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2025 CHICAGO**



**APRIL 25-30**

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#AACR25

## DEL-AI: Proteome-Wide *In Silico* Screening of Multi-Billion Compound Libraries Using Machine Learning Foundation Models

Paul Novick, PhD

Nurix Therapeutics, San Francisco, CA



# Disclosure Information

## Paul Novick

I have the following relevant financial relationships to disclose:

Employee of: Nurix Therapeutics

Stockholder in: Nurix Therapeutics

# Disclosure Information

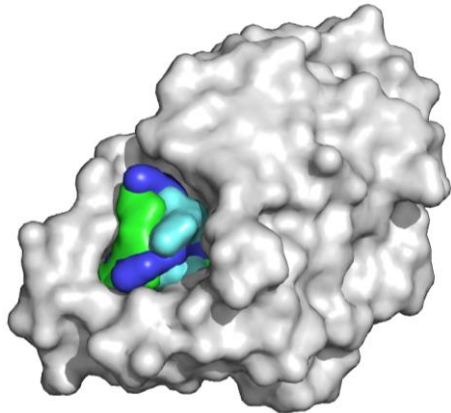
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# Small Molecule Drug Discovery Begins with a Binder

Lead Identification is a central challenge in small molecule drug discovery

How can this be done efficiently for novel therapeutic targets?



Fragment Screening

High Throughput Screening (HTS)

Virtual Screening

DNA Encoded Libraries (DEL)

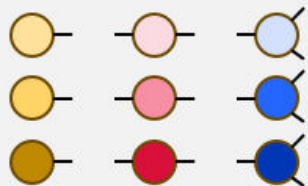
DEL + Machine Learning (DEL AI)

Library Size (Log10)

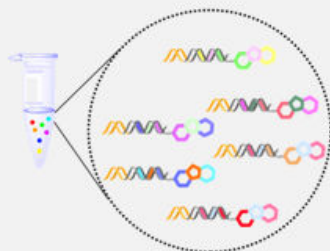
# DEL is a Productive Lead ID Technology Generating Massive Datasets

## DEL Libraries

1000's of Building Blocks



Combinatorial Synthesis

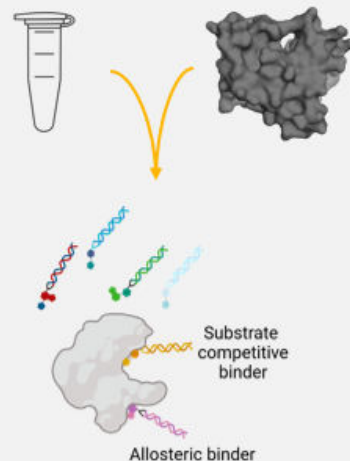


Over 5 Billion DEL Ligands

## DEL Screening

DEL

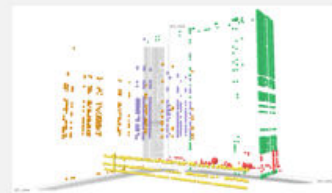
Protein



Over 6 Trillion DEL Datapoints

## DEL Hit Validation

Ligand Selection and Confirmation



Druggability

Kinase  
Other Enzymes  
Nuclear Receptor  
Protease  
Epigenetic  
Deubiquinating  
Ligase  
Transcription Factor

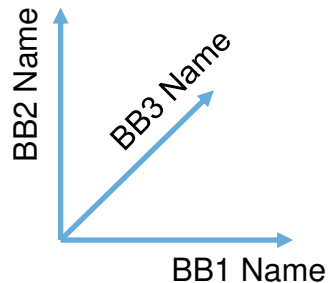
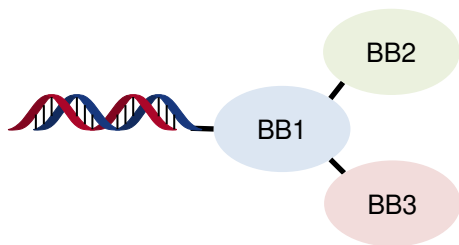
Over 60 High Affinity Series

# A Primer on DEL Data Interpretation

When reviewing DEL data in a Cube representation, we are looking for structural patterns in the data.

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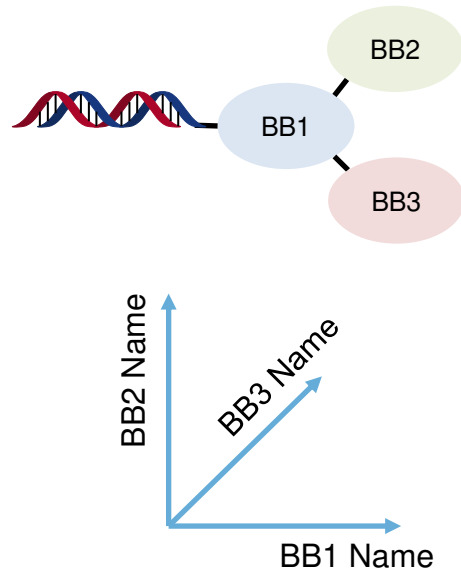


BB = chemical Building Block

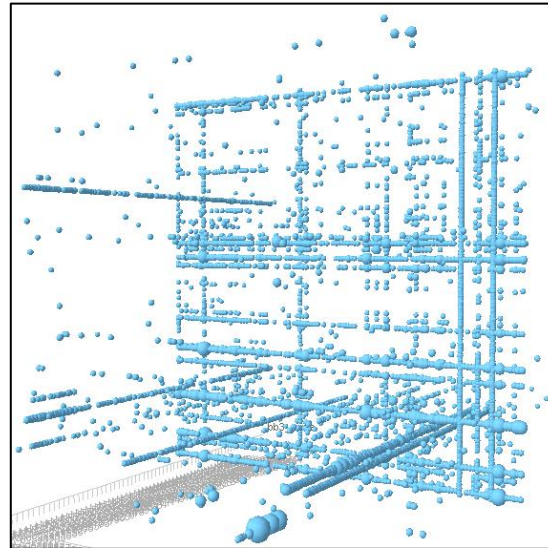


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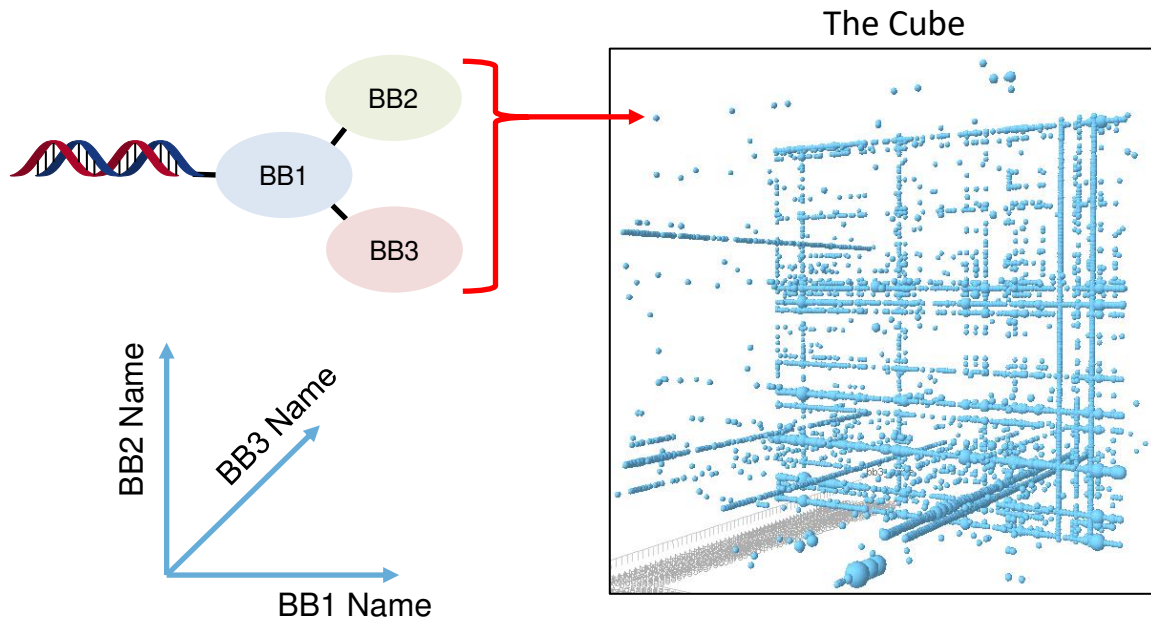
The Cube





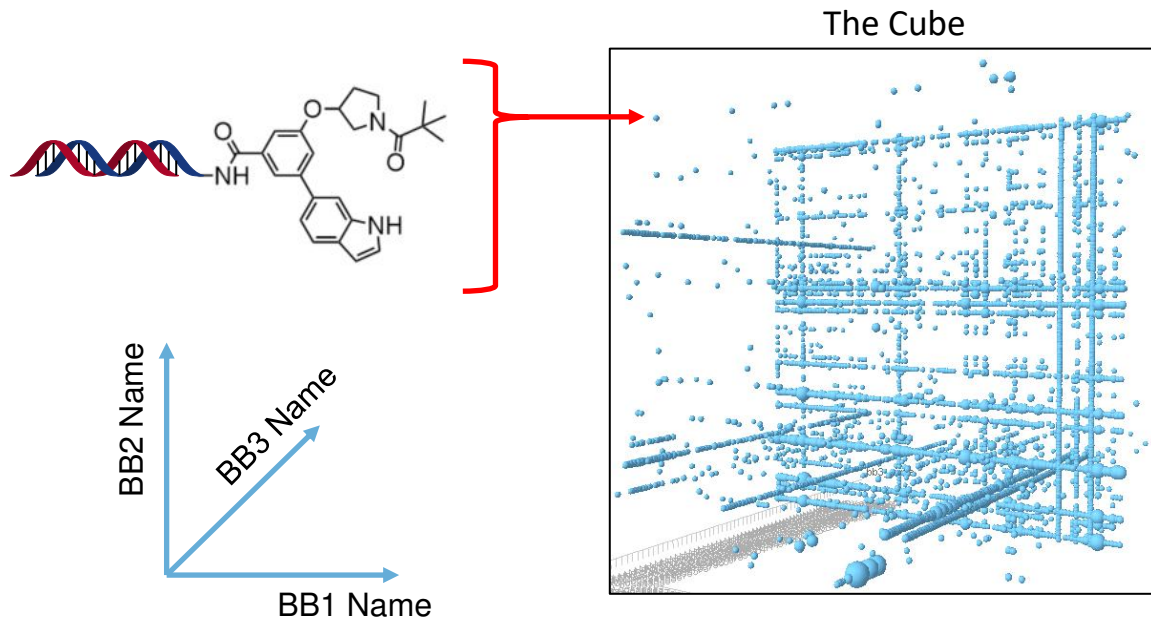
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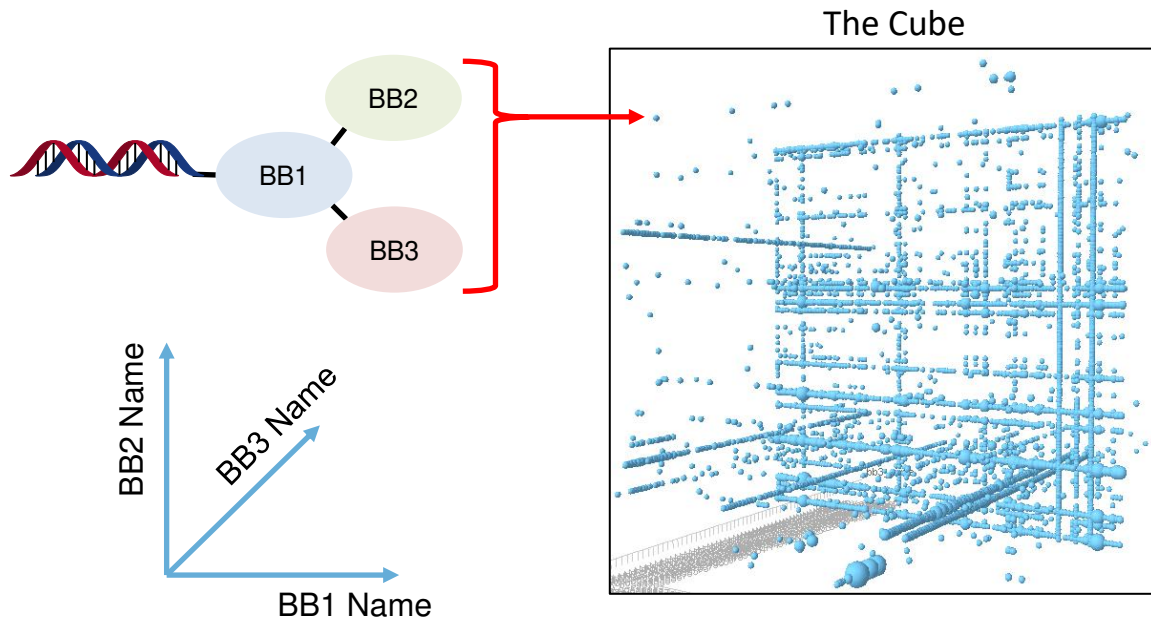
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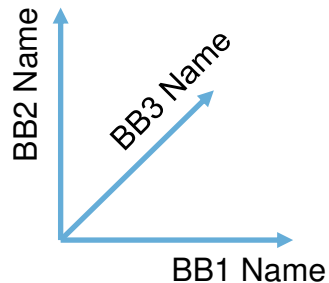
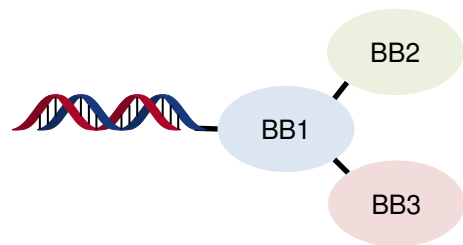
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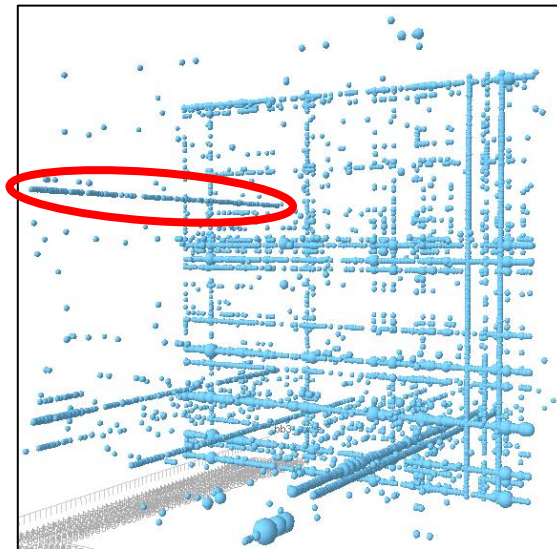


# A Primer on DEL Data Interpretation

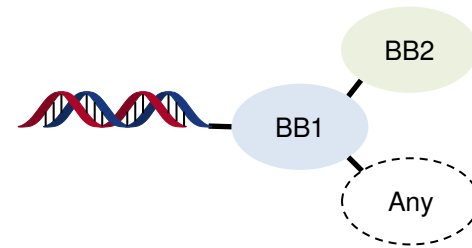
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The Cube

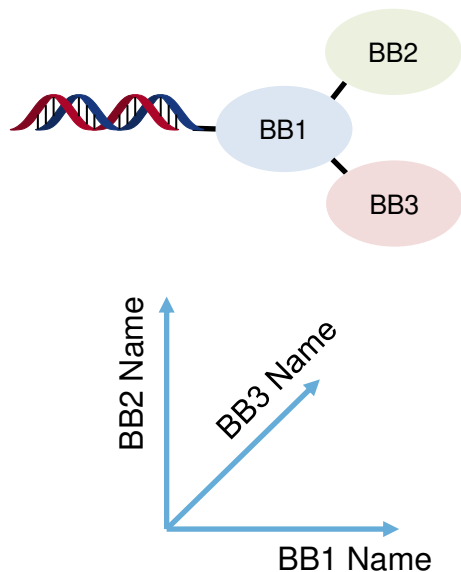


Lines: 2 shared building blocks

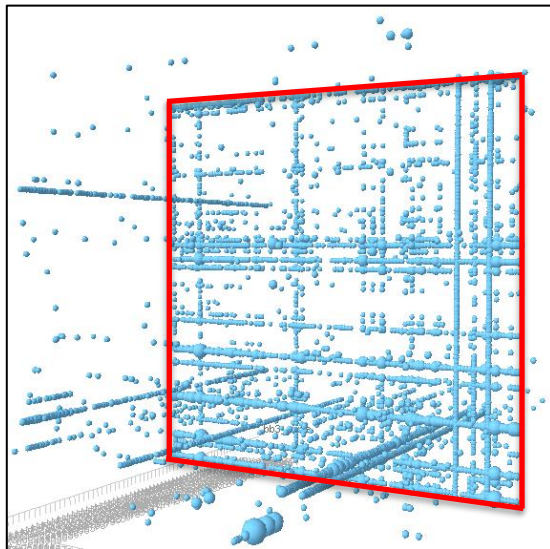


# A Primer on DEL Data Interpretation

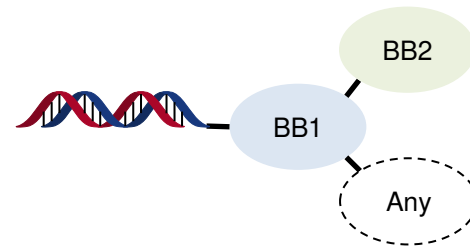
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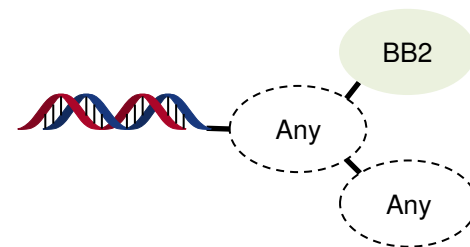
The Cube



Lines: 2 shared building blocks



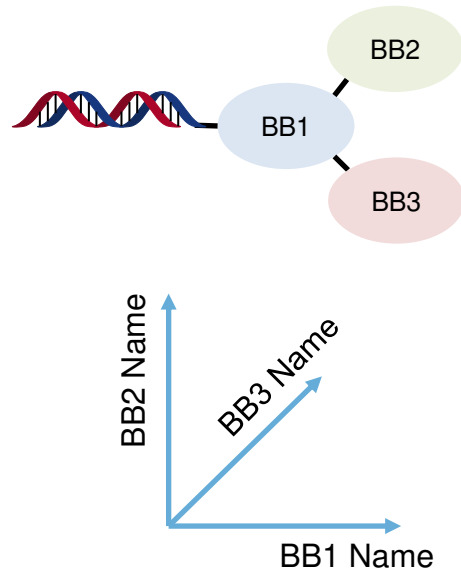
Planes: 1 shared building block



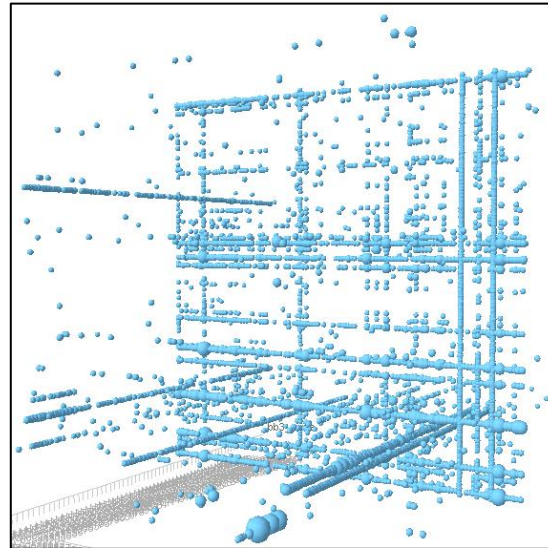


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When reviewing DEL data in a Cube representation, we are looking for structural patterns in the data.



The Cube

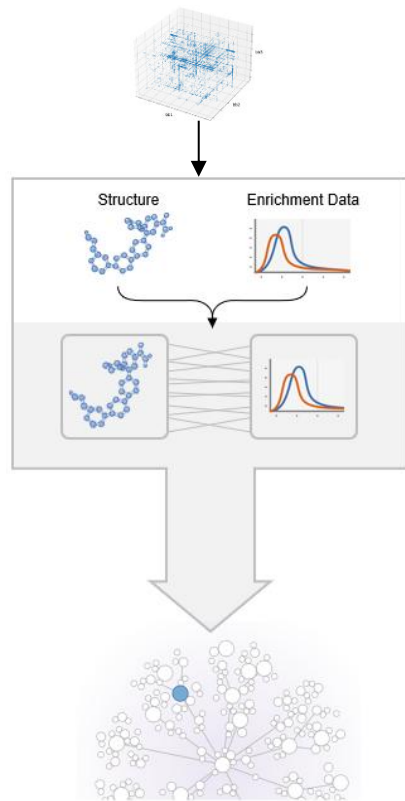


In comparing two sets of DEL data, we evaluate the similarity of these patterns.

# DEL Foundation is a Generalized Model Able to Prospectively Predict DEL Data

## Traditional DEL ML Approaches

- Established DEL ML approaches train models on single target datasets
- These models predict binding to a single protein and are inefficient to scale to ligand discovery across diverse targets
- Rely on time and resource intensive quality protein production and DEL screen execution.



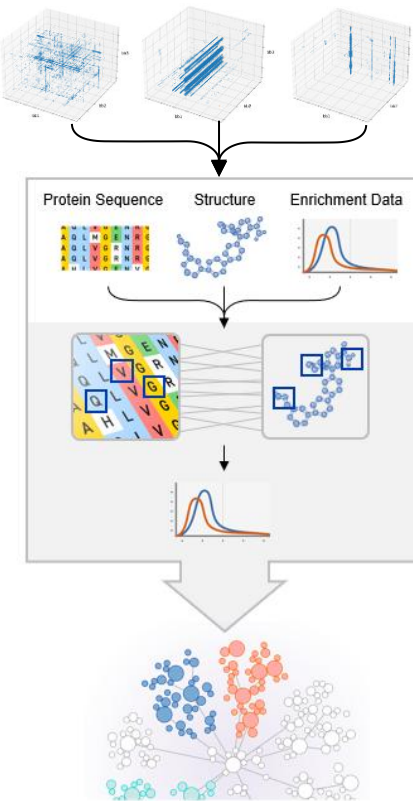
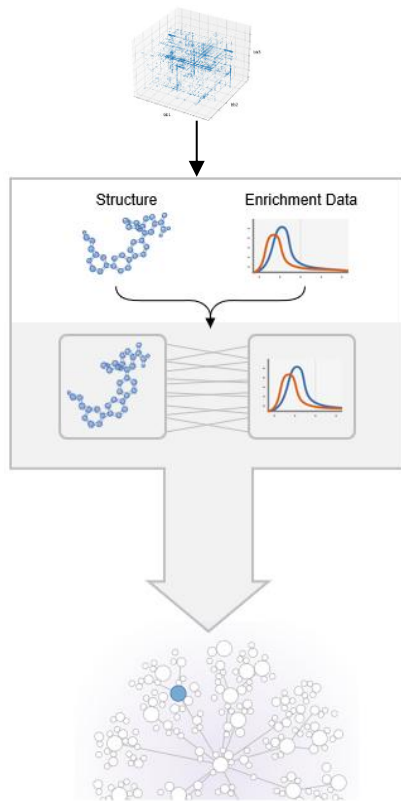


# DEL Foundation is a Generalized Model Able to Prospectively Predict DEL Data

## Traditional DEL ML Approaches

## DEL Foundation Model

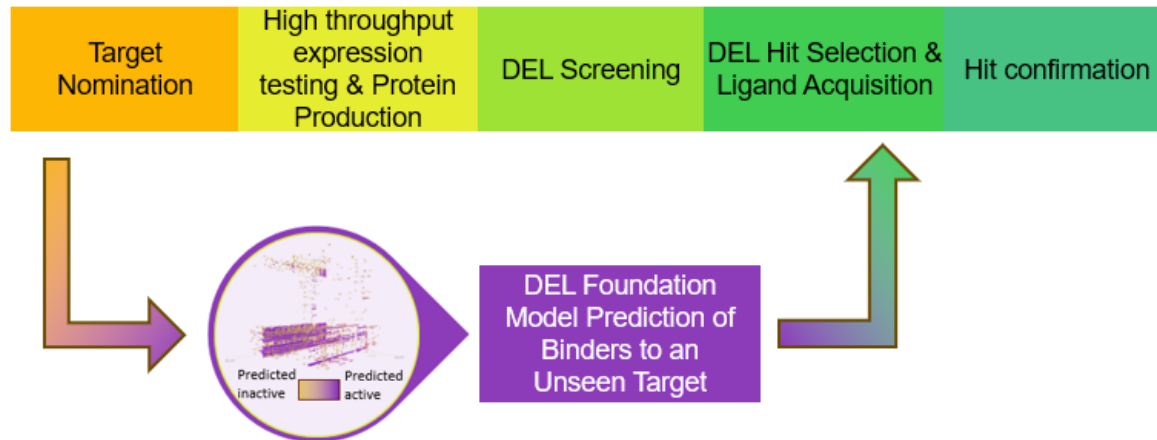
- Established DEL ML approaches train models on single target datasets
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- DEL Foundation Model is trained on DEL datasets from diverse protein targets
- These models learn a generalized relationship between protein sequence and molecular structure
- DEL Foundation is thus able to predict DEL data on proteins without the need for experimental data

# DEL Foundation Enables Efficient Ligand ID for Unseen Targets

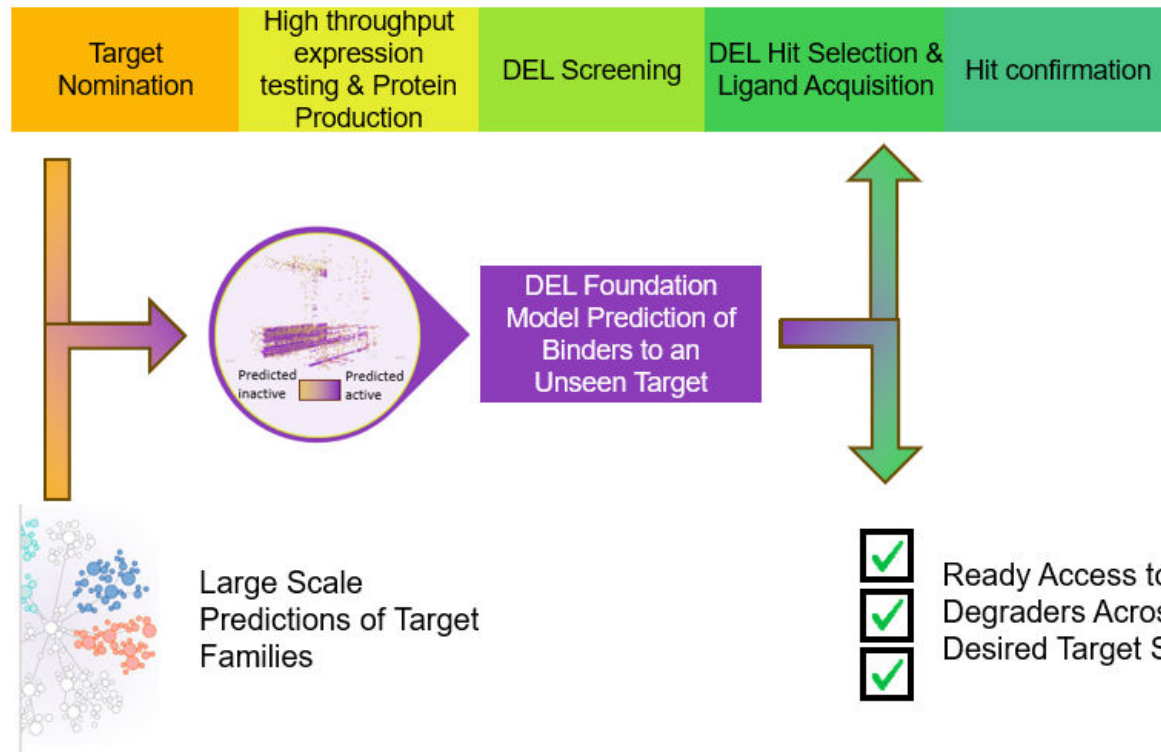
DEL Foundation-based Lead ID bypasses multiple resource intensive processes and unlocks targets which are otherwise “un-DEL-able”



# DEL Foundation Enables Efficient Ligand ID for Unseen Targets

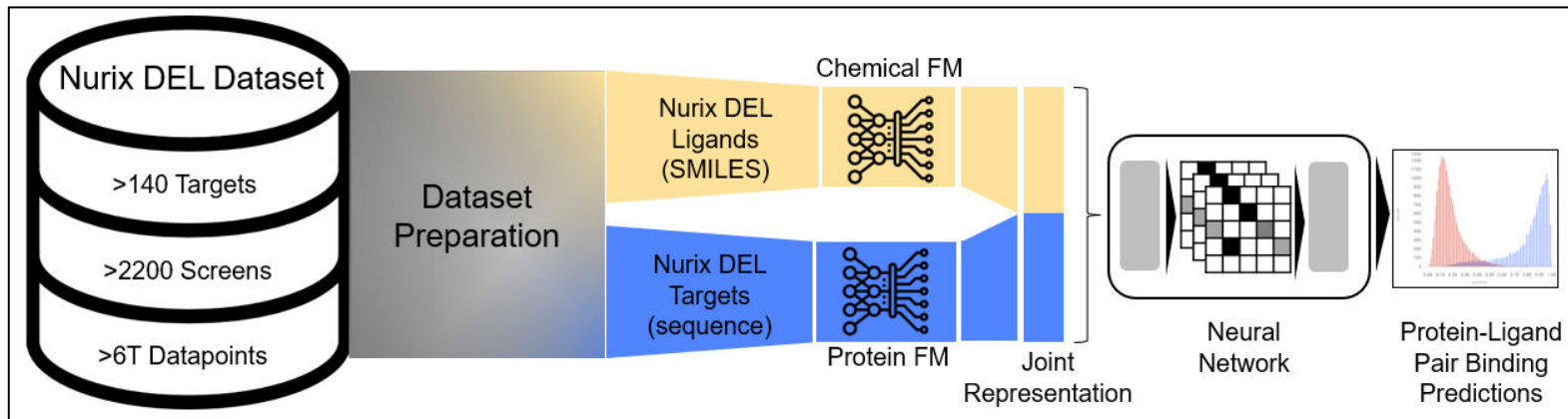
DEL Foundation-based Lead ID bypasses multiple resource intensive processes and unlocks targets which are otherwise “un-DEL-able”

DEL Foundation models allow access to broad swaths of the proteome



# DEL Foundation Leverages Nurix's Proprietary and Highly Ordered Datasets

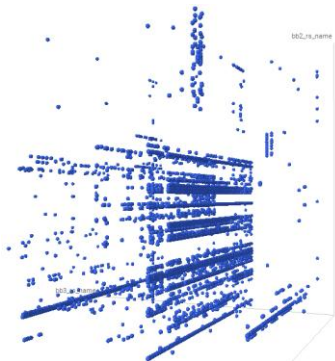
Collaboration between Nurix, Loka Inc., and Amazon Web Services



Schematic of Data Processing and Model Architecture

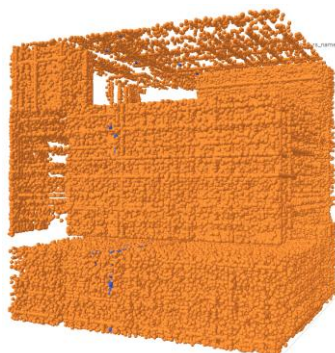
# DEL Foundation Dataset Construction and Definition of Terms

Retrospective datasets constructed from experimental data



## Experimental Actives

Ligands enriched in the DEL screen



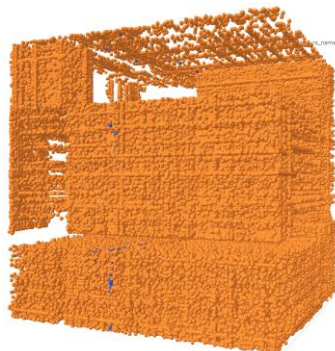
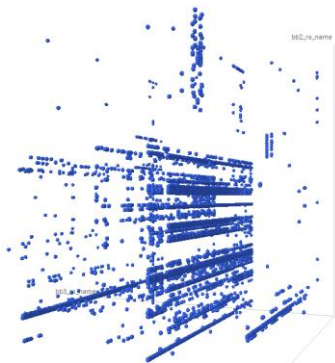
## Experimental Inactives

Ligands which did not enrich in the DEL screen, sampled from full DEL library



# DEL Foundation Dataset Construction and Definition of Terms

Retrospective datasets constructed from experimental data



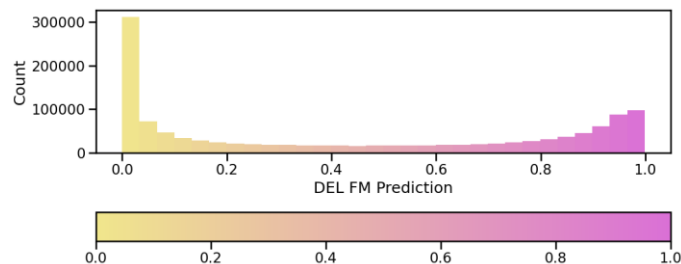
## Experimental Actives

Ligands enriched in the DEL screen

## Experimental Inactives

Ligands which did not enrich in the DEL screen, sampled from full DEL library

Datasets not in the training dataset are evaluated by DEL Foundation (DEL FM)



## DEL FM Inactives

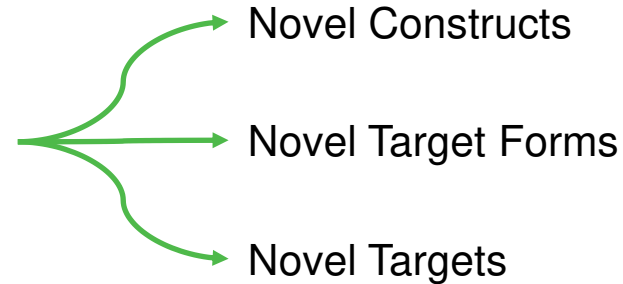
Ligands predicted as non-binders (low DEL FM score)

## DEL FM Actives

Ligands predicted as binders (high DEL FM score)

# Different Lenses on Prospective DEL Foundation Predictions

Can DEL Foundation prospectively predict binders for new proteins?



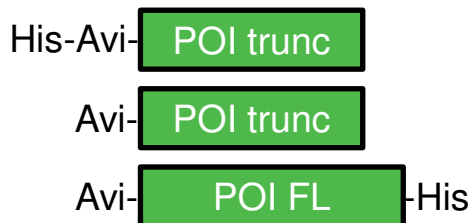
Can DEL Foundation prospectively predict binders from new libraries?



# High Accuracy Predicting Experimental Data on New Constructs

Binders predicted by DEL Foundation align closely to experimental data for a novel construct outside the training dataset.

## Constructs in Training

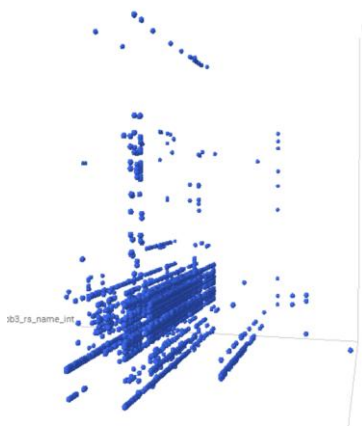


## Constructs in Holdout



POI = Protein Of Interest

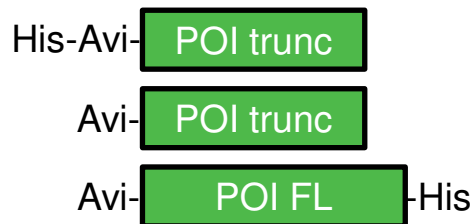
## Experimental Actives



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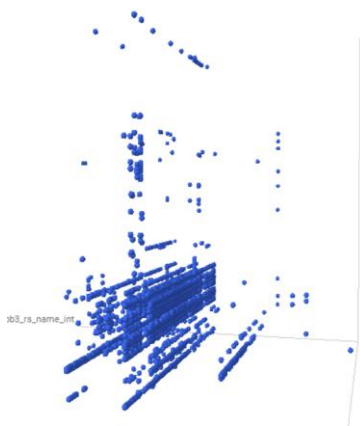


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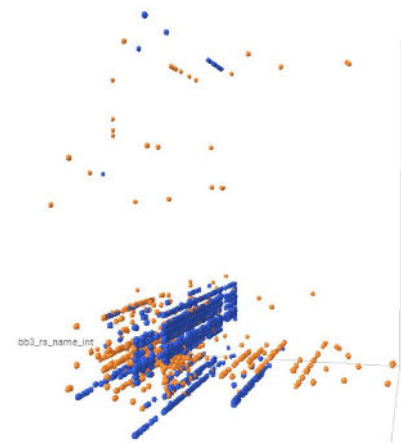


POI = Protein Of Interest

## Experimental Actives



## DEL FM Actives with Experimental Annotation



**Experimental Actives**  
**Experimental Inactives**

# High Accuracy Predicting Experimental Data on New Target Forms

Binders predicted by DEL FM largely recapitulate experimental data of a protein complex. Additionally, DEL FM ignores an experimentally observed plane considered promiscuous.

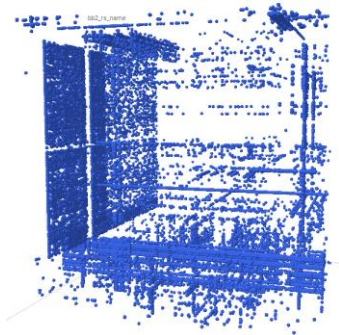
## Target Form in Training

6H-Avi-  POI trunc

## Target Form in Holdout

Avi-  POI FL  BP

## Experimental Actives



POI = Protein Of Interest  
BP = Binding Partner

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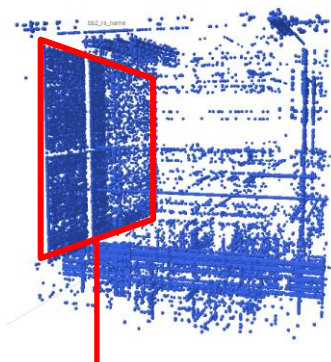
## Target Form in Training

6H-Avi- **POI trunc**

## Target Form in Holdout

Avi- **POI FL** **BP**

## Experimental Actives



Plane of promiscuous binders

POI = Protein Of Interest  
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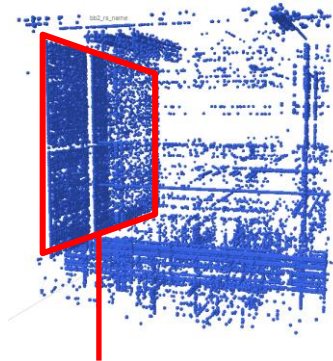
## Target Form in Training

6H-Avi- **POI trunc**

## Target Form in Holdout

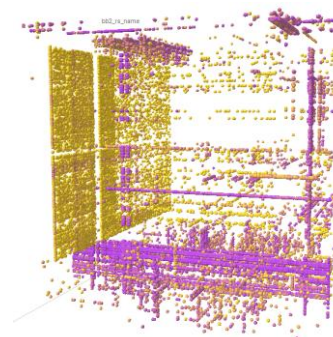
Avi- **POI FL** **BP**

## Experimental Actives



Plane of promiscuous binders

## DEL FM Scoring of Experimental Actives



0  1  
DEL FM Score

POI = Protein Of Interest  
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# High Accuracy Predicting Experimental Data on New Target Forms

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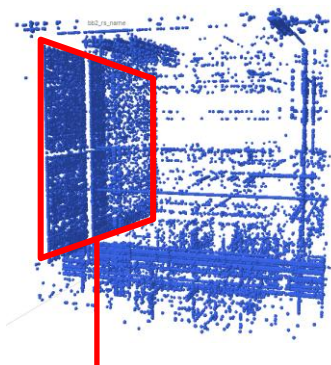
Target Form in Training

6H-Avi- **POI trunc**

Target Form in Holdout

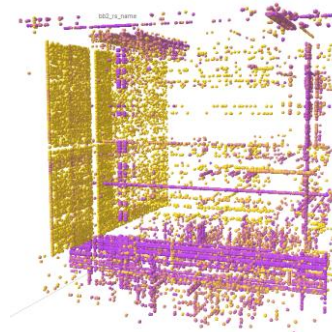
Avi- **POI FL** **BP**

Experimental Actives



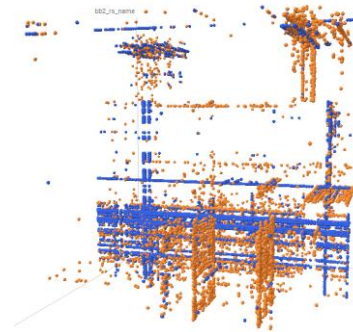
Plane of promiscuous binders

DEL FM Scoring of Experimental Actives



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DEL FM Score

DEL FM Actives with Experimental Annotation



**Experimental Actives**  
**Experimental Inactives**

POI = Protein Of Interest  
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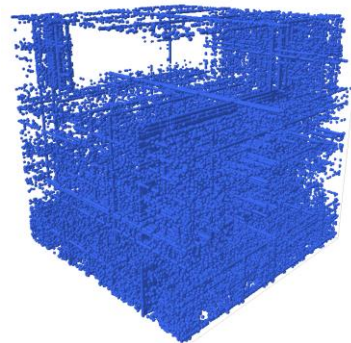
# DEL Foundation Identifies Confirmed Binders from High Background Screen

DEL FM predicts subset of experimental signal, inclusive of confirmed ligands.

## Target Forms in Training



## Experimental Actives



## Targets in Holdout



POI = Protein Of Interest  
pPOI = phosphorylated POI  
BP = Binding Partner



# DEL Foundation Identifies Confirmed Binders from High Background Screen

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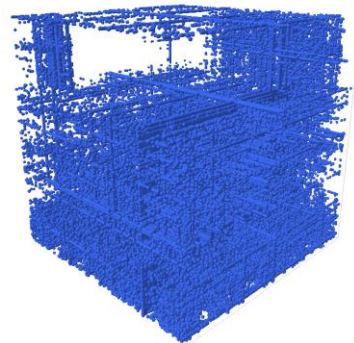
## Target Forms in Training



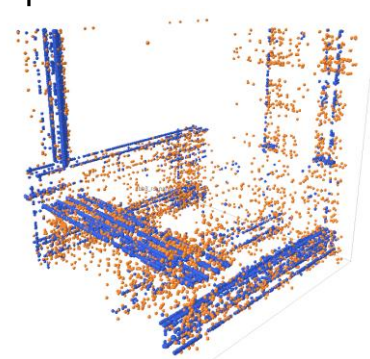
## Targets in Holdout



## Experimental Actives



## DEL FM Actives with Experimental Annotation



POI = Protein Of Interest  
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**Experimental Actives**  
**Experimental Inactives**

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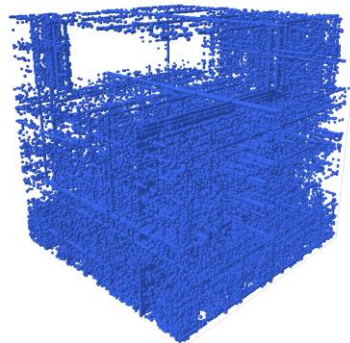


## Targets in Holdout

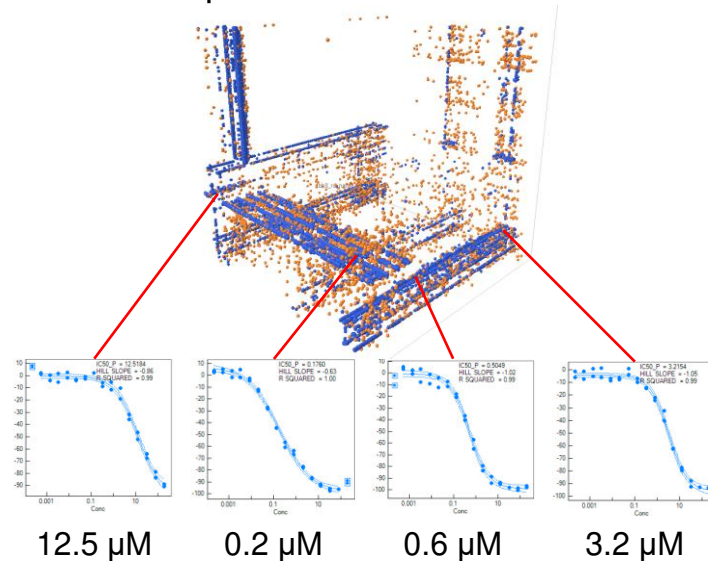


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## Experimental Actives



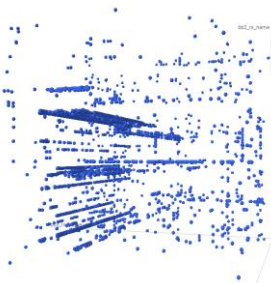
## DEL FM Actives with Experimental Annotation



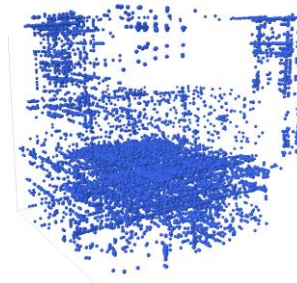
# Predicting Small Molecule Binders to Novel Proteins Beyond Training Data

DEL Foundation predicts most dominant patterns in experimental data despite low sequence similarity of query proteins to those in the training set.

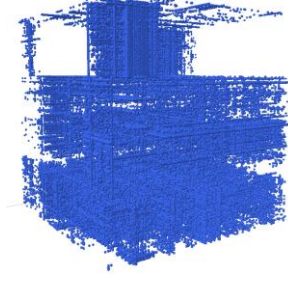
Target 1  
71% Seq Sim



Target 2  
79% Seq Sim



Target 3  
53% Seq Sim

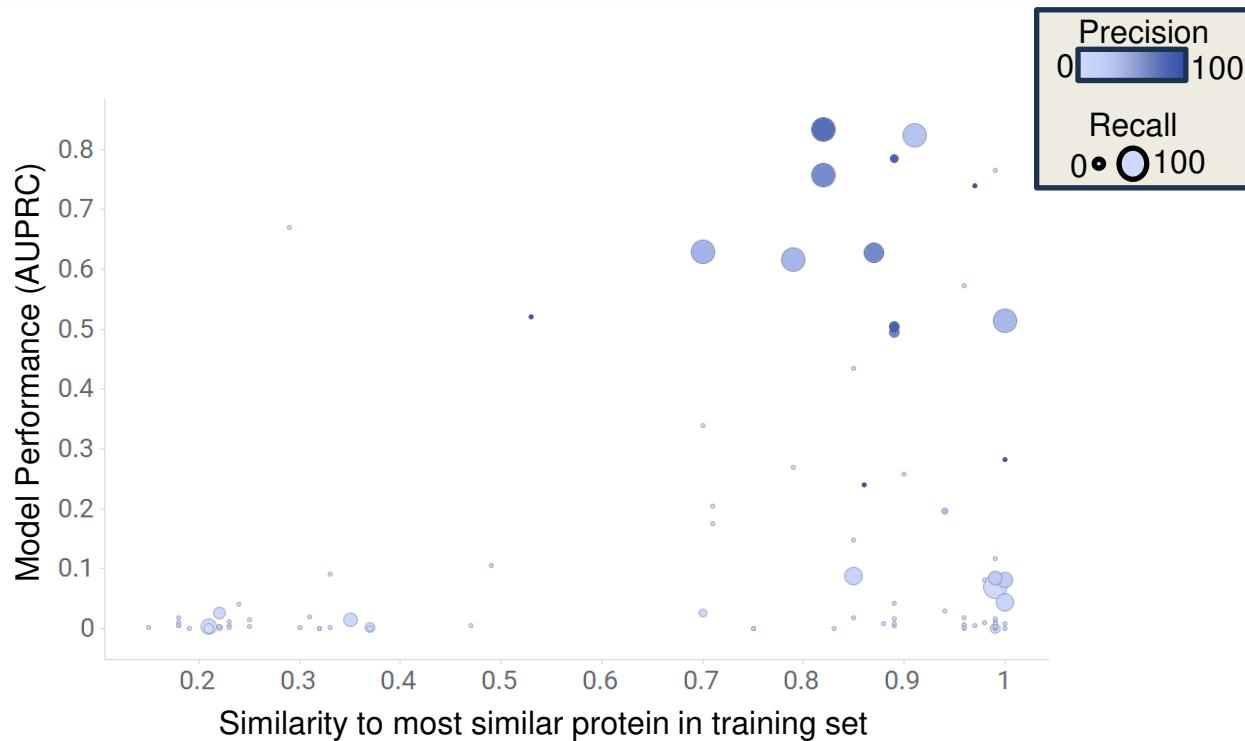


Experimental  
Actives

DEL FM Actives  
with Experimental  
Annotation

Experimental  
Actives  
Experimental  
Inactives

# Performance of DEL FM Correlates with Sequence Similarity



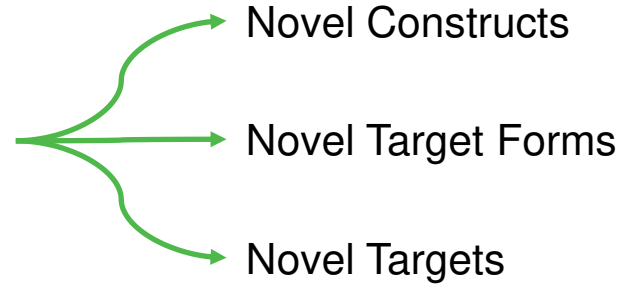
# Performance of DEL FM Correlates with Sequence Similarity



Evaluating the global relationship between sequence similarity and model performance, we expect DEL Foundation to provide actionable predictions for targets with as low as 0.5 similarity to a target in the training set.

# Different Lenses on Prospective DEL Foundation Predictions

Can DEL Foundation prospectively predict binders for new proteins?



Can DEL Foundation prospectively predict binders from new libraries?

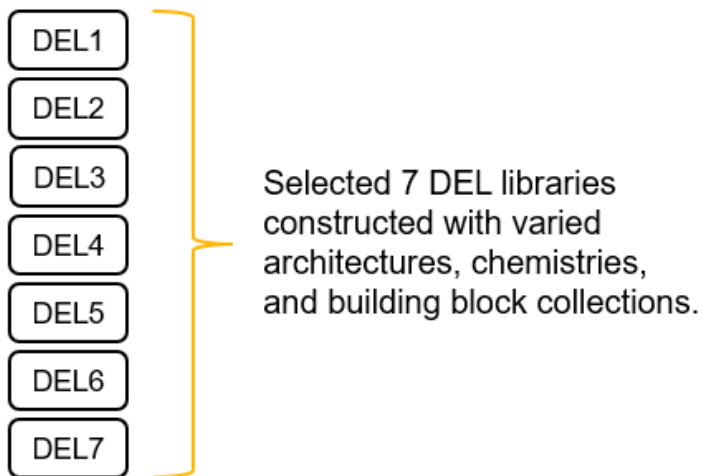


# DEL Foundation Can Predict Binders from Libraries Beyond Training Set

ML models that can generalize to new chemical space expand application scope, especially towards use for Lead Optimization.

A recent public competition was unable to make predictions for libraries outside the training set.<sup>1</sup> We tested the ability of DEL FM to succeed on this task.

## LOO\* Experimental Design



\*LOO = Leave One Out

<sup>1</sup> Blevins, A; BELKA; NeurIPS, 2024

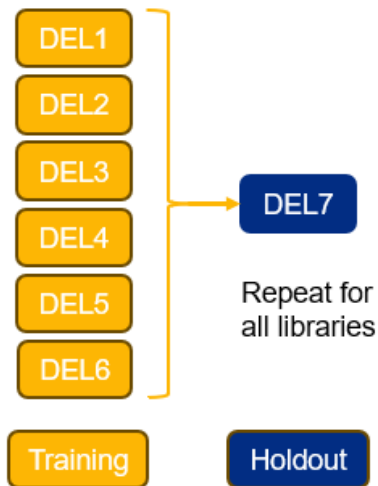


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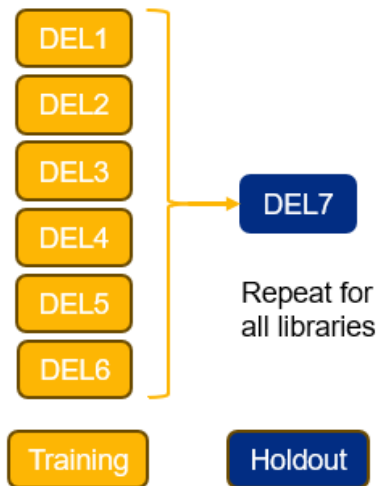
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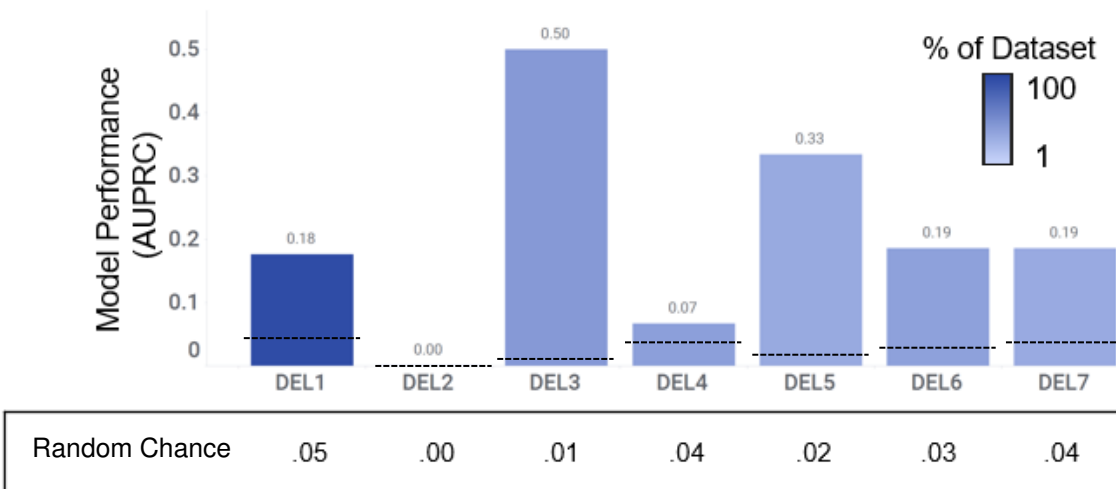
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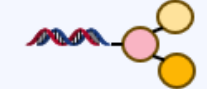
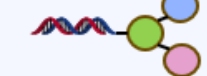


## Holdout Predictions




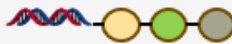




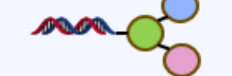
# Diversity of DEL Libraries in Foundation Model Training Set

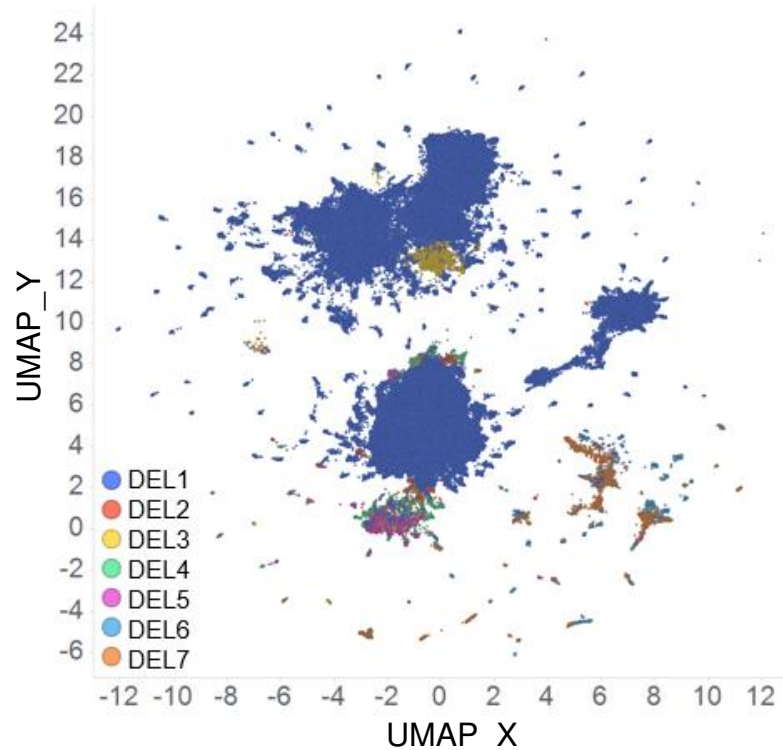
Analysis of libraries in training set demonstrates structural diversity consistent with design

Library	% of Dataset	Architecture
DEL1	72%	
DEL2	1%	
DEL3	7%	
DEL4	6%	
DEL5	4%	
DEL6	6%	
DEL7	4%	

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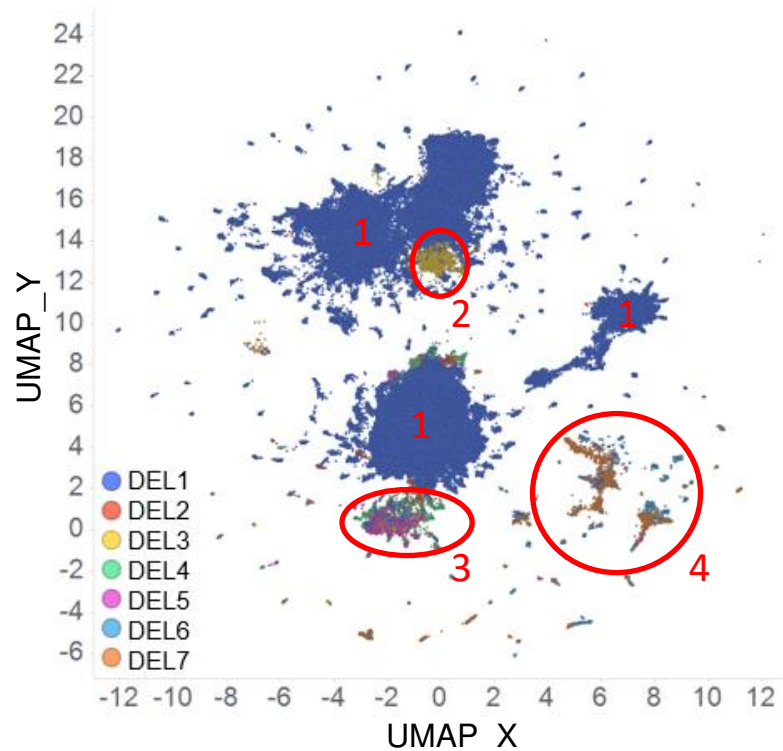
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Group 1: DEL1, DEL2

Group 2: DEL3

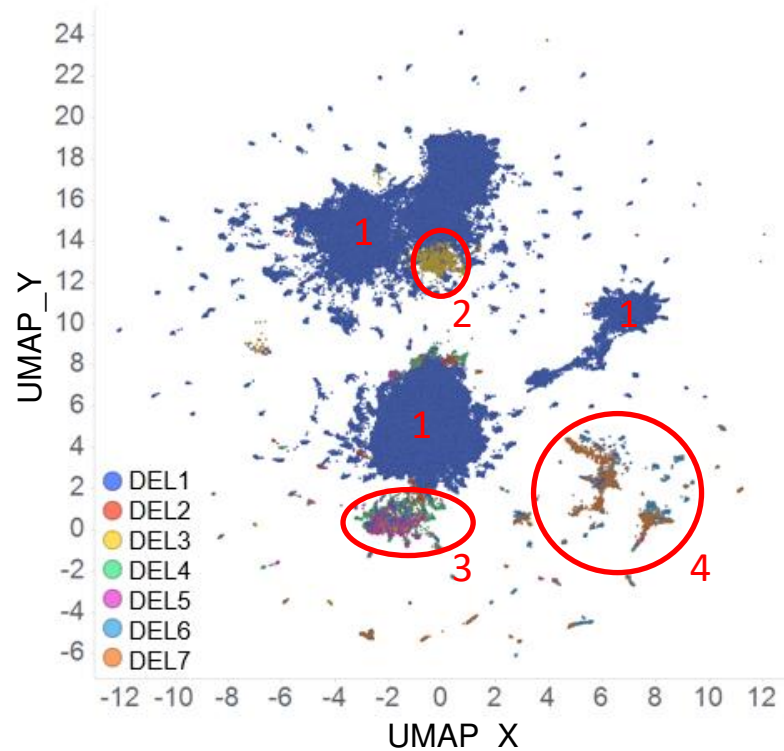
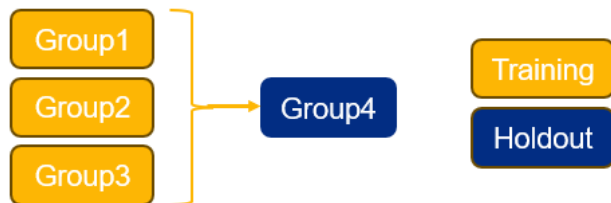
Group 3: DEL4, DEL5

Group 4: DEL6, DEL7



# Diversity of DEL Libraries in Foundation Model Training Set

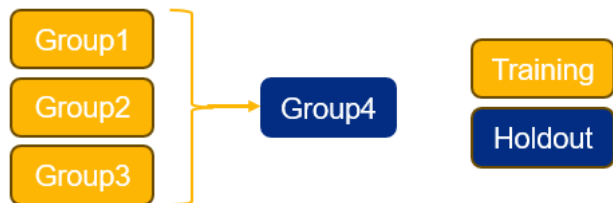
DEL FM predicts binders from unseen libraries representing distinct regions of chemical space



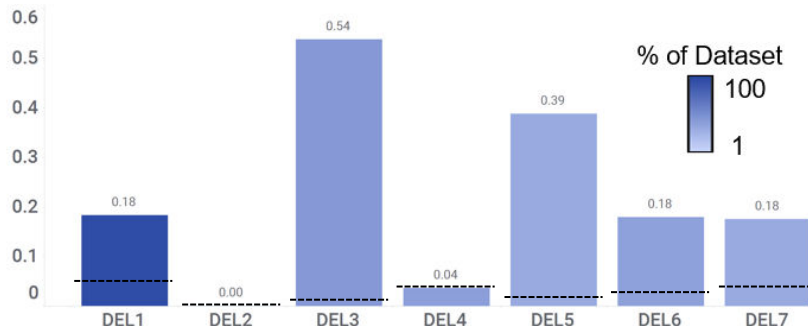


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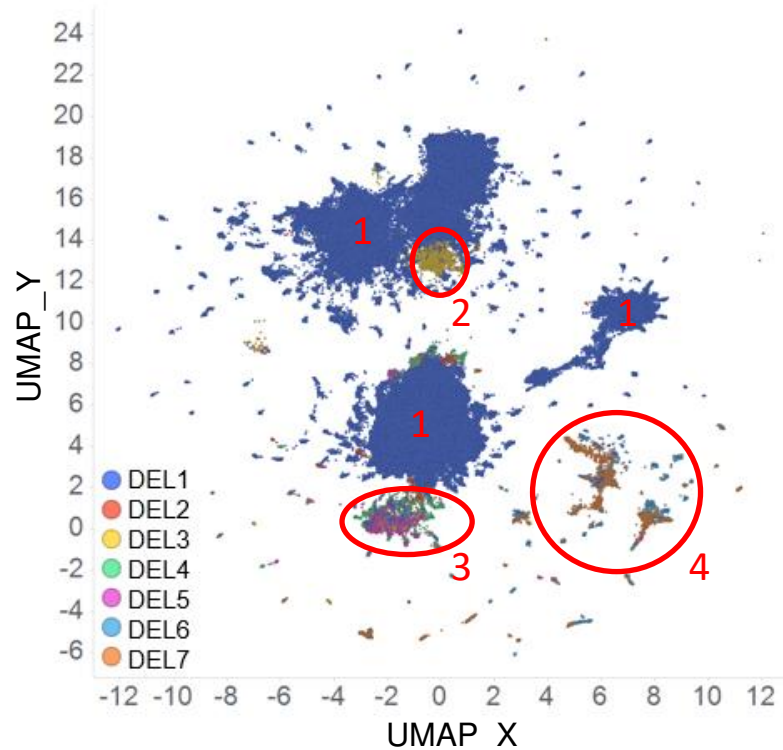
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Holdout Predictions



Random Chance	DEL1	DEL2	DEL3	DEL4	DEL5	DEL6	DEL7
.05	.05	.00	.01	.04	.02	.03	.04

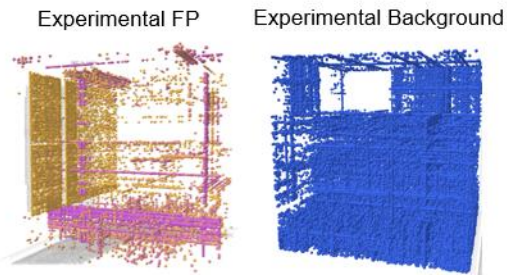


# Continued Development of DEL FM Addresses Realities of Experimental DEL

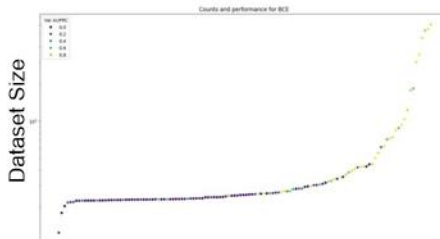
## Insufficient Metrics for Evaluating Model Performance

Is a model which fully recapitulates experimental data the goal?

If not, how should we measure performance?



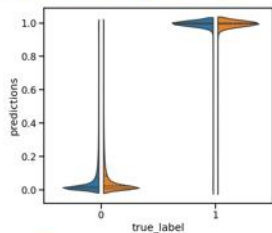
## Heterogeneous Datasets Affect Model Learnings



DEL Datasets are very heterogeneous in size which can impact the model's ability to learn from the full diversity of targets in the training set.

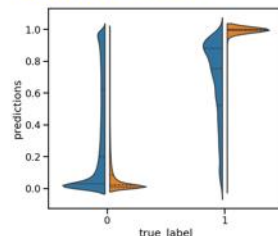
## Data Sampling Encourages Shortcut Learning

Predicting **Protein X** dataset vs **Close Homologue** sequence



■ Closely-Related Off-Target Protein Predictions  
■ On-Target Protein Predictions

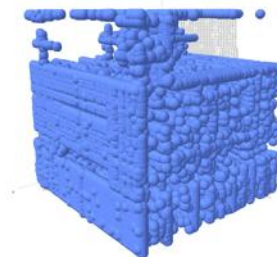
Predicting **Protein X** dataset vs **Distantly-Related** sequence



■ Unrelated Off-Target Protein Predictions  
■ On-Target Protein Predictions

## High Background of False Positives on Full Library Predictions

Huge size of DEL collections results in high background even with extreme precision.



- DEL Foundation is a first-in-class ML model able to prospectively predict DEL data
- DEL Foundation predicts DEL data for novel protein targets with performance correlated with similarity of the query protein sequence to training data
- DEL Foundation generalizes to unseen DEL libraries and unseen chemical space
- DEL Foundation transforms the scale and approach of Lead ID at Nurix

# Acknowledgments



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