
Modelling drug combinations for cancer

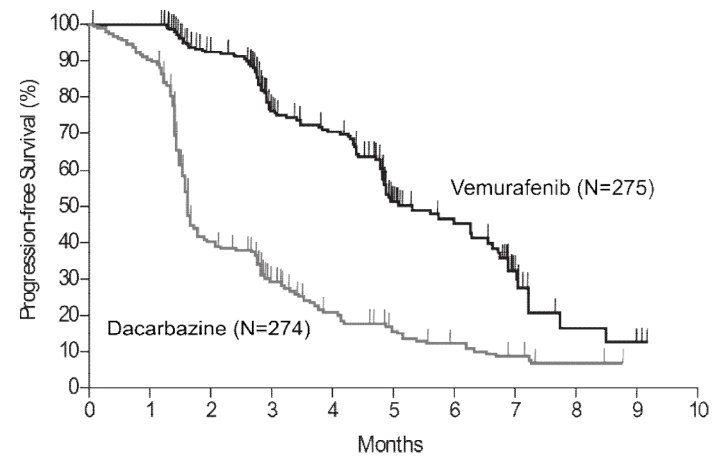
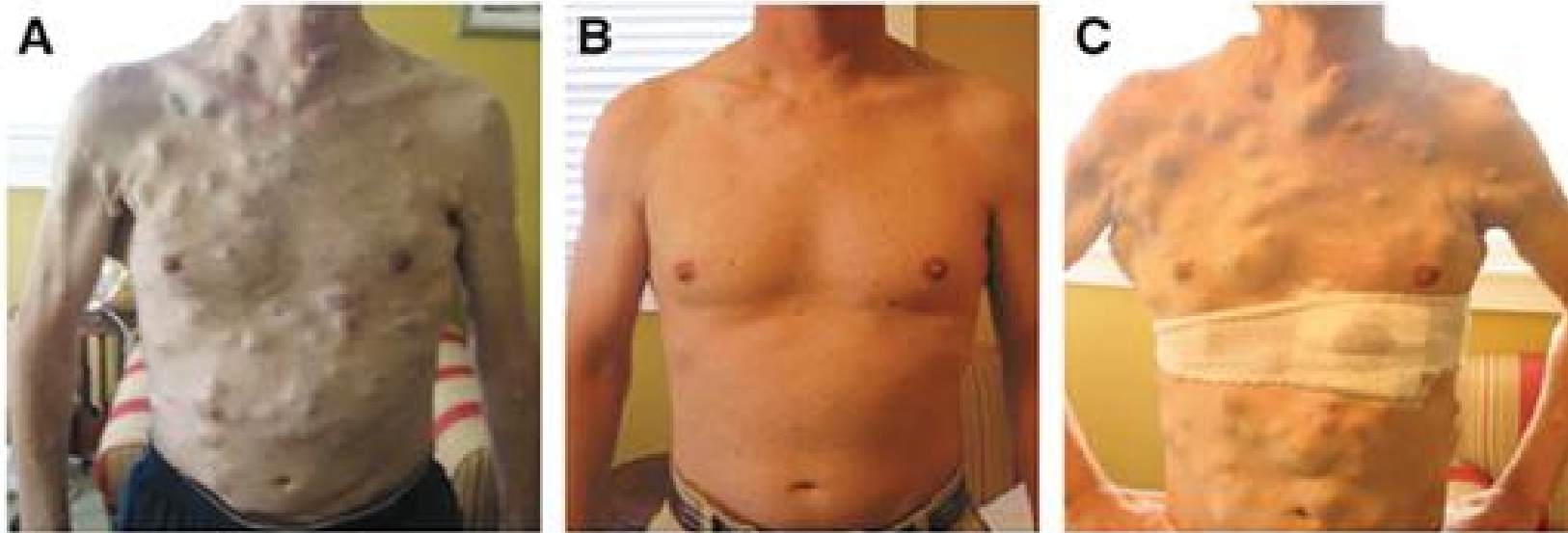
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Fighting cancer



Two Drugs Are Better than One—Modeling Drug Combinations in Cancer Therapy

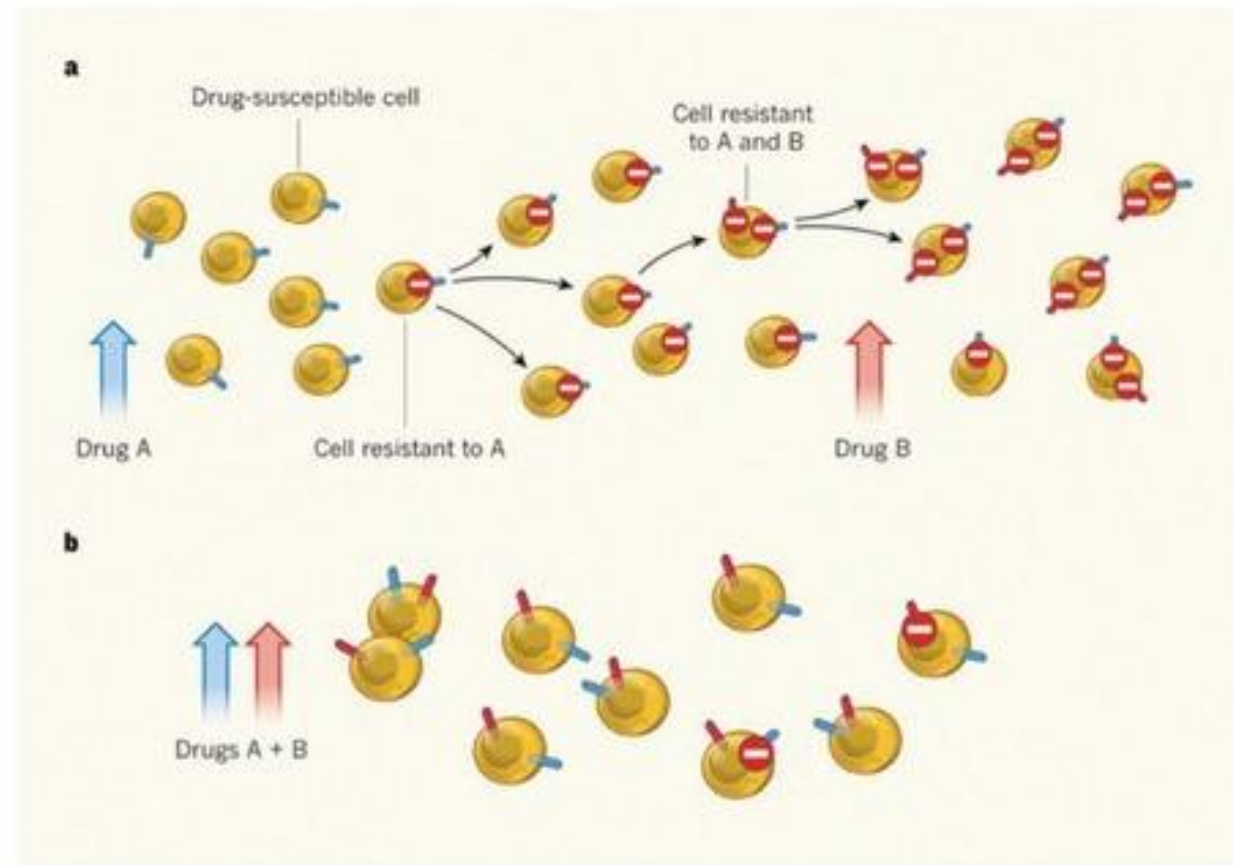
Margaret K. Callahan

+ Author Affiliations

Science Translational Medicine 17 Jul 2013;
Vol. 5, Issue 194, pp. 194ec116
DOI: 10.1126/scitranslmed.3006923

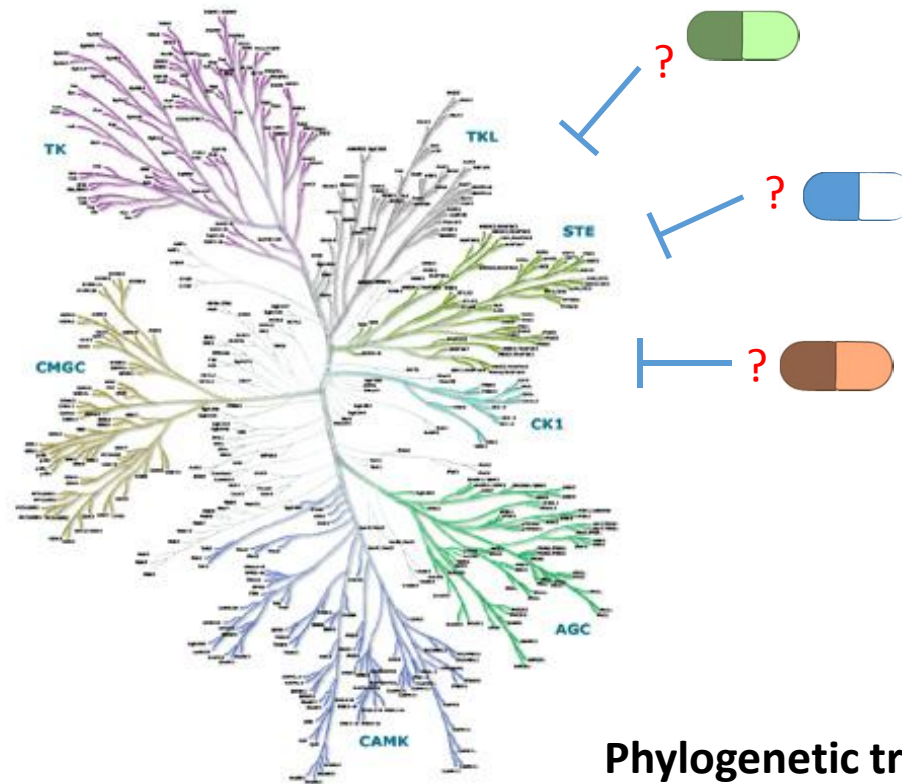
+ Maximize cancer selectivity

- Minimize drug resistance



Needs for predictive and testable models

- If it is necessary to inhibit multiple targets, how do we choose/predict which ones?



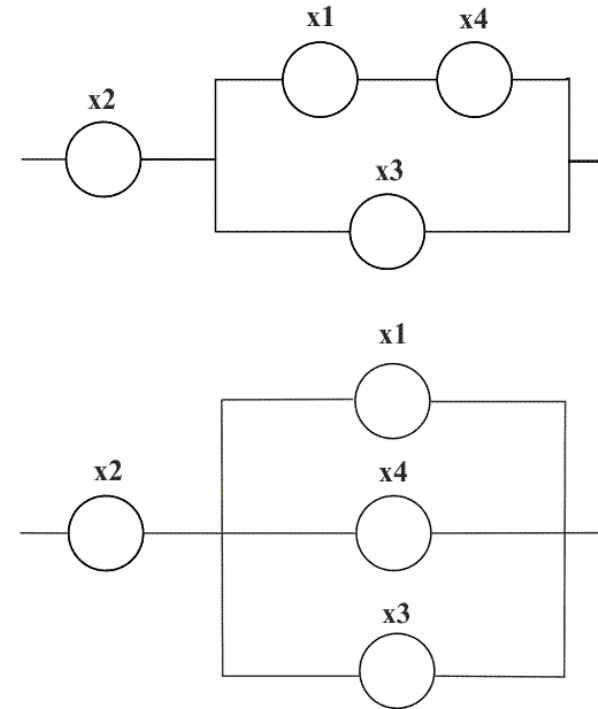
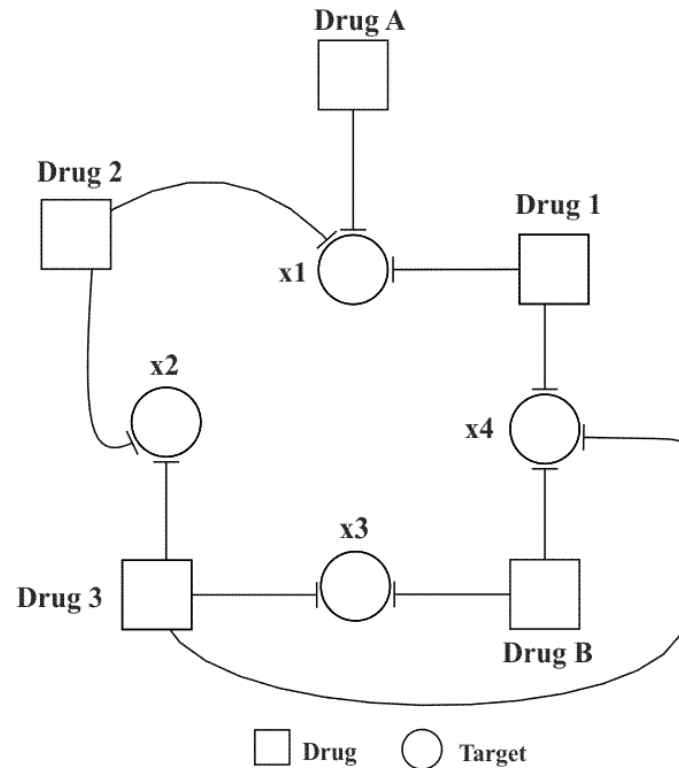
Phylogenetic tree of the human kinome

<http://www.cellsignal.com>

The research questions

- If drug A kills 30% of the cancer cells and drug B kills 20%, can we answer the following questions:
 - 1) What is the effect if drug A and B are **combined**?
 - 2) Whether such a combinatorial effect is **beneficial** compared to monotherapies?
 - 3) How to evaluate the statistical and therapeutic **significances**?
-

Target inhibition network approach



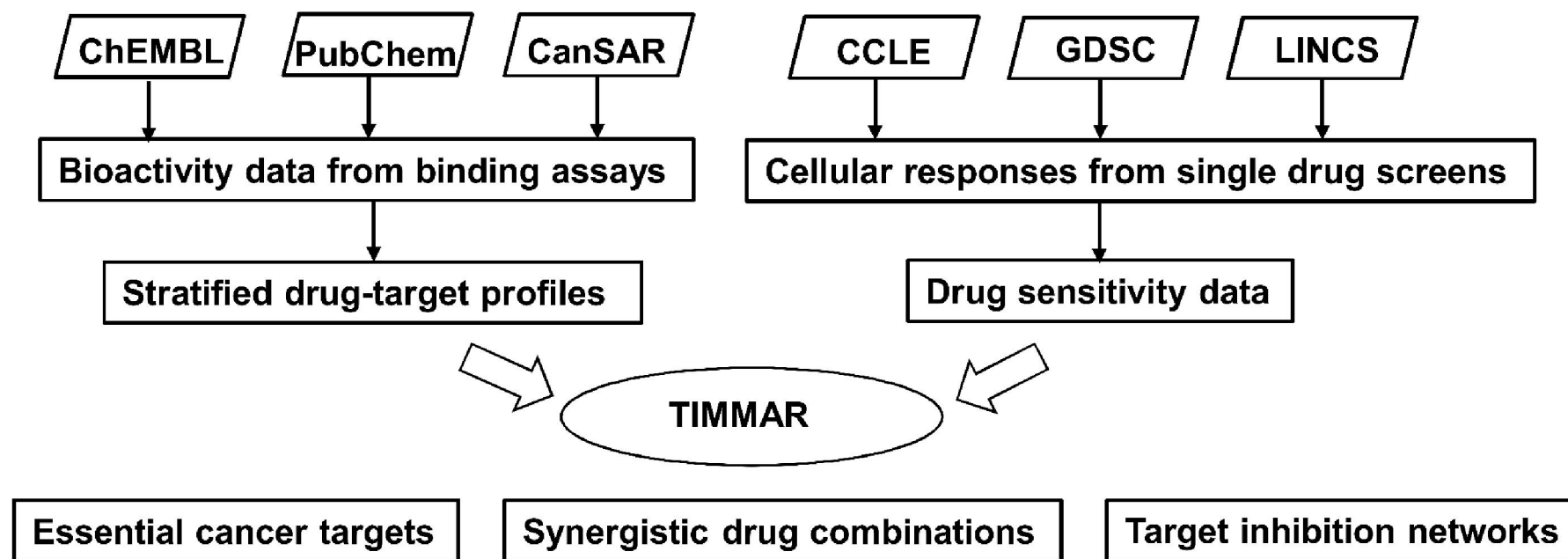
Drug target network + Drug sensitivity data = Target inhibition network

Assumption: A drug combination can be inferred from their target combinations

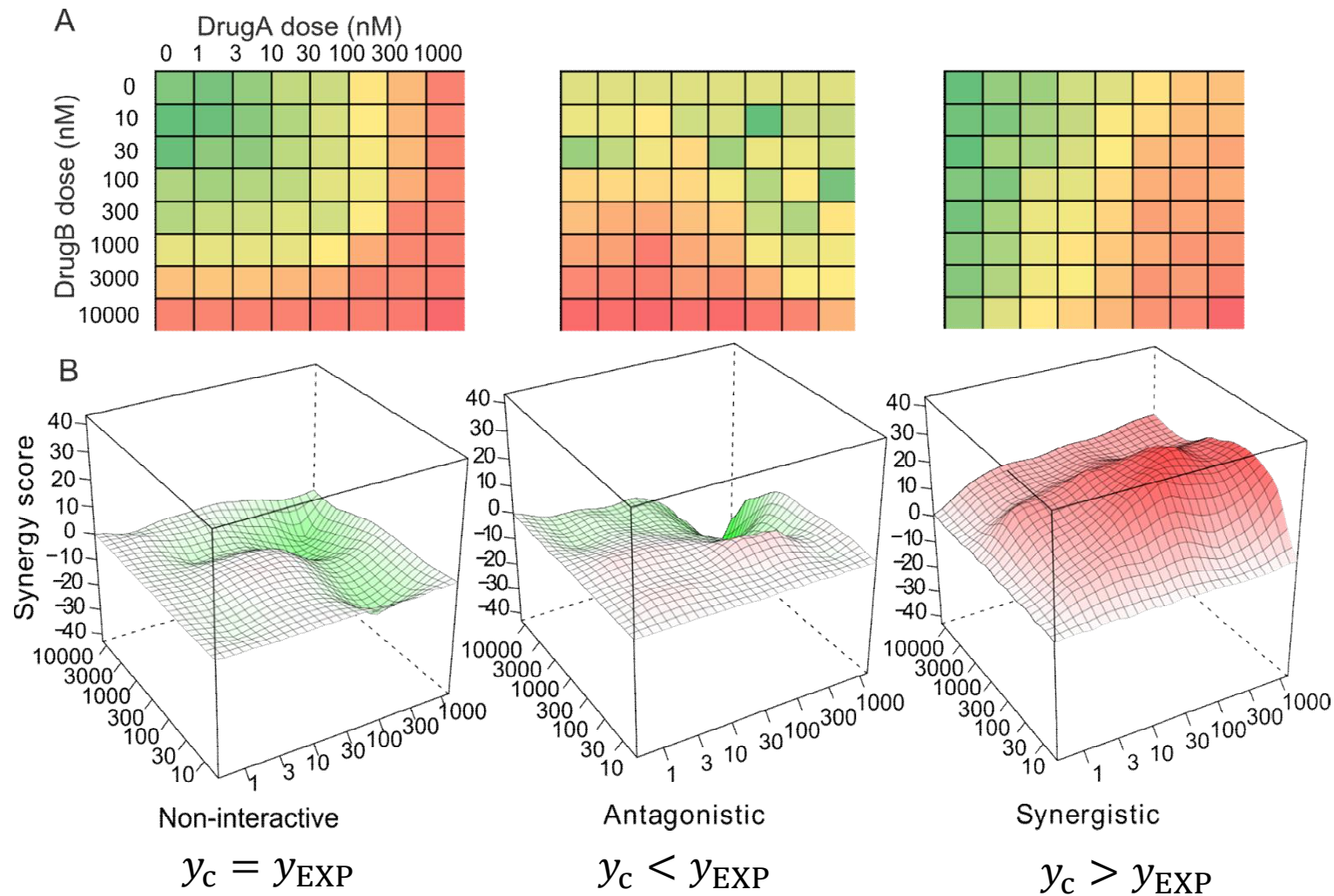
Pal and Berlow, 2012, Pacific Symposium on biocomputing, 351-362

Tang et al. PLoS Comput Biol 2013; 9(9): e1003226.

TIMMA @R



Test of drug combinations



Test of drug combinations

Reference models

- Highest single agency
- Bliss independence

$$y_{\text{HSA}} = \max(y_1, y_2)$$

$$y_{\text{BLISS}} = y_1 + y_2 - y_1 y_2.$$

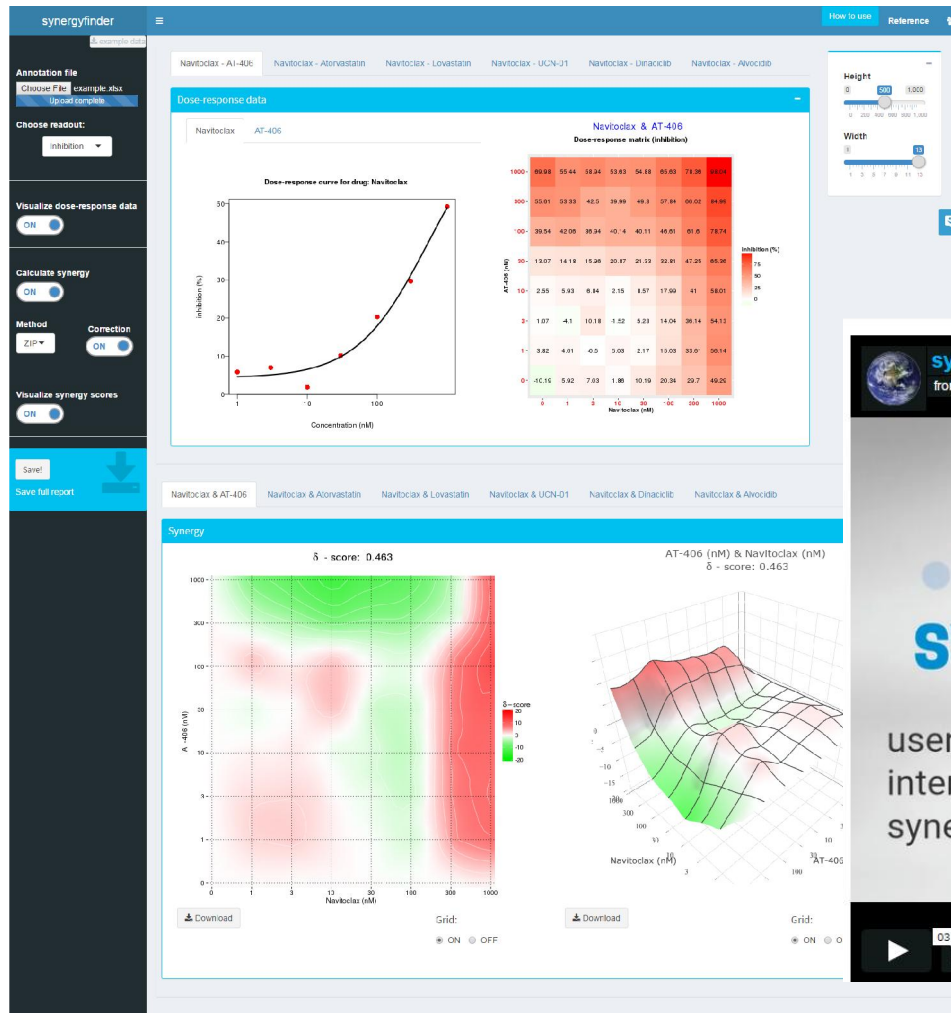
- Loewe additivity

$$\frac{x_1}{X_{\text{LOEWE}}^1} + \frac{x_2}{X_{\text{LOEWE}}^2} = 1,$$

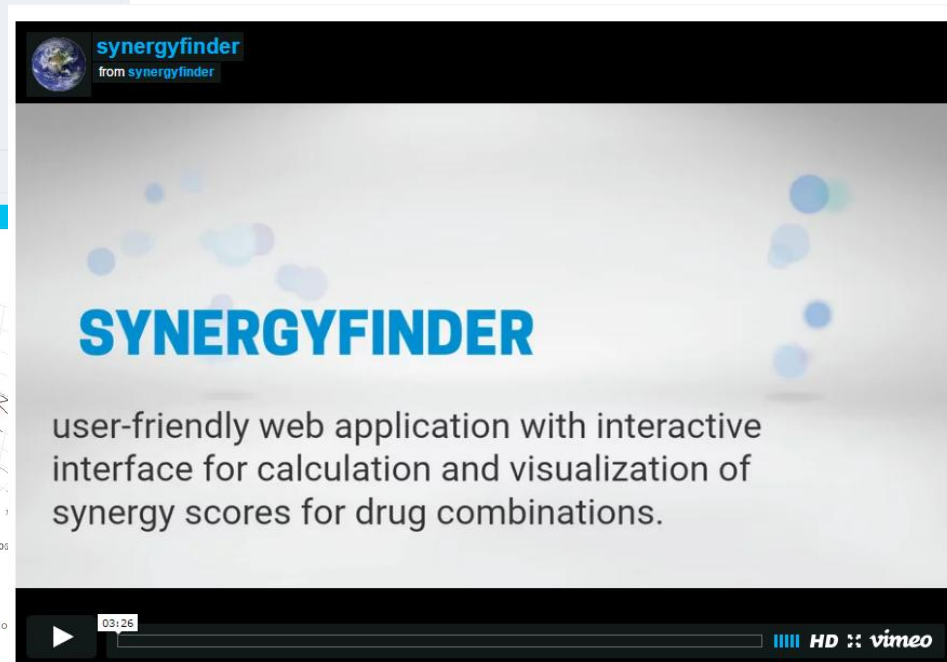
- Zero interaction potency

$$\delta(\theta) = \frac{1}{2} \left(\frac{\frac{1}{1 + \left(\frac{m_2}{x_2}\right)^{\lambda_2}} + \left(\frac{x_1}{m_{2 \rightarrow 1}}\right)^{\lambda_{2 \rightarrow 1}}}{1 + \left(\frac{x_1}{m_{2 \rightarrow 1}}\right)^{\lambda_{2 \rightarrow 1}}} + \frac{\frac{1}{1 + \left(\frac{m_1}{x_1}\right)^{\lambda_1}} + \left(\frac{x_2}{m_{1 \rightarrow 2}}\right)^{\lambda_{1 \rightarrow 2}}}{1 + \left(\frac{x_2}{m_{1 \rightarrow 2}}\right)^{\lambda_{1 \rightarrow 2}}} \right) - \left(\frac{\left(\frac{x_1}{m_1}\right)^{\lambda_1}}{1 + \left(\frac{x_1}{m_1}\right)^{\lambda_1}} + \frac{\left(\frac{x_2}{m_2}\right)^{\lambda_2}}{1 + \left(\frac{x_2}{m_2}\right)^{\lambda_2}} - \frac{\left(\frac{x_1}{m_1}\right)^{\lambda_1}}{1 + \left(\frac{x_1}{m_1}\right)^{\lambda_1}} \frac{\left(\frac{x_2}{m_2}\right)^{\lambda_2}}{1 + \left(\frac{x_2}{m_2}\right)^{\lambda_2}} \right),$$

SynergyFinder @Bioconductor @web

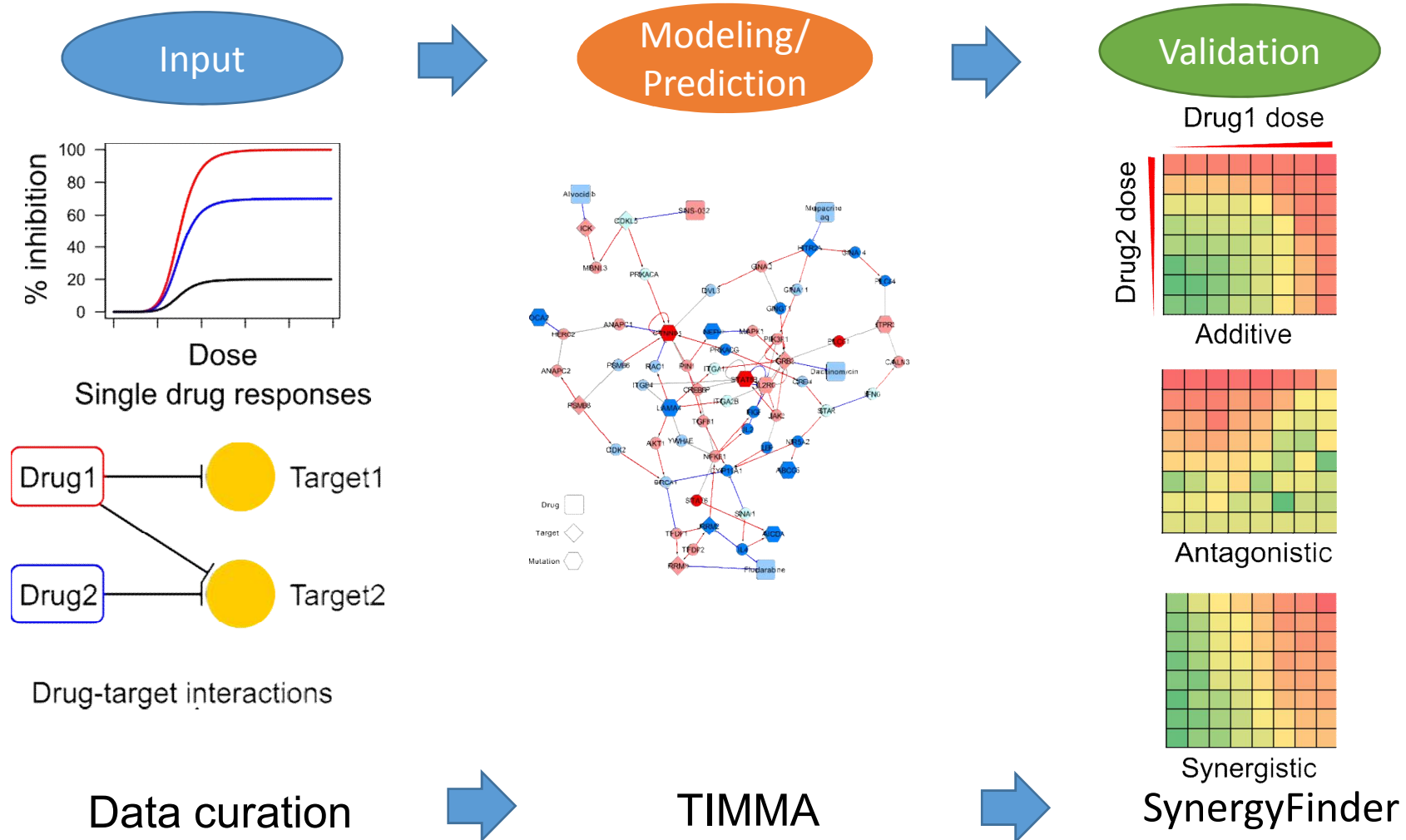


<https://synergyfinder.fimm.fi>



Ianevski et al. Bioinformatics, 2017, 33, 2413-2415

The drug combination prediction pipeline



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