

# ML module #4

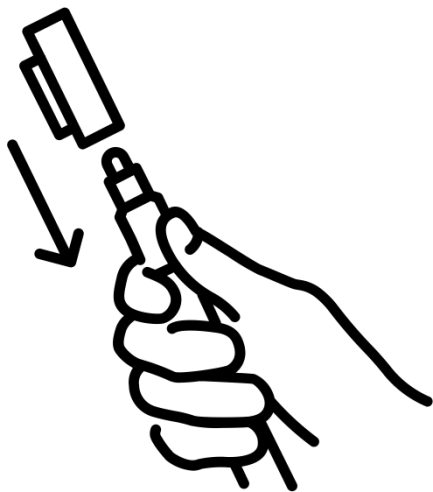
## (Recap & Metrics)

Benjamin Sanchez-Lengeling

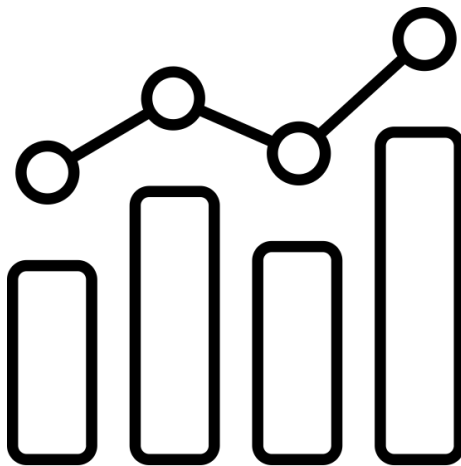
CrossTALK: Cross-Training in AI and Laboratory Knowledge for  
Drug Discovery.



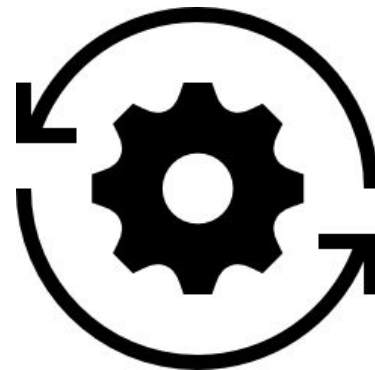
# Panorama



Recap

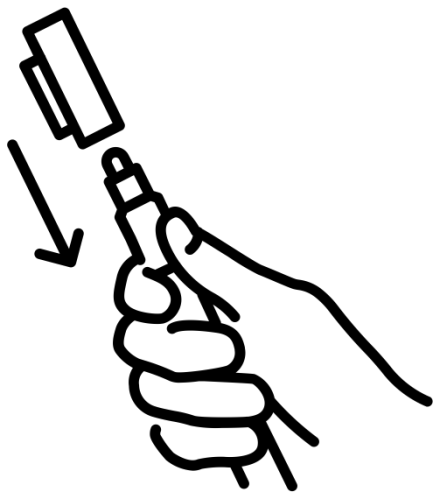


Metrics



Working sesh

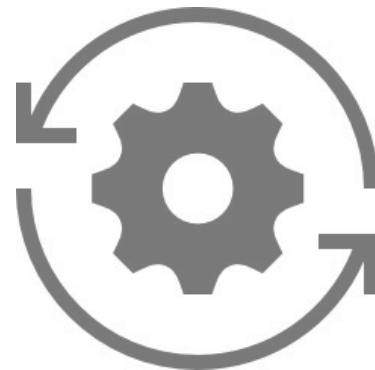
# Panorama



Recap



Metrics

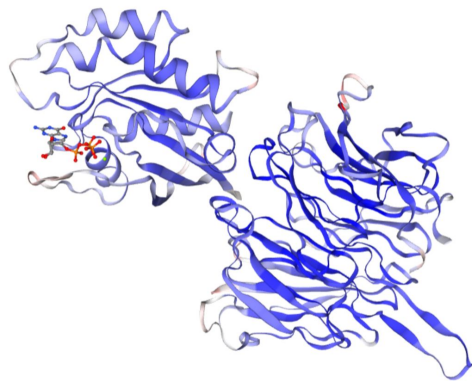


Working sesh

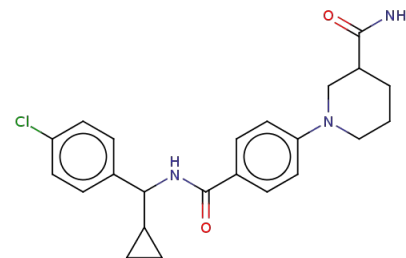
# Recap: From Problem to Experiment

## Simplified:

Some diseases are caused by malfunctioning Proteins, To “fix them” we need to physically interact with it using a “drug molecule”.



A4D1P6 (WDR91\_HUMAN)

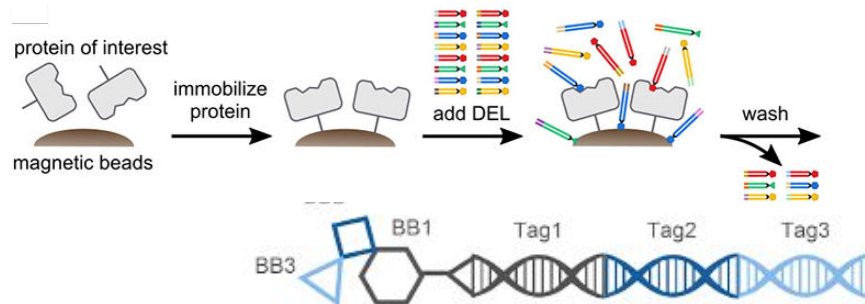


18 molecules with binding data

(<https://www.bindingdb.org/uniprot/A4D1P6>)

## DEL Experiments

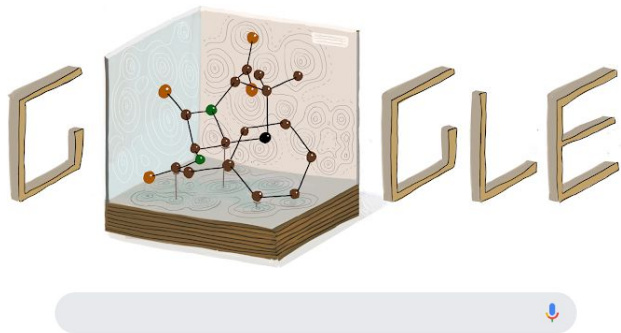
Allow us to test MASSIVE number of molecules



# Recap: Computational solutions



Desired solution:  
“Molecular search engine”



Filters:  
Lipinski's rule of 5

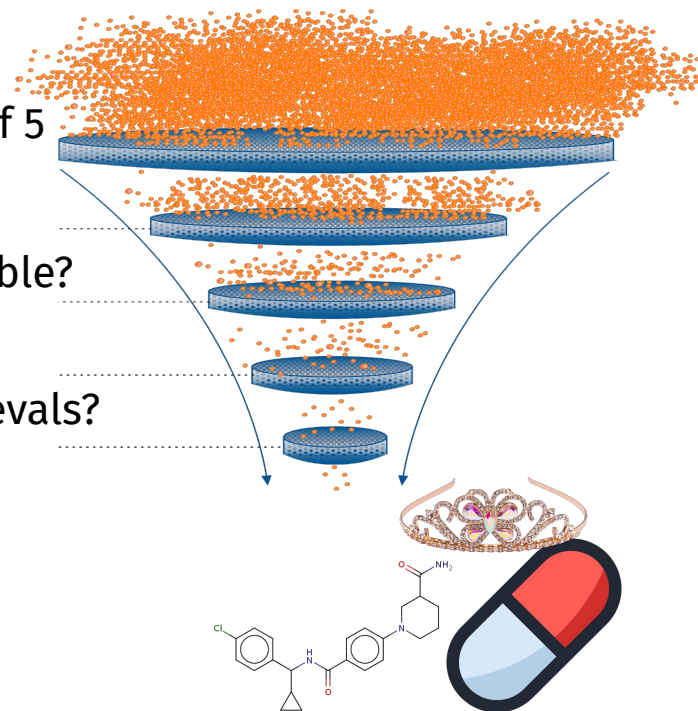
Does it bind?

Orally bioavailable?

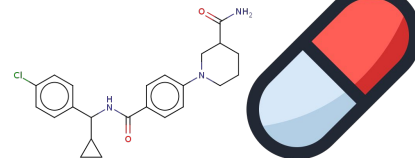
Toxic?

Animal/Tissue evals?

Human evals?

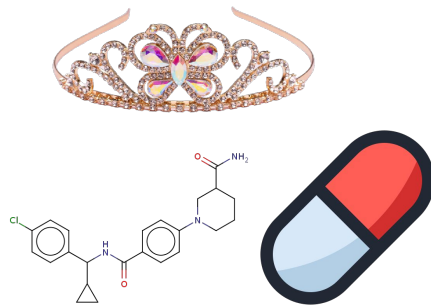


More hits, more shots on goal!

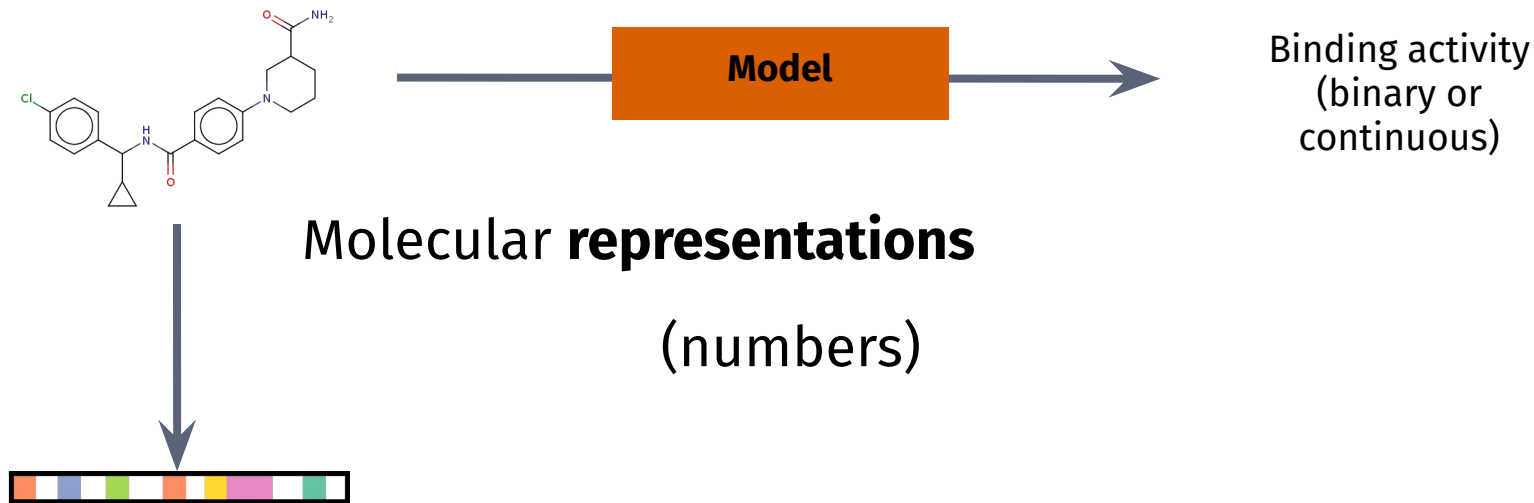


## Recap: Caveats, Hits are not drugs

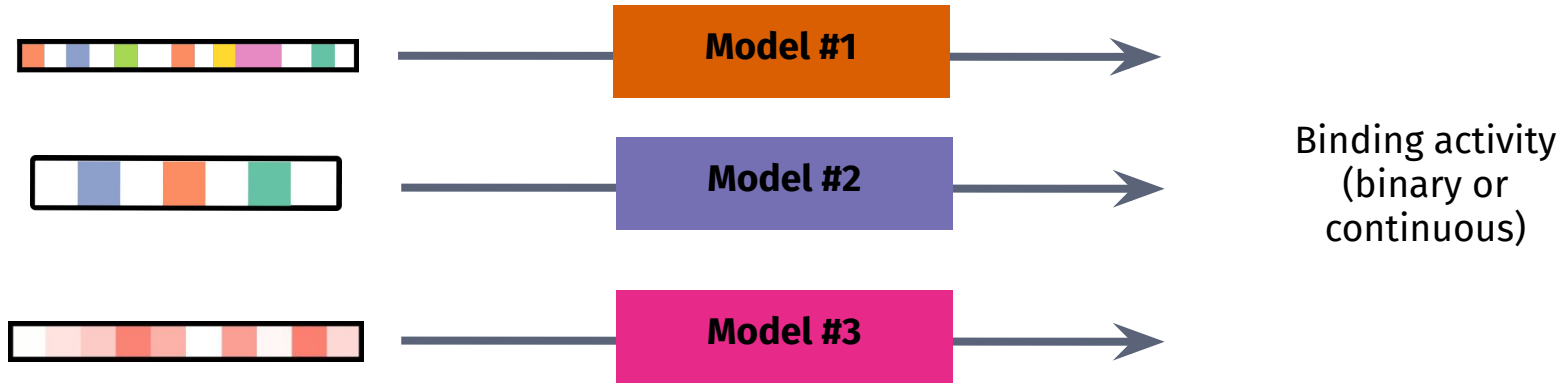
- Low potency
- Low specificity
- Insoluble in water
- Unstable
- Unable to get into cells
- False positives



# Recap: Starting from the “simplest” problem (but still hard!)



## Recap: Which model is the best? (and why?)

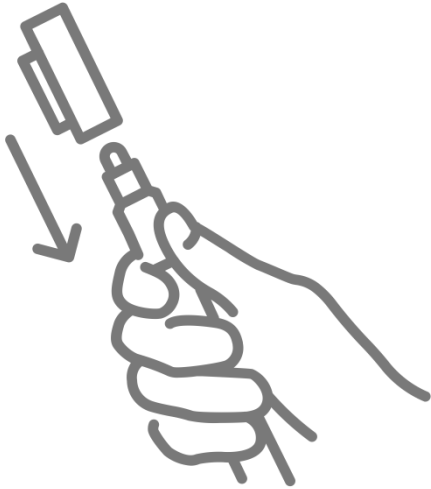


**Metrics!**

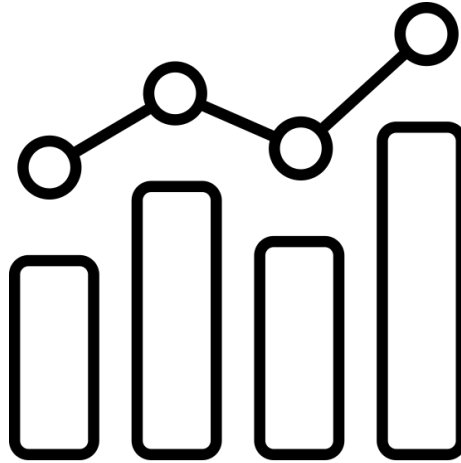


# Panorama

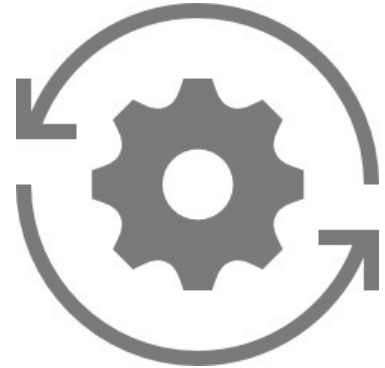
Section slides prepared by Cait Harrigan



Recap



Metrics



Working sesh

# AUROC - area under receiver operating characteristic

Asks: what is the probability that a random true positive will be ranked higher than a random true negative? *Measures ranking at all thresholds*

	Predict hit	Predict no hit
ASMS hit	TP	FN
ASMS no hit	FP	TN

$$\frac{TP}{TP + FN}$$

True positive rate *aka recall*

$$\frac{FP}{FP + TN}$$

False positive rate

# AUROC - area under receiver operating characteristic

Asks: what is the probability that a random true positive will be ranked higher than a random true negative? *Measures ranking at all thresholds*

	Predict hit	Predict no hit
ASMS hit	TP	FN
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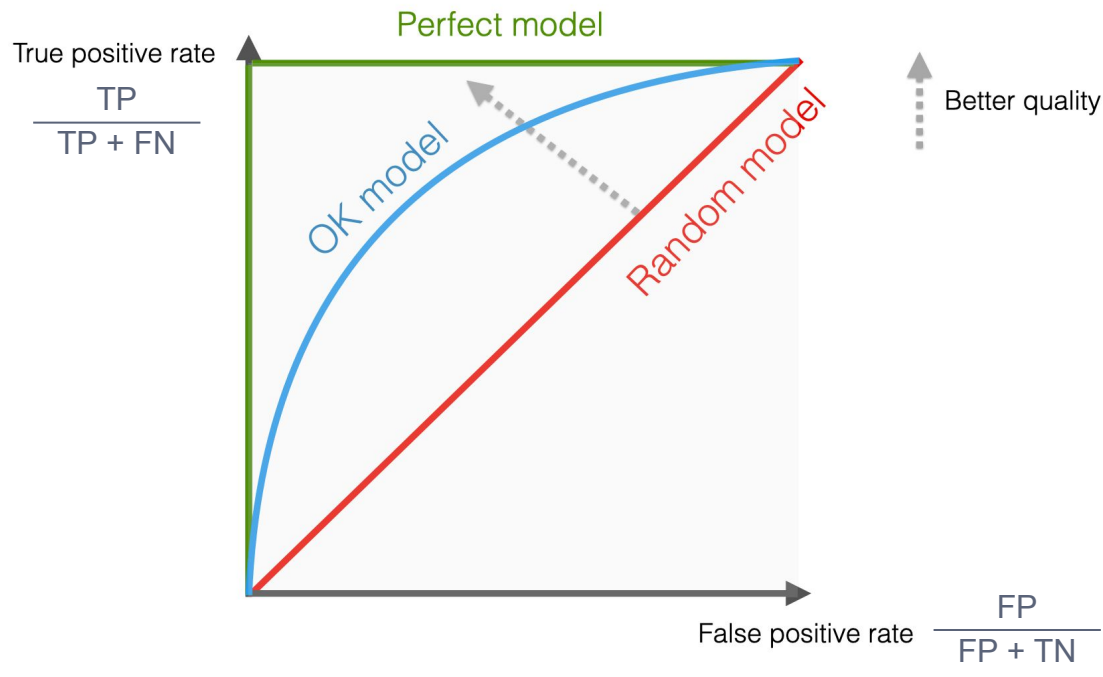
<b>Perfect model</b>	Predict hit	Predict no hit
ASMS hit	<b>100%</b>	<b>0%</b>
ASMS no hit	<b>0%</b>	<b>100%</b>

<b>Random model</b>	Predict hit	Predict no hit
ASMS hit	<b>50%</b>	<b>50%</b>
ASMS no hit	<b>50%</b>	<b>50%</b>

Row percentages 

# AUROC - area under receiver operating characteristic

	Predict hit	Predict no hit
ASMS hit	TP	FN
ASMS no hit	FP	TN



# AUPRC - area under precision recall curve

Asks: how hit-rich are my top ranked predictions? *Measures expected precision at all thresholds*

	Predict hit	Predict no hit
ASMS hit	TP	FN
ASMS no hit	FP	TN

$$\frac{TP}{TP + FN}$$

True positive rate aka recall

$$\frac{TP}{TP + FP}$$

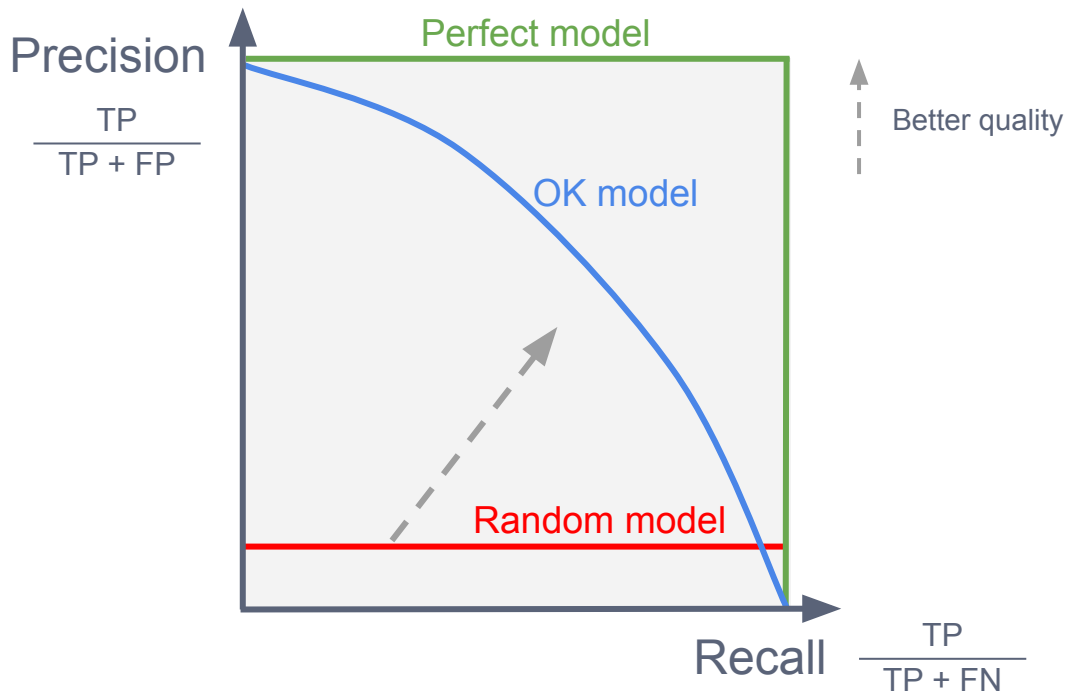
Precision

Interested in a row % and a column %

# AUPRC - area under precision recall curve

Asks: how hit-rich are my top ranked predictions? *Measures expected precision at all thresholds*

	Predict hit	Predict no hit
ASMS hit	TP	FN
ASMS no hit	FP	TN



We care most about the top ranked molecules *not necessarily performance at all thresholds*

**Predictions from model**

Molecule	Predicted probability
E	0.65
B	0.40
F	0.20
A	0.12
C	0.03
D	0.01

**Test labels from ASMS**

Molecule	ASMS Hit (ground truth)
A	1
B	1
C	0
D	1
E	1
F	0

Hits at 3 *How many TP are in top 3?*

Molecule	Predicted probability
E	0.65
B	0.40
F	0.20
A	0.12
C	0.03
D	0.01

Molecule	ASMS Hit (ground truth)
A	1
B	1
C	0
D	1
E	1
F	0



# Hits at 3 = 2

Molecule	Predicted probability
E	0.65
B	0.40
F	0.20
A	0.12
C	0.03
D	0.01



Molecule	ASMS Hit (ground truth)
A	1
B	1
C	0
D	1
E	1
F	0

Precision at 3 *what % of top 3 are TP?*

Molecule	Predicted probability
E	0.65
B	0.40
F	0.20
A	0.12
C	0.03
D	0.01

Molecule	ASMS Hit (ground truth)
A	1
B	1
C	0
D	1
E	1
F	0

Precision at 3 =  $2/3 = 0.66$

Molecule	Predicted probability	
E	0.65	✓
B	0.40	✓
F	0.20	✗
A	0.12	
C	0.03	
D	0.01	

Molecule	ASMS Hit (ground truth)
A	1
B	1
C	0
D	1
E	1
F	0

Recall at 3 *what % of TP are in the top 3?*

Molecule	Predicted probability
E	0.65
B	0.40
F	0.20
A	0.12
C	0.03
D	0.01

Molecule	ASMS Hit (ground truth)
A	1
B	1
C	0
D	1
E	1
F	0

Recall at 3 =  $2/4 = 0.5$

Molecule	Predicted probability	
E	0.65	✓
B	0.40	✓
F	0.20	
A	0.12	✗
C	0.03	
D	0.01	✗

Molecule	ASMS Hit (ground truth)
A	1
B	1
C	0
D	1
E	1
F	0

Why not threshold? It's too stringent  
Want to get credit for ranking B highly!

Molecule	Predicted probability	Pred proba >0.5	
E	0.65	1	✓
B	0.40	0	✗
F	0.20	0	
A	0.12	0	✗
C	0.03	0	
D	0.01	0	✗

Molecule	ASMS Hit (ground truth)
A	1
B	1
C	0
D	1
E	1
F	0

# Summary





- **AUROC** measures ranking ability at all thresholds
- **AUPRC** measures expected precision at all thresholds
- **Hits @ K** measures number of True Positives in top K
- **Precision @ K** measures percentage of top K which are True Positives
- **Recall @ K** measures percentage of True Positives which are in the top K

Drumrolls




# Leaderboard! (as of thursday night)

This leaderboard is calculated with approximately 30% of the test data. The final results will be based on the other 70%, so the final standings may be different.

#	Team	Members	Score	Entries	Last	Join
1	Oleksii Nakhod	 	0.93482	9	17h	
2	Walter Virany	 	0.91056	4	5h	


# Kaggle: Final Eval Metric has landed

 CROSSTALK AI FOR DRUG DISCOVERY · COMMUNITY PREDICTION COMPETITION · PRIVATE · 13 DAYS TO GO

CrossTalk\_round3

CrossTalk workshop @ UoT

Join Competition



Overview

Data

Code

Models

Discussion

Leaderboard

Rules

Overview

CrossTALK Bootcamp <https://datasciences.utoronto.ca/crosstalk-bootcamp/>


Build DEL-ML models to discover hits! An approach [first introduced in 2020](#).

A baseline model for this challenge was published by [Wellnitz et al](#) in 2024.

Out github repo is at: <https://github.com/rajaonsonella/crosstalk-uoft>

Goal: Use a machine learning model trained on the training set to predict the true positives in the test set.

Competition Host

CrossTalk AI for Drug Discovery 

Prizes & Awards

Kudos

Does not award Points or Medals

Participation

11 Entrants

4 Participants

2 Teams

13 Submissions

Tags

Custom Metric

Start

9 days ago

Close

13 days to go

“Penalized”  
Hits @ 200

Submission and Description

Private Score ⓘ

Public Score ⓘ

Benchmark ⓘ



random\_submission.csv

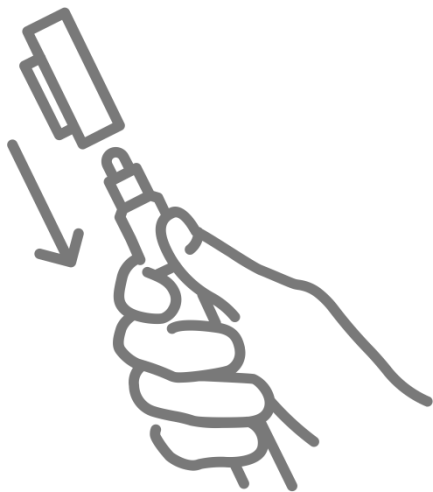
Complete · 2m ago

-50.00000

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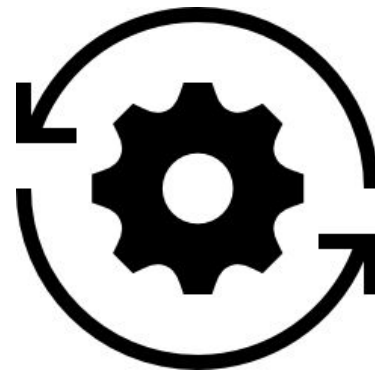
# Panorama



Recap



Metrics



Working sesh

## Some “ML tricks”

- XGboost Tricks / Feature engineering
- Ensembles are always better, many models and average predictions
- Uncertainties help to re-rank stuff
- Hyperparameter tuning
- “Balanced” / “Adversarial” splits
- Compute, get a 24GB RAM computer
- Internet / Reddit
  - r/MachineLearning
  - Kaggle forums ([example](#))

## Next sessions: TabPFN + Ranking

- TabPFN is a tabular foundation model
- Ranking is a “ordered” classification

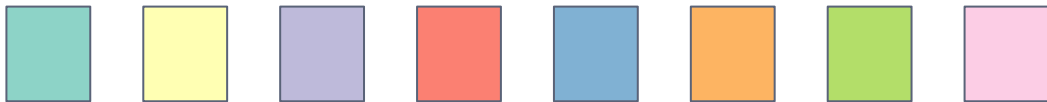
# For color palette

<https://colorbrewer2.org/#type=sequential&scheme=BuGn&n=3>

Dark2



Set3



Cividis (continuous)



PiYG (divergent)

