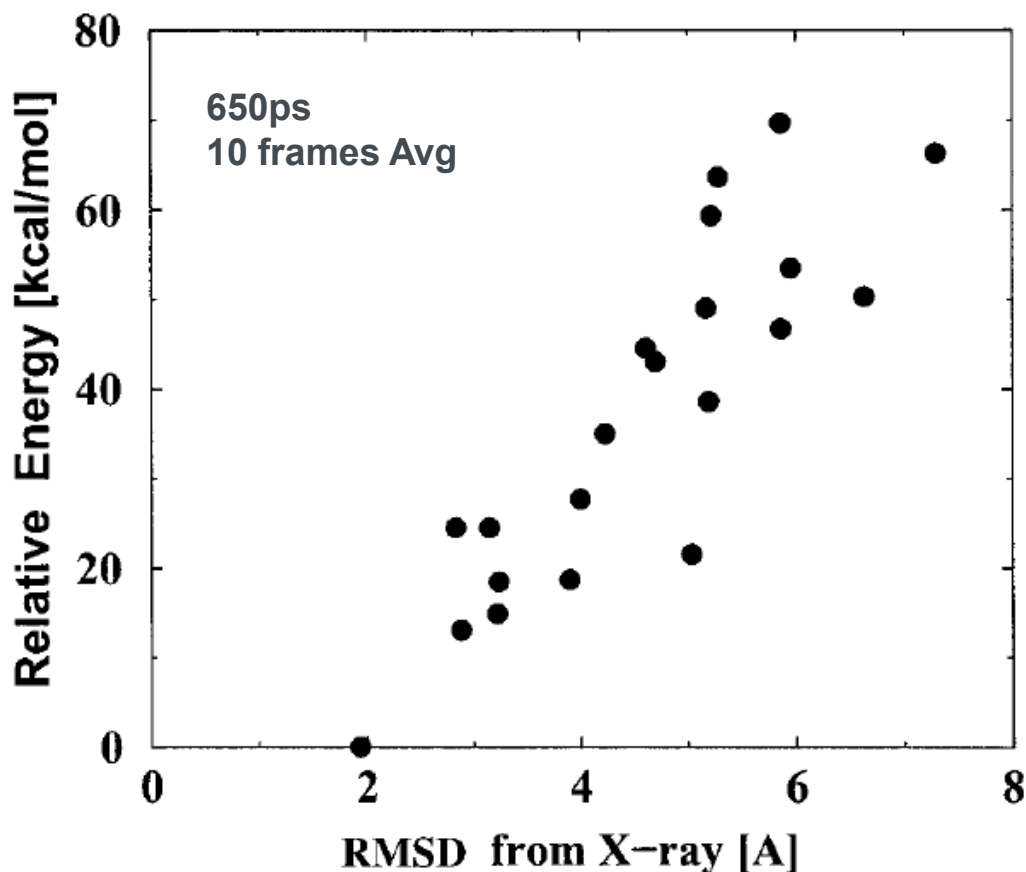


Towards accurate binding affinity prediction with pmemdGT: an efficient implementation of GPU-accelerated Thermodynamics Integration. T. Lee, Y. Hu, B. Sherborne, Z. Guo, D.M. York. submitted.

Thank You!

Pose exploration with MD

Multiple studies show that the low energy snapshots correlate with best pose prediction



**average energy of the 10 lowest energy snapshots for each trajectory of 22 MD simulations differed by the initial position.*

Onufriev, A.; Bashford, D.; Case, D. Proteins, 2004, 55, 383-394.

Hou, et al. J Comput Chem. 2011 Apr 15;32(5):866-77