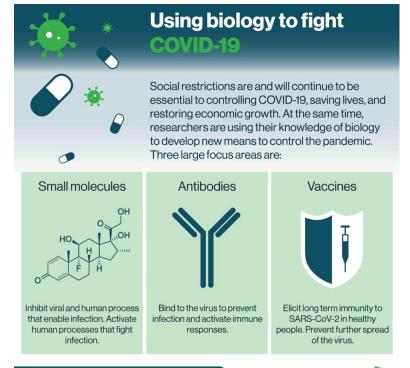
# In silico prediction for potential non-phospholipidosis-inducing inhibitors against in vitro replication of SARS-CoV-2

Junqi Lu, Anish Karpurapu

# Background

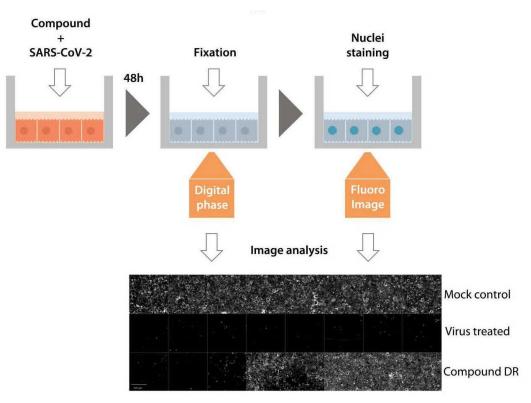
## Drug repurposing to mitigate COVID19 emergency

#### U.S. Deaths From Covid-19 **Match Toll Of Three Major Wars** U.S. Covid-19 deaths compared to the number of Americans who died in selected wars\* 500.193 500,310 Vietnam War 58,220 36,574 Korean War Covid-19 World War II 405,399 \* As of Feb 23, 2021. Sources: U.S. Department for Veteran Affairs, Johns Hopkins University statista 🔽

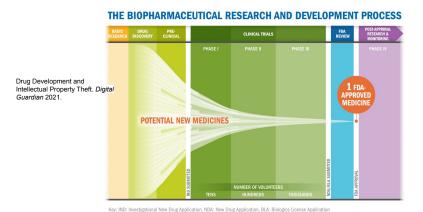


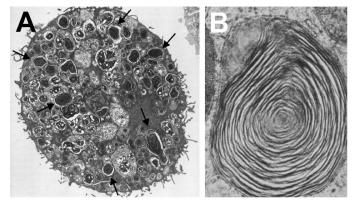
#### In vitro screening is standard for drug repurposing

- Ellinger at al screened 5632 compounds for their inhibition of SARS-CoV-2-induced cytotoxicity in Caco-2 cells
- Compounds tested at 10 μM (0.1% in DMSO)
- Inhibition of 75% as the potency cut-off
- 271 hits

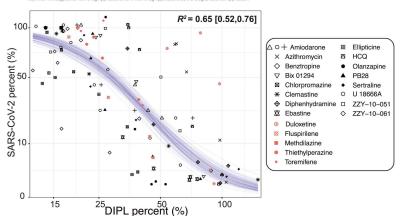


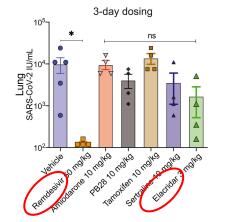
## Phospholipidosis: major confounding factor for in vivo translation





Breiden, Bernadette and Sandhoff, Konrad. "Emerging mechanisms of drug-induced phospholipidosis" Biological Chemistry, vol. 401, no. 1, 2020, pp. 31-46. https://doi.org/10.1515/hsz-2019-0270

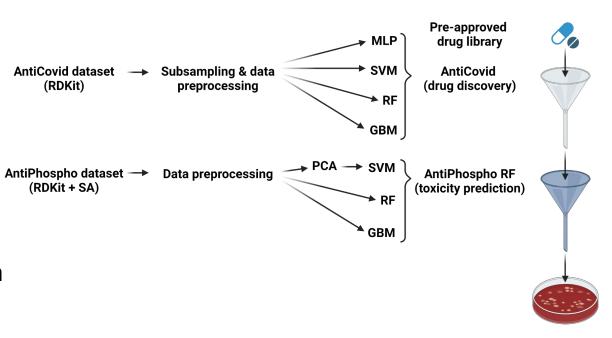




Tummino, T., Rezelj, V., Fischer, B., Fischer, A. et al., Drug-induced phospholipidosis confounds drug repurposing for SARS-CoV-2. Science 2021, 373, 541-547.

## Methodology

- 20% hold-out testing set
- 10× cross-validation
- Challenges
  - Small datasets
  - Class imbalance
- Baseline success:
  - Hold-out testing set
  - Adversarial controls
  - Compare to random model



# **COVID-19 Antiviral Model Training**

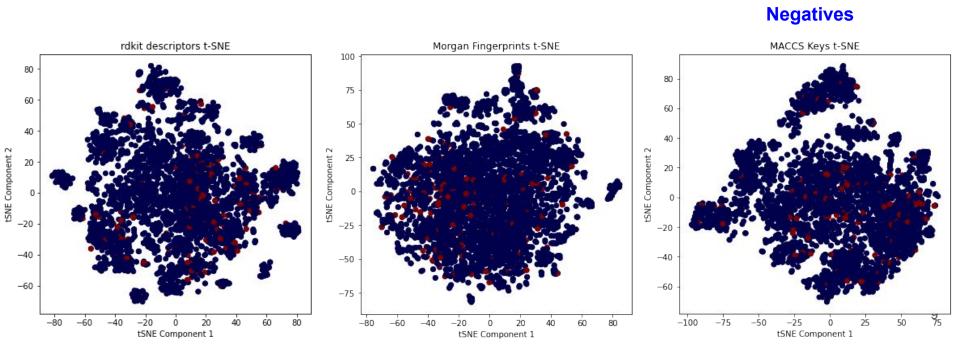
#### The joys of small datasets...

- Typical for wet lab data
- Urgent COVID19 situation



## AntiCOVID - exploratory data analysis

• 5632 compounds with 271 hits

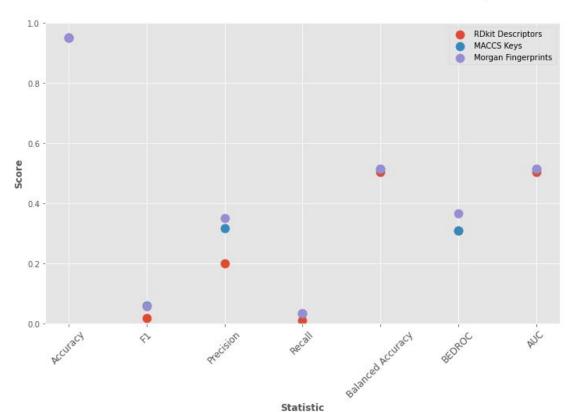


**Positives** 

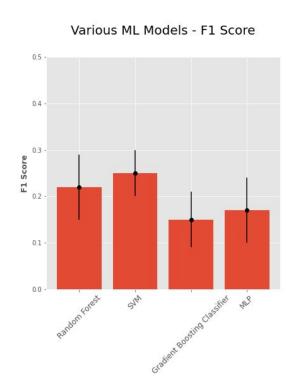
## AntiCOVID - descriptors used

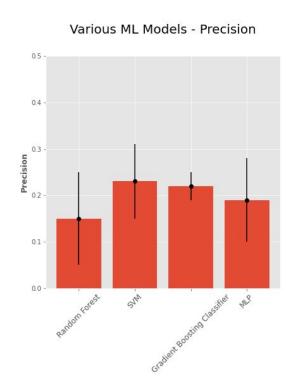
- Baseline Random Forest
- Focus on F1 score and Precision

#### Random Forest Metrics for Various Molecular Descriptors



## AntiCOVID - models performances with 95% CI





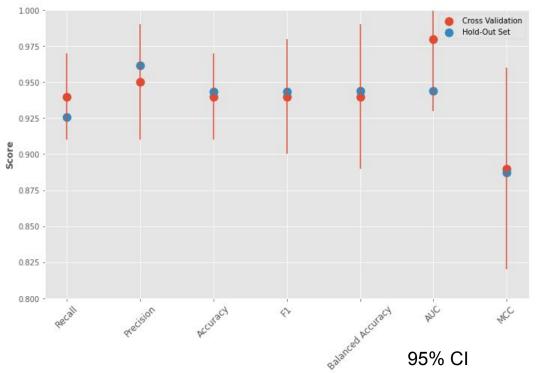
## AntiCOVID - balanced subsampled dataset

- Problem: imbalance dataset
- Our Solution: subsample the dataset
  - $\circ$  271/5632 hits  $\to$  271/542 hits
  - $\circ$  5%  $\rightarrow$  50%
- Keep hits and "randomly" sample 271 non-hits
  - "Random" → k-medoid on negatives where k = 271
  - Create new dataset

## AntiCOVID - balanced subsampled dataset

- RDKit descriptors
- Random Forest Grid Search
- Good results on cross validation and hold-out set

#### Random Forest Metrics on Curated Balanced Dataset



Statistic

#### AntiCOVID - adversarial control

y-shuffling

Accuracy: 0.5471698113207547

F1Score: 0.5471698113207548

Precision: 0.5576923076923077

Recall: 0.5370370370370371

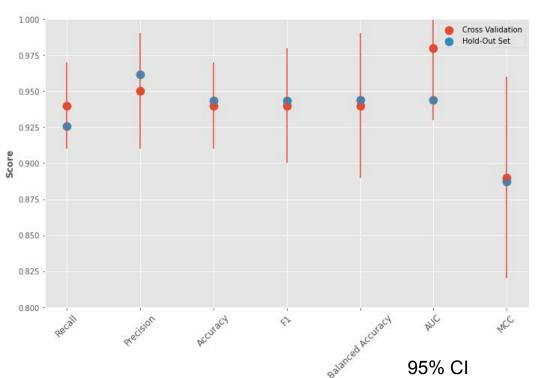
Balanced Accuracy Score: 0.547364

Matthews: 0.09472934472934473

AUC: 0.5473646723646725

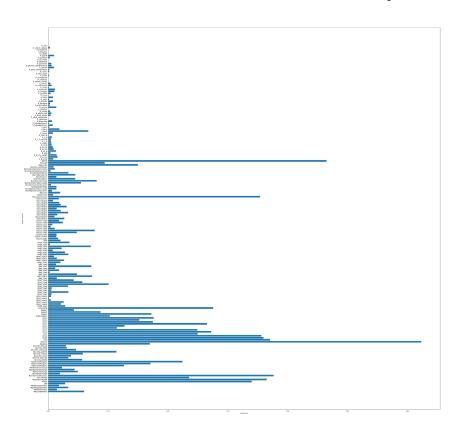
BEDROC: 0.5924550000647925

#### Random Forest Metrics on Curated Balanced Dataset

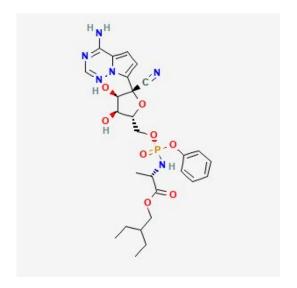


Statistic

## AntiCOVID - final RF model's feature importances

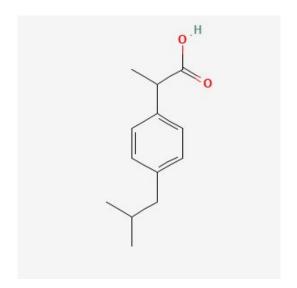


## AntiCOVID - test out compounds



#### Remdesivir

- → FDA-approved anti-COVID-19
- → predicted anti-COVID-19



#### Ibuprofen

- → exacerbate COVID-19 symptoms
- $\rightarrow$  predicted NOT anti-COVID-19

#### AntiCOVID - sanity check

Run model on whole dataset as well

#### Results on new balanced hold-out set

Accuracy: 0.9433962264150944 F1Score: 0.9433962264150944 Precision: 0.9615384615384616

Recall: 0.9259259259259

Balanced Accuracy Score: 0.943732193

Matthews: 0.8874643874643875

AUC: 0.9437321937321939 BEDROC: 0.999903717534156

#### Results on whole dataset

Accuracy: 0.27438687073575513

F1Score: 0.1187010078387458

Precision: 0.06315538608198284

Recall: 0.9851301115241635

Balanced Accuracy Score: 0.61121076783

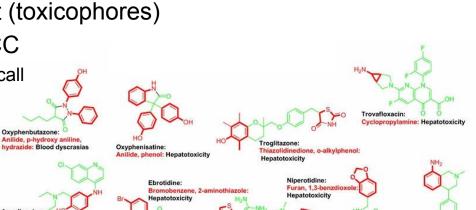
Matthews: 0.11542108722760078

AUC: 0.6112107678303783 BEDROC: 0.252245062588847

## Phospholipidosis Model Training

## AntiPhospho model training

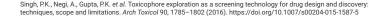
- Challenges: extremely tiny dataset (185 data points)
  - Tree-based models & SVM
  - RF, GBM, SVM (PCs explain 0.95 variances) → RF
- Descriptors: RDKit + Structural Alert (toxicophores)
- Metrics used: recall, ROC-AUC, MCC
  - Toxicity prediction model prefers high recall
- Additional success
  - Cherry picking unknown molecule test
  - Prediction on AntiCovid's dataset



p-hydroxy aniline: Hepatotoxicity

Blood dyscrasias

185 DATA POINTS



niline: Hepatotoxicity

#### AntiPhospho model performances

#### On 20% hold-out testing set

On	sh	uffled	featu	ıres
----	----	--------	-------	------

	Recall	AUC	MCC
svm	0.90	0.832353	0.674702
rf	0.90	0.832353	0.674702
gbm	0.85	0.836765	0.673529
meta rf	0.85	0.866176	0.730208

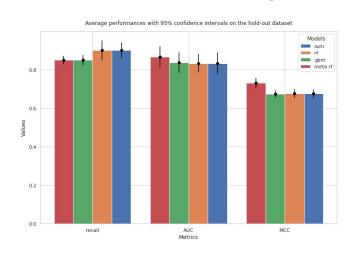
	Recall	AUC	MCC
svm	0.25	0.360294	-0.287115
rf	0.60	0.447059	-0.110531
gbm	0.80	0.547059	0.109323
meta rf	0.45	0.430882	-0.137831

#### Meta RF is kept as AntiPhospho

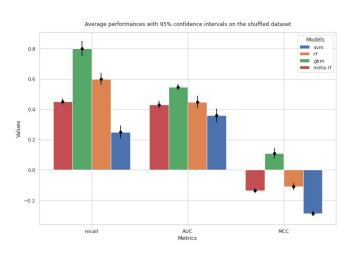
In literature: Meta Learner –RF, Base Learners (Best models +Second best models of GBM, RF, DLNNWOD, DLNNWD) has Recall as 0.86, AUC as 0.89, and MCC as 0.77

#### AntiPhospho model performances

#### On 20% hold-out testing set



#### On shuffled features

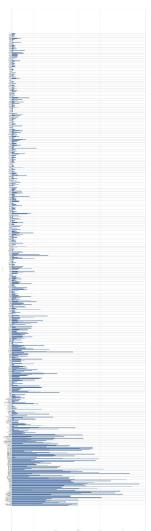


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# AntiPhospho base RF's feature importances

 Chi4n is the most important feature



#### Cherry picking test set of 3 new compounds

- Remdesivir: the only FDA-approved anti-SARS-CoV-2 drug; non-phospholipidosis-reducing
- Elacridar: an antiviral compound; non-phospholipidosis-reducing
- DLAD: my tested drug (next slide)

	0	1
Remdesivir	0.980198	0.019802
Elacridar	0.722772	0.277228
DLAD	0.831683	0.168317

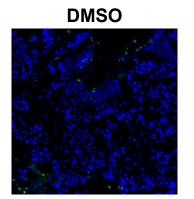
## DIY in vitro drug-test

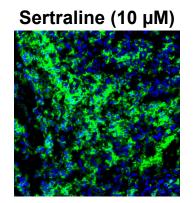
Potential Utility of Synthetic D-Lactate Polymers in Skin Cancer

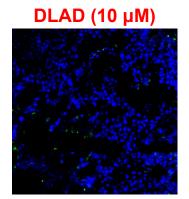
Anushka Dikshit ∗ Junqi Lu ∗ Amy E. Ford ⋄ ... Georgia Beasley • David Gooden • Jennifer Y. Zhang 🌣 🖾 • Show all authors

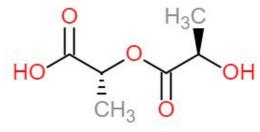
Open Access • Published: July 29, 2021 • DOI: https://doi.org/10.1016/j.xjidi.2021.100043 •

- Cherry-picking rationale:
  - 2-(2-hydroxy-1-oxopropoxy)propionic acid (DLAD) prohibits skin cancer progression by pushing cellular metabolism profile from anaerobic to aerobic respiration
  - Normal cells prefer aerobic [generate more energy per glucose], while cancer cells and virus-infected cells prefer anaerobic [generate energy faster]
- 83% sure non-phospholipidosis-inducing
- In vitro results: non-phospholipidosis-inducing









DAPI LAMP-2

## 34% SARS-CoV-2 positives are phospholipidosis-inducing

 AntiPhospho predicted 34% of the active anti-SARS-CoV-2 molecules from the in vitro screening to be phospholipidosis-inducing

	Classes	Counts
0	0	178
1	1	92



## 37% AntiCovid's predictions are phospholipidosis-inducing

 AntiPhospho predicted 37% of the AntiCovid's positive predictions to be phospholipidosis-inducing

	Classes	Counts
0	0	34
1	1	20



#### Summary

- AntiCOVID has great performance on the subsampled dataset, but not overall
- AntiPhospho has great performance overall with way simpler structure
- K-medoids strategy to undersample imbalanced dataset
- Meta learner with simple base learners to boost performance
- Performance validated by hold-out testing set, adversarial control, orthogonal data, and biological mechanism logics
- Limitation of machine learning: correlation ≠ causation

## Thank you!

Instructor: Daniel Reker, PhD

TAs: Roujia Wang, Zilu Zhang



