

26/01/2021

treated with tunicamycin. Nuclei in magenta, and PDI in green.



Al in early drug discovery group in J&J







Maciej Kańduła







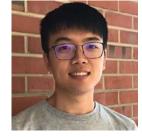


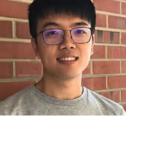
Oscar Mendez Lucio



















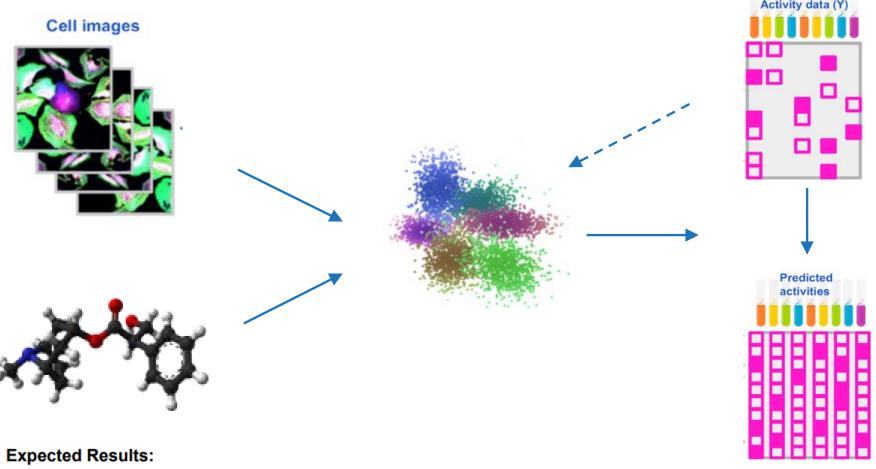








Can we learn joint representation for molecules from chemical structures and their image phenotype?





Dr Gunter Klambauer ULinz



Maciej Kańduła



Thanh Le Van

- 1. Deep learning models that can learn a single representation for molecules from their low-level chemical structures such as ECFP features, SMILES strings or molecule graphs, and the corresponding microscopy images.
- 2. Applications demonstrated the advantages of the new representation in a number of domains, including but not limited to a) multi-task learning to predict activity responses of molecules in a number of assays or protein targets; b) tox prediction; c) few-shot learning and domain adaptation to quickly adapt the learned model to a new domain, where only unlabelled data are available and only a small number of images are generated from different cell lines.
- Pluggable module with the models developed for One-Chemistry model in collaboration with ESR1 and ESR2.
- Experimental validation of the models within the research project of ESR16.



Can we integrate microscopy images from different sources to inform compounds design?

■ BROAD IMAGING JUMP-Cell Painting Joint Undertaking for Morphological Profiling Extracted features Goals Public Cell Painting dataset funded by MLSC Data will be public 1 year after the end of JUMP-CP project AMGEN compound Create a community AstraZeneca 2 compound Develop best practices compound Biogen compounds Align public data set and janssen T compound future partner-produced data MERCK compound Selected compounds to test Takeda compound Decided on compound-exchange Eisai compounds logistics compounds







Oscar Mendez Lucio

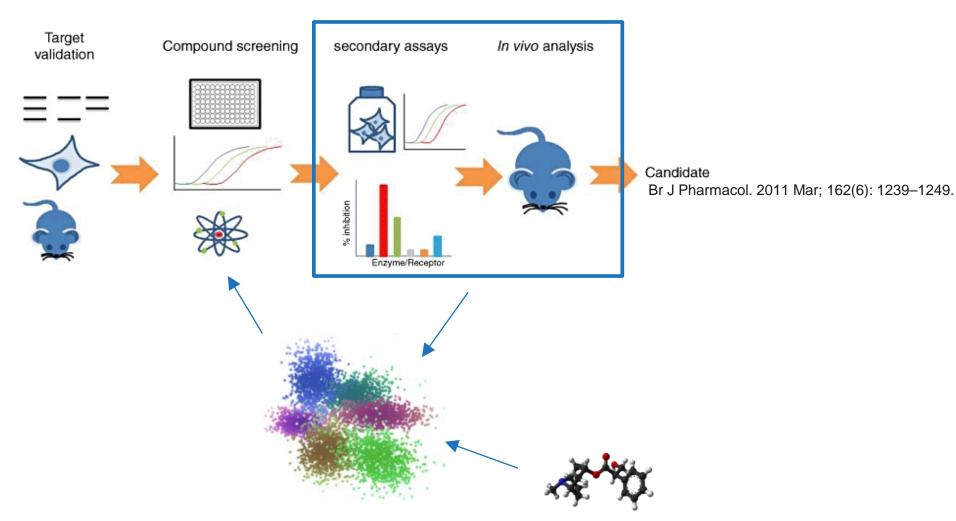
Steffen Jaensch

Expected Results:

- 1. Developed methodology to integrate various microscopy datasets from different experimental settings.
- 2. Publicly available source code for the pipeline for feature extraction from microscopy images using deep learning.
- 3. Publicly available predictive models and interpretability framework that associates observed morphological changes with predicted biological activity and structural motifs of the small molecules.
 - Pluggable module for One-Chemistry model in collaboration with ESR1 and ESR2.



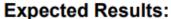
Can we bring information from preclinical studies to early drug development?





Prof. Samuel Kaski UAalto

Discovery Sciences (DS)



- Developed methodology for interpretability of the molecular space through decomposable representations coupled with intuitive explanations.
- Incorporation of the methodology into One-Chemistry model in collaboration with ESR1 and ESR2.
- Integration of multiple assays with improved in vivo prediction performance.
- Experimental validation of the technique in ESR16's research project.

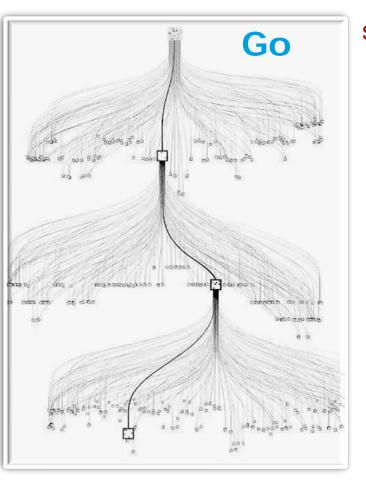


Can we predict single-step synthesis?

product

retrosynthesis

building block

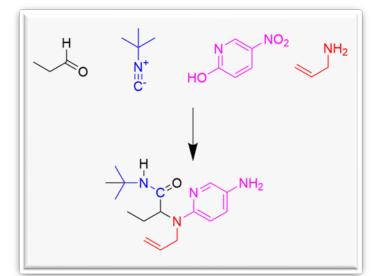


scaffold

synthesis

forward

active compound



Nature 550, 354-359 (19 October 2017)



Dr. Igor Tetko **HMGU**



Expected Results:

- Publicly available software for predicting the most likely reactions for synthesis of a target compound including reactants, reagents, conditions of a suggested reaction.
- Interpretation techniques to clarify why the model chooses a particular path.
- Pluggable module into One-chemistry model in collaboration with ESR1 and ESR2.



Can we learn representation for reactivity?

Reference QM data



Deep Tensor Neural Network



Output

- Energetics
- Transition state geometry
- QM descriptor set



Evaluation



Prof. Alexandre Tkatchenko ULUX

Discovery Sciences (DS)

Expected Results:

- Publicly available robust an extensive quantum chemistry dataset of transition state geometries and energies, generated in a standardized and reproducible manner, suitable for machine learning purposes.
- 2. Publicly available model trained on this dataset that is capable of predicting transition state geometries and energies, enabling such predictions at a fraction of the current cost, both in terms of computational expense and time required.
- Pluggable model for One-Chemistry model in collaborations with ESR1 and ESR2.



