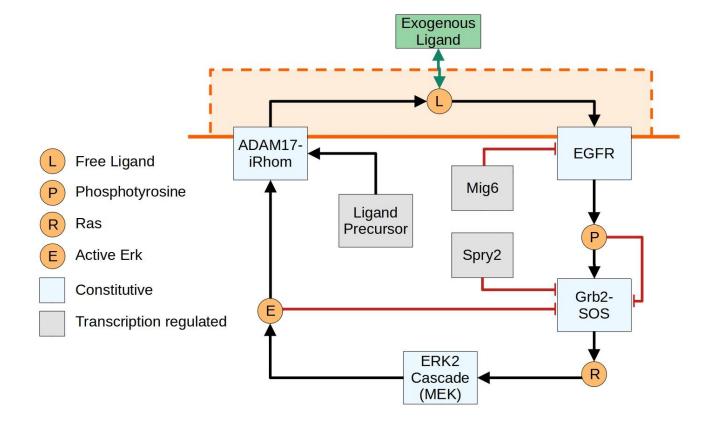
Modeling the EGF Pathway: Challenges and Pitfalls

Michael Kochen
2022 CSBC West Coast Symposium

Coarse-grained modeling

- Granularity in line with quantitative data
- Facilitate ease of interpretation
- Expand as warranted
- EGF model ->

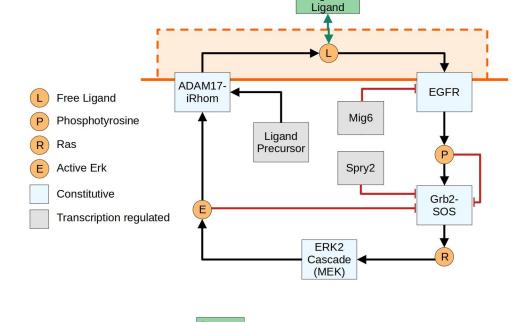


EGFR rate equation

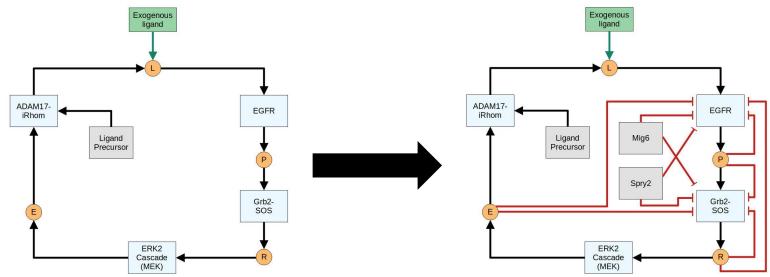
$$\left(\frac{1}{\left(1+\frac{Mig6}{k_i}\right)}\right)^w \frac{k_s \left(\frac{L}{k_s^m}\right)^{m_s}}{\left(1+\frac{L}{k_s^m}\right)^{m_s}} - \frac{k_p \left(\frac{P}{k_p^m}\right)^{m_p}}{\left(1+\frac{P}{k_p^m}\right)^{m_p}}$$

Ensemble modeling

- True model is always unknown
- Ensemble of plausible models
- Approach
 - Generate variants (1024)
 - Collect best scoring models

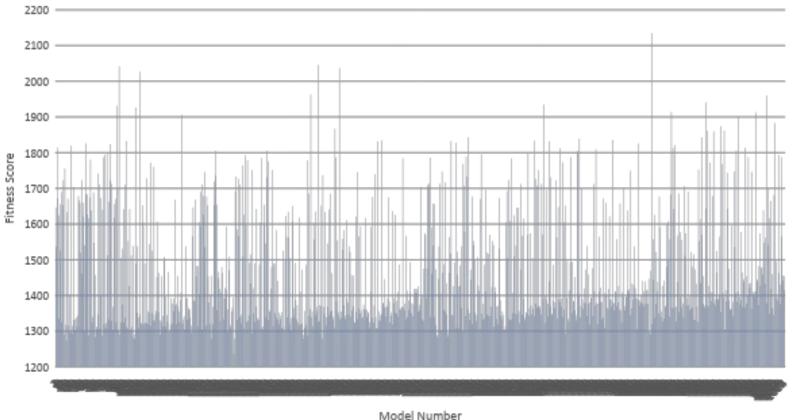


Exogenous



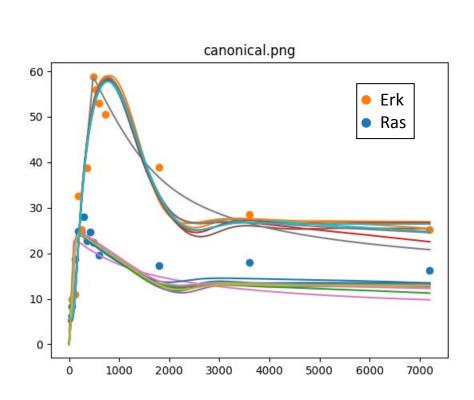
Fitness scores: Best of 10 for each model

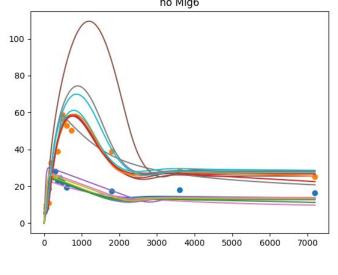
- 1024 models
- 10 runs per model
- ~ 7h per model
- BlackBoxOptim + Roadrunner
- EMSL (PNNL) Tahoma cluster

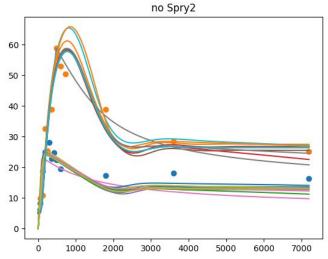


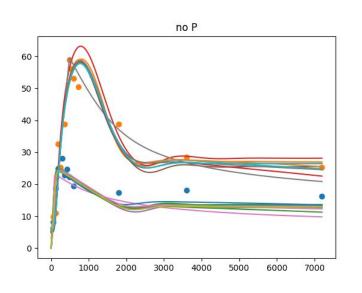
Exogenous Ligand ADAM17-**EGFR** Free Ligand iRhom Mig6 Phosphotyrosine Ligand Ras Precursor Active Erk Spry2 Constitutive Grb2-SOS Transcription regulated ERK2 Cascade (MEK)

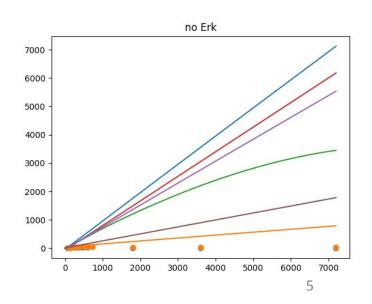
Effects from removing regulatory edges No Mig6 No Spry2





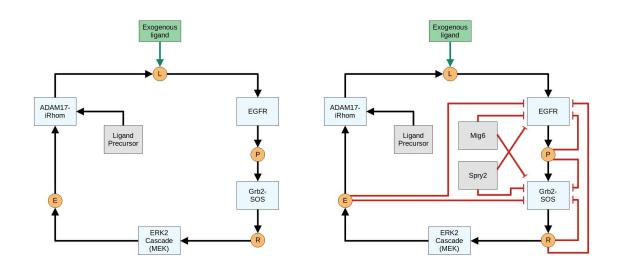


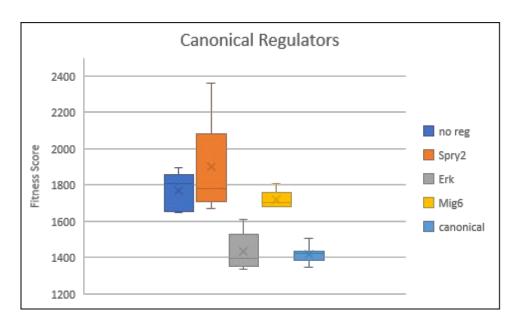


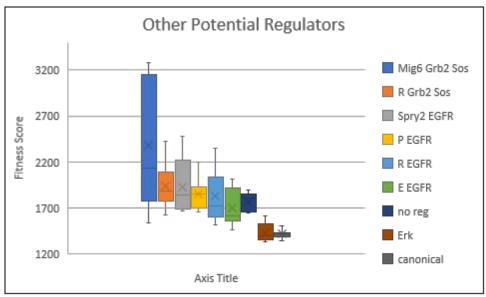


Single regulator models

Does any single regulatory interaction make a difference?

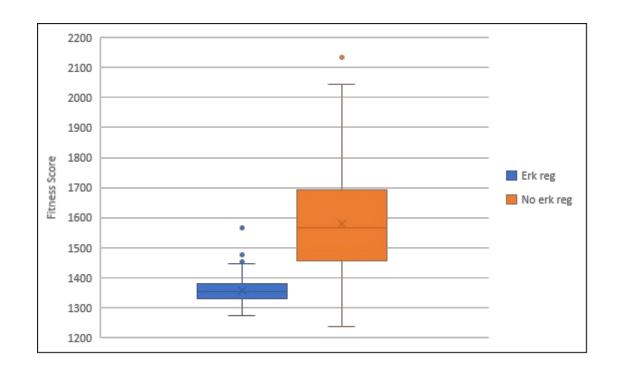






Erk regulation of Grb2-Sos: present vs absent

- 1024 models: best of 10
- Two groups
- Erk models have the clear advantage
- Still possible to design a model without Erk regulation of Grb2-Sos that outperforms



Conclusions and Implications

- Erk inhibition on Grb2-Sos is clearly important.
- Little effect from other rewirings (with a few exceptions).
- Implications for more complicated models.
 - Lower data to complexity ratio.
 - Potentially many model variants may fit.
 - Many implausible models may also fit.
- How much confidence should you really have in your model?
- What kind of data and how much does it take to correctly constrain model topology?

SBbadger

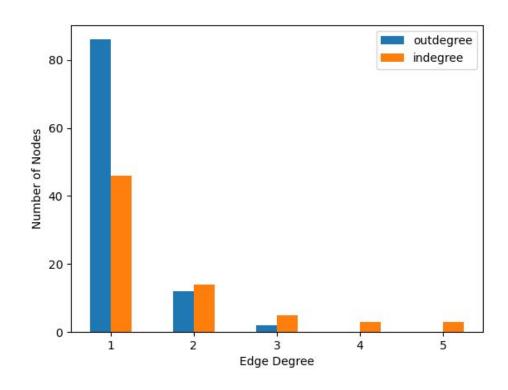
- Python package for the generation of synthetic reaction networks
 - pip install sbbadger
 - https://github.com/sys-bio/SBbadger
 - https://arxiv.org/abs/2202.13004
- Definable Properties
 - Degree distributions
 - Reaction types
 - Size
 - Reaction kinetics
 - Mass action
 - Lin-log
 - Generalized Michaelis-Menten
 - Modular (Liebermeister)

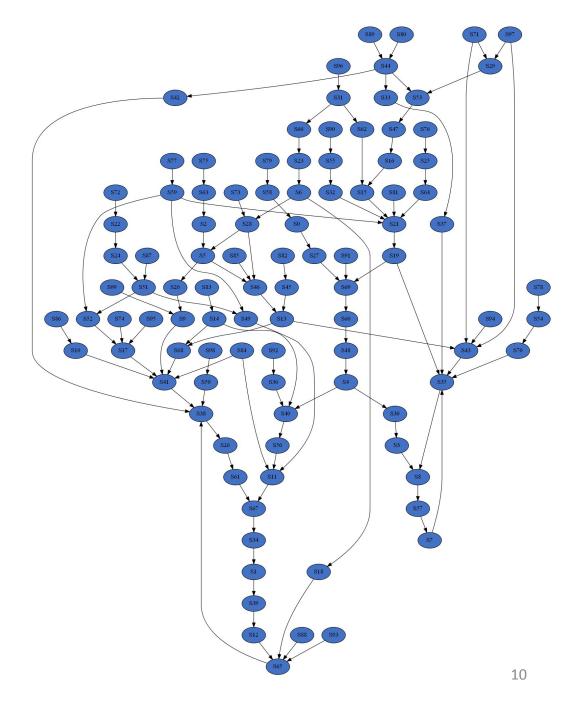
in/out degree distributions

Power law: $\frac{k^{-\alpha}}{zeta(a)}$

• Outdegree: $\alpha = 3$

• Indegree: $\alpha = 2$





Going forward

- Generate mechanistic benchmark models with properties typically seen in the literature and use them to evaluate and develop model inference algorithms.
- Example: various implementations of Sparse Identification of Nonlinear Dynamics (SINDy).
- Gauge the required amount, type, and placement of data for accurate model reconstruction.

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