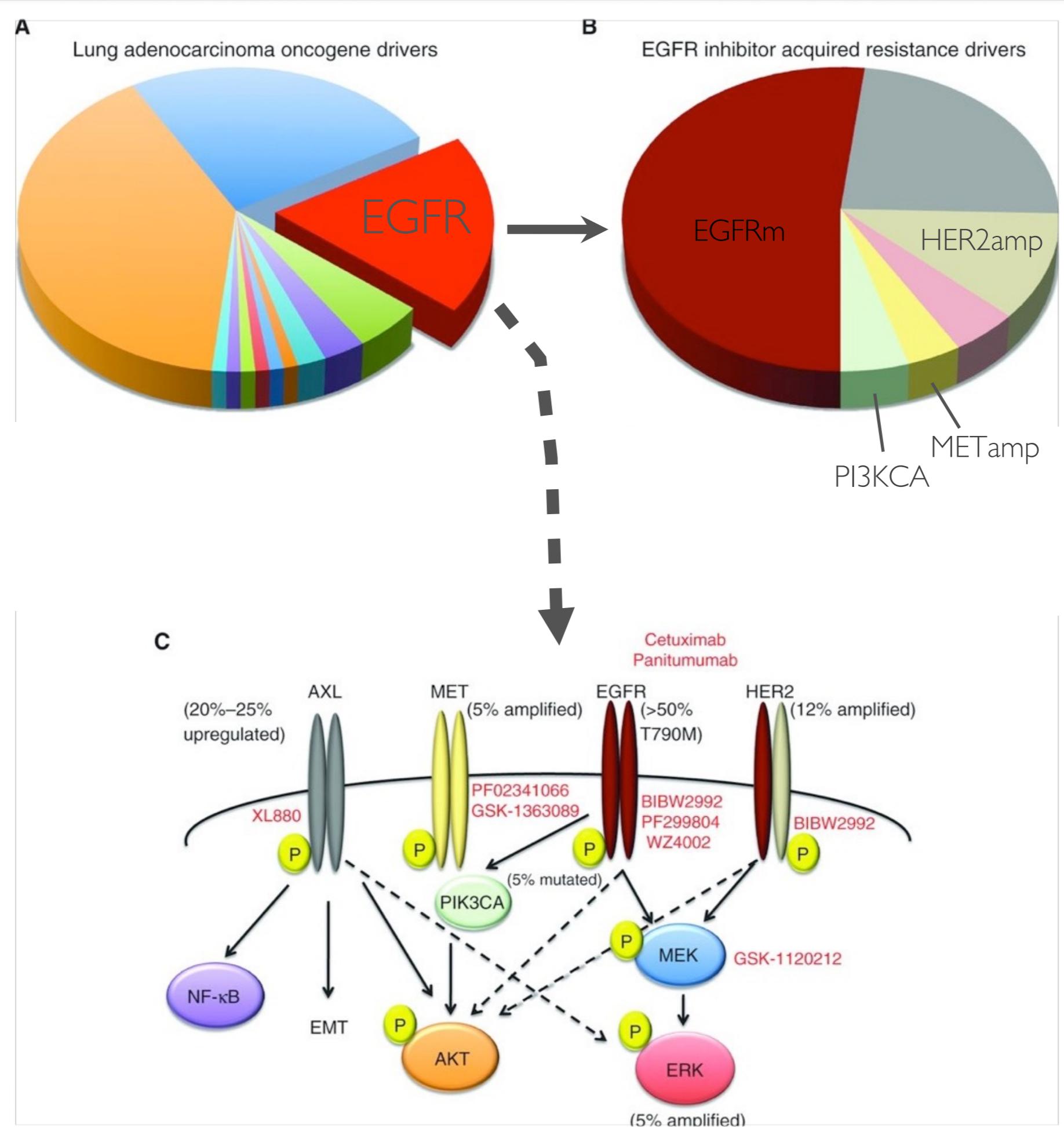


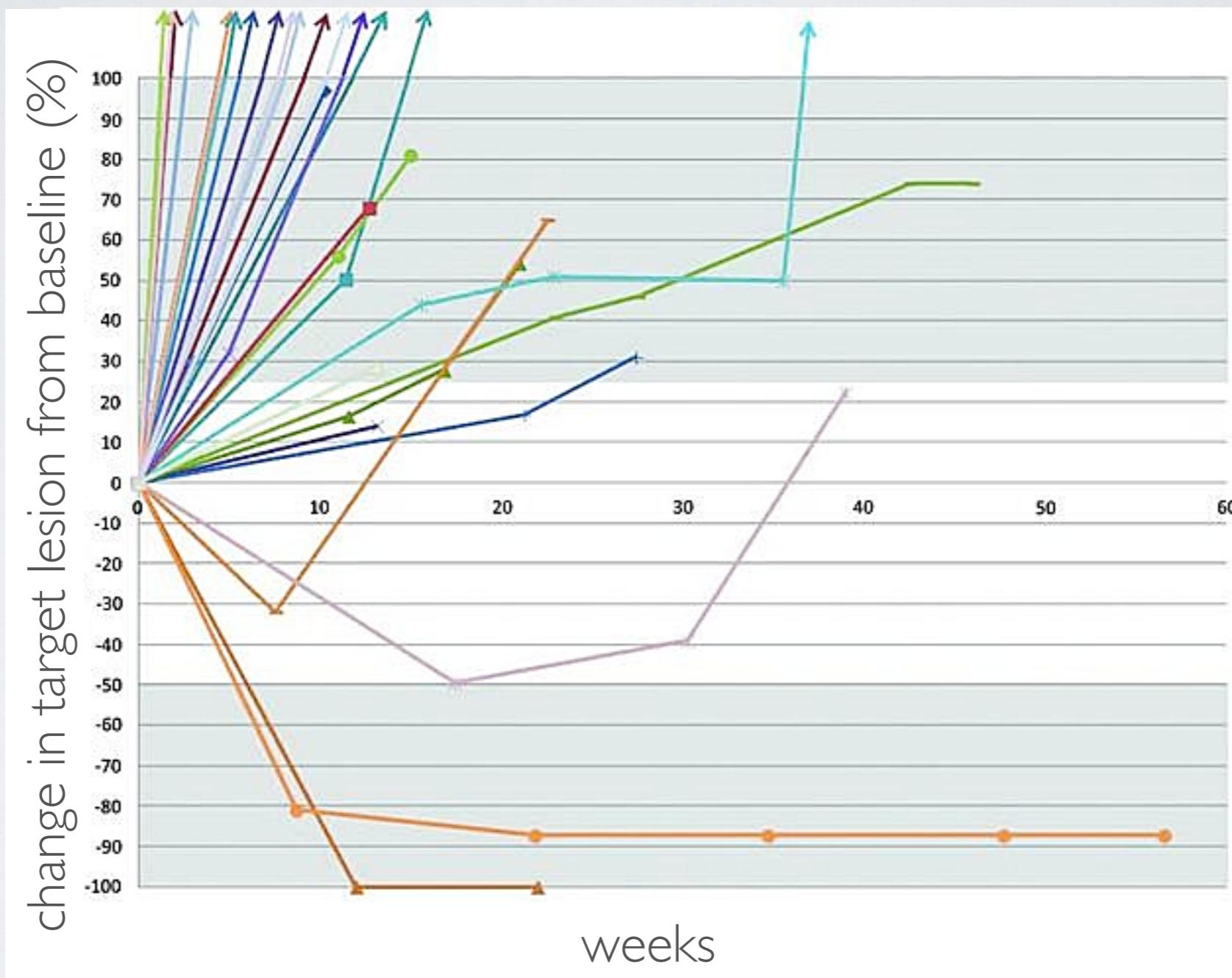
# An adaptive patient-specific treatment approach for EGFR-driven stage IV lung cancer

Team Lung:

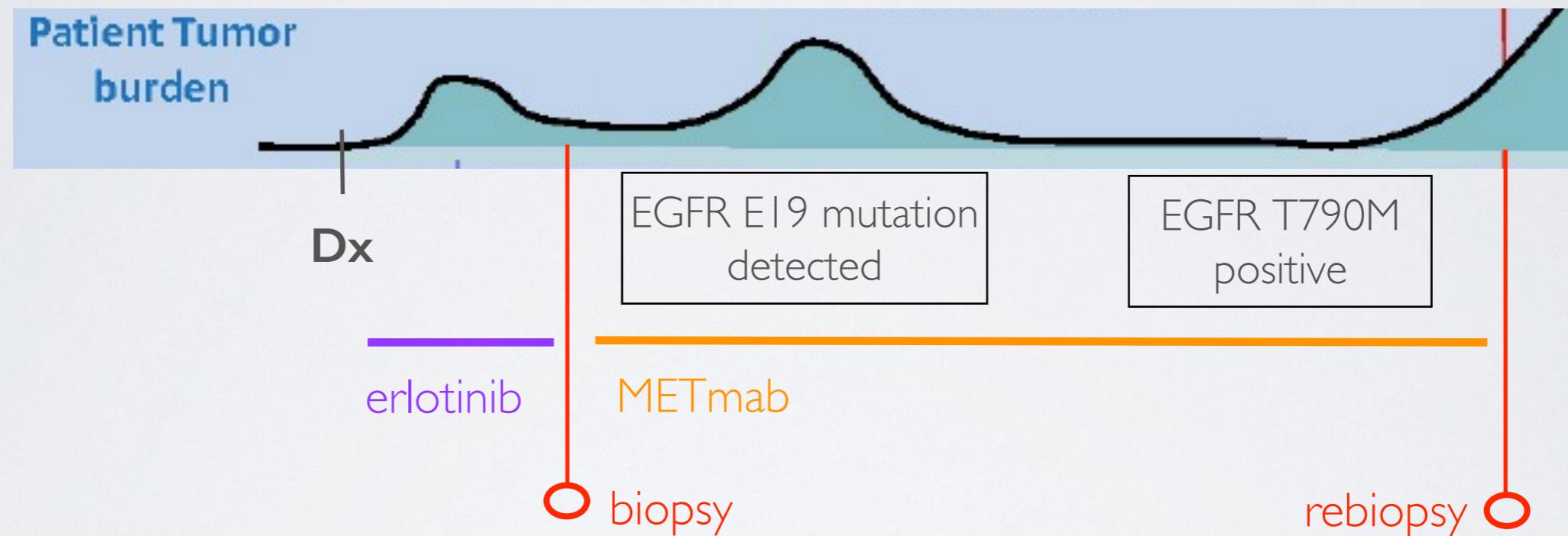
Ben Creelan, Jill Gallaher, Philip Gerlee, Olya Grove,  
Lori Hazelhurst, Hildur Knutsdottir, Dan Nichol,  
Josh Scurll and Marc Sturrock



# Patient-specific treatment response



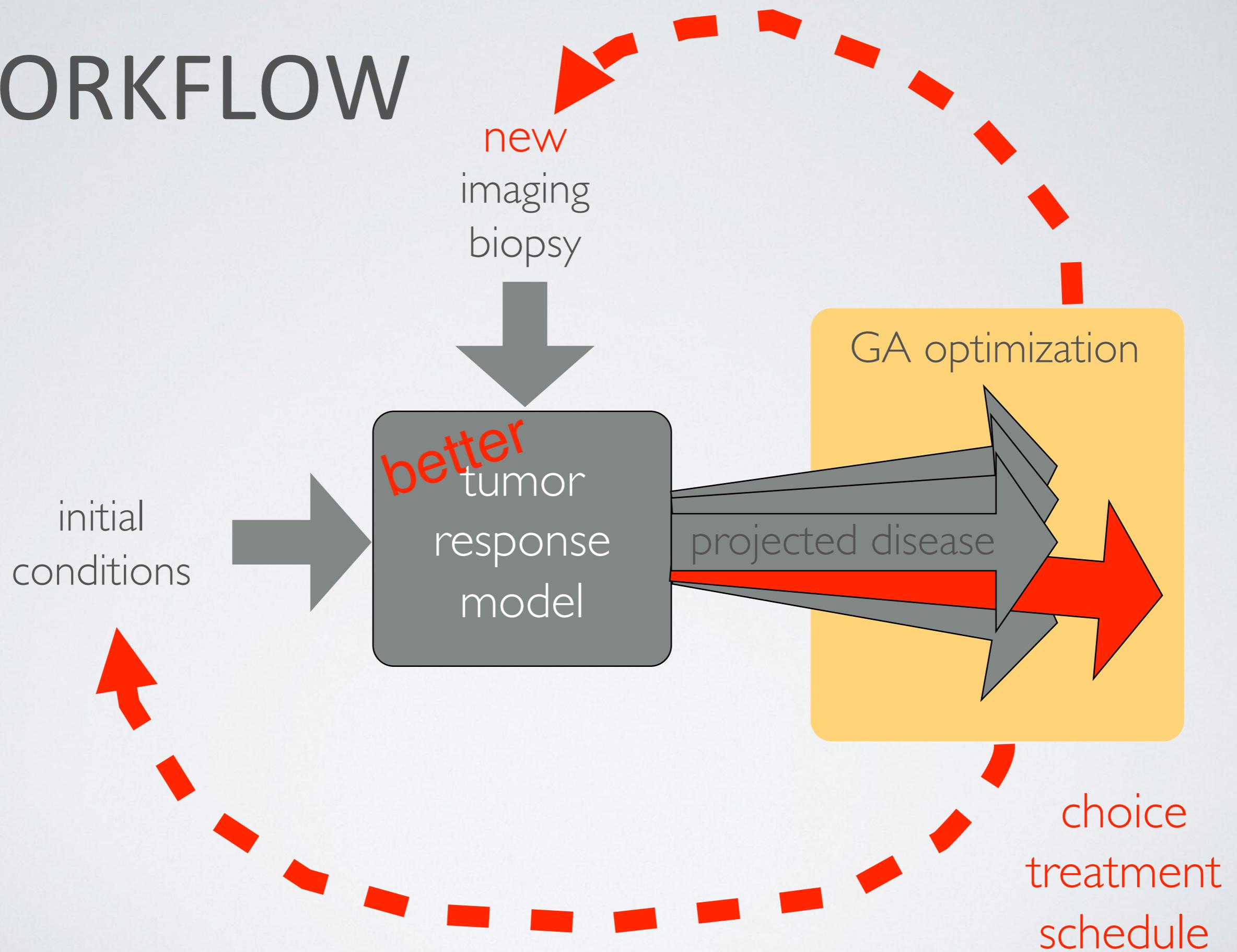
Using math modeling with patient-specific data,  
maximize days gained while avoiding toxicity



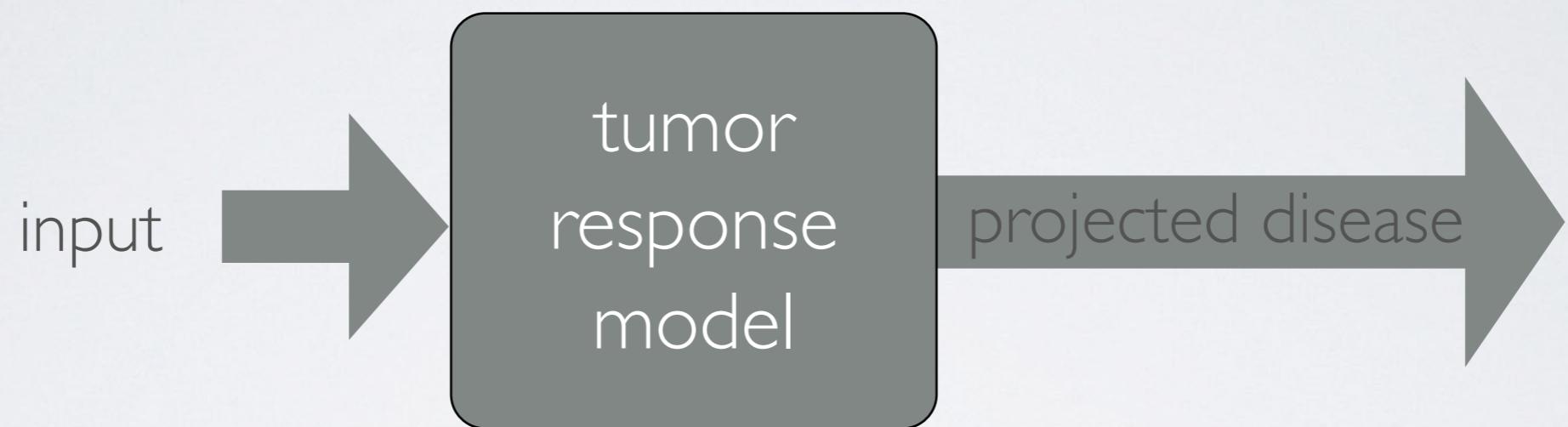
# Outline

- Strategy
- Signaling network model
- Optimization technique
- Feedback/Refinement

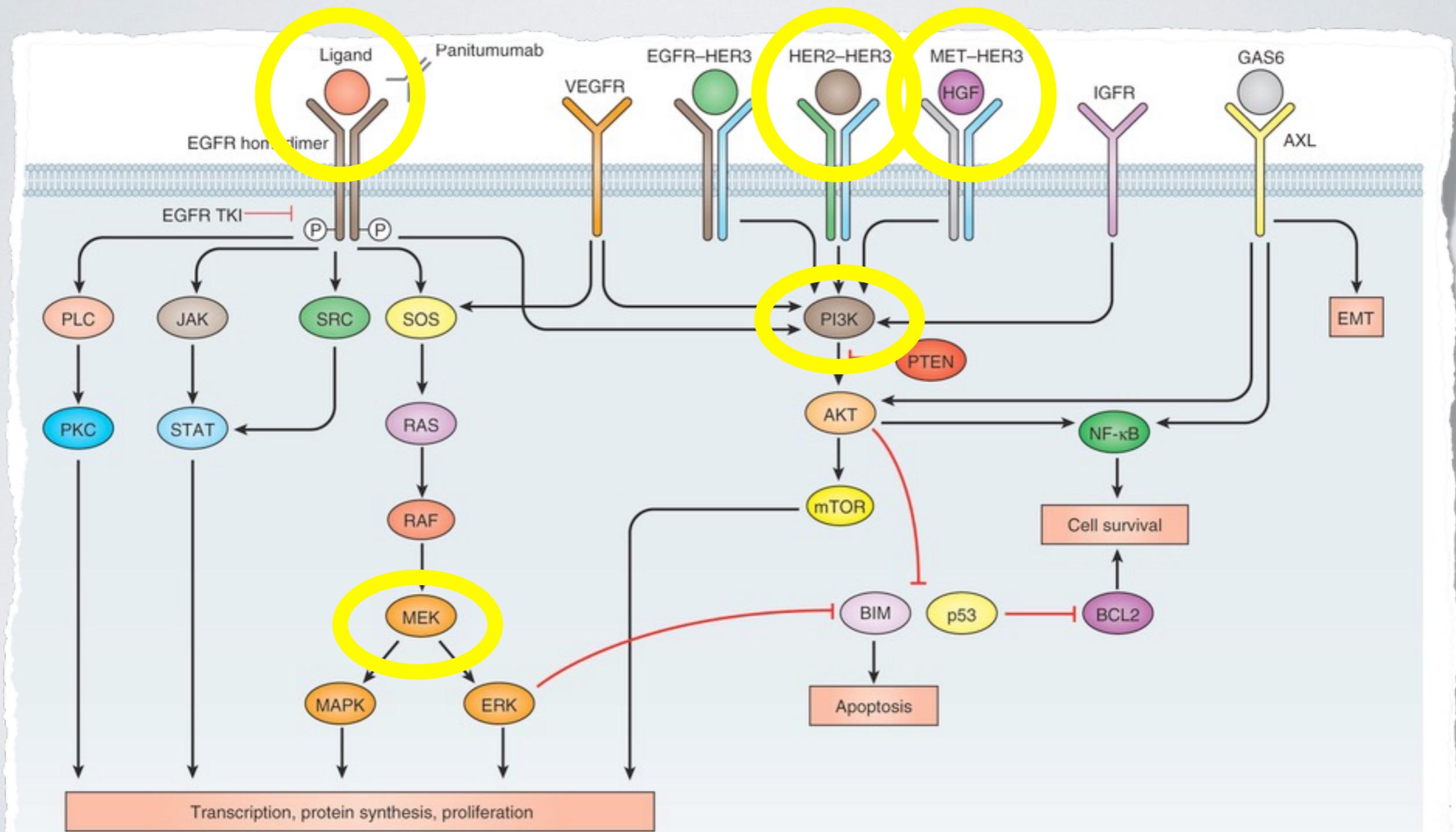
# WORKFLOW

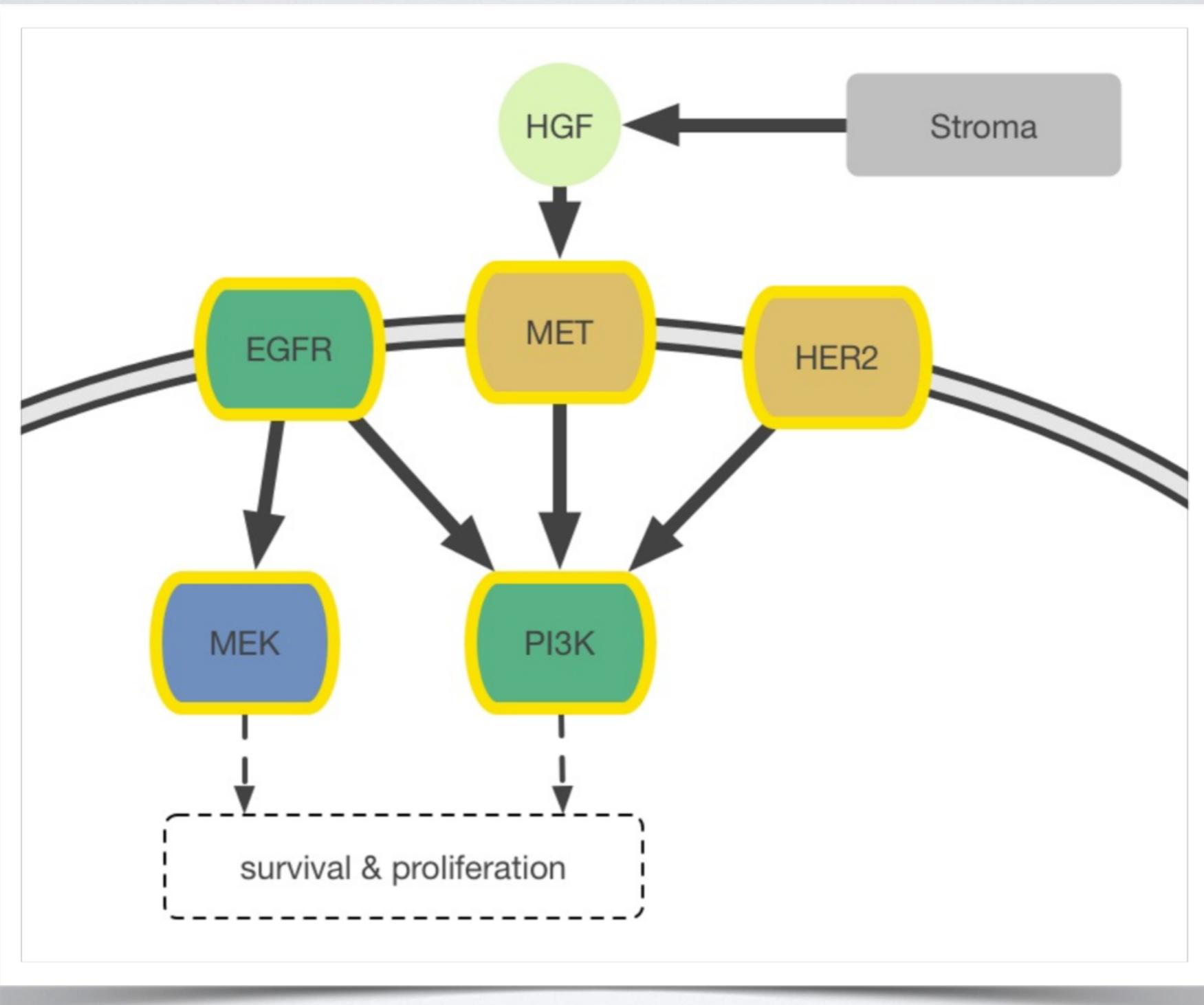


# Less is more.



# EGFR PATHWAY





druggable targets

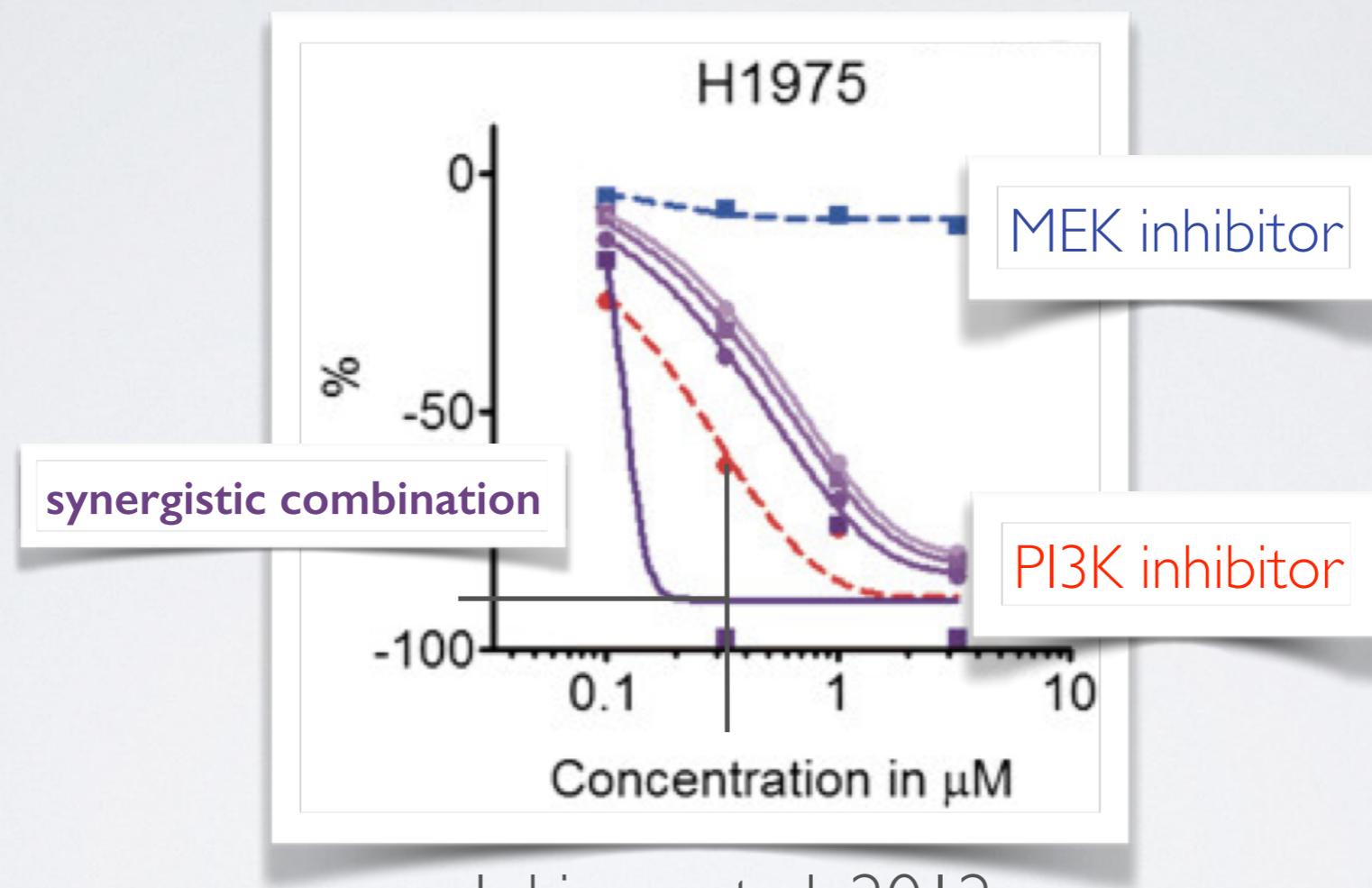


escape routes



possible resistant nodes

# synergism with MEK & PI3K inhibition



EGFR = 1  
 MET = 2  
 HER2 = 3  
 MEK = 4  
 PI3K = 5

# EQUATIONS

clone dynamics

$$\frac{dN_i(t, d)}{dt} = \overbrace{(\alpha_0 + \alpha_i^d - \beta_i^d) N_i}^{\text{total birth and death}} + \overbrace{\sum_{i'} W_{i'i} N_{i'}}^{\text{mutations}} + \overbrace{S_i^d M^\tau}^{\text{stromal stimulation}}$$

$$i = n_1 n_2 n_3 n_4 n_5$$

$$d = d_1 d_2 d_3 d_4 d_5, \text{ where } d_j \in \{0, 1\}$$

size

$$M = \sum_{i'} N_{i'},$$

amplification

$$\alpha_i^d = \delta_{n_2 1} \delta_{d_2 0} \alpha_M + \delta_{n_3 1} \delta_{d_3 0} \alpha_H$$

death

$$\begin{aligned} \beta_i^d = & \delta_{n_1 0} \delta_{d_1 1} \beta_E + \delta_{n_2 1} \delta_{d_2 1} \beta_{\text{MET}} + \delta_{n_3 1} \delta_{d_3 1} \beta_H + \delta_{d_4 1} \beta_{\text{MEK}} + \delta_{n_5 0} \delta_{d_5 1} \beta_P^{(1)} \\ & + s_{4,5} \delta_{d_4 1} \delta_{n_5 0} \delta_{d_5 1} (\beta_{\text{MEK}} + \beta_P^{(1)}) + \delta_{n_5 0} \delta_{n_1 0} \delta_{d_1 0} \delta_{n_2 1} \delta_{d_2 0} \delta_{n_3 1} \delta_{d_3 0} \beta_P^{(2)} \end{aligned}$$

response

$$S_i^d = (1 + \eta_M \delta_{n_2 1}) \delta_{d_2 0}$$

synergism

toxicity

$$\frac{d\Phi}{dt} = \varphi_m - \kappa \Phi$$

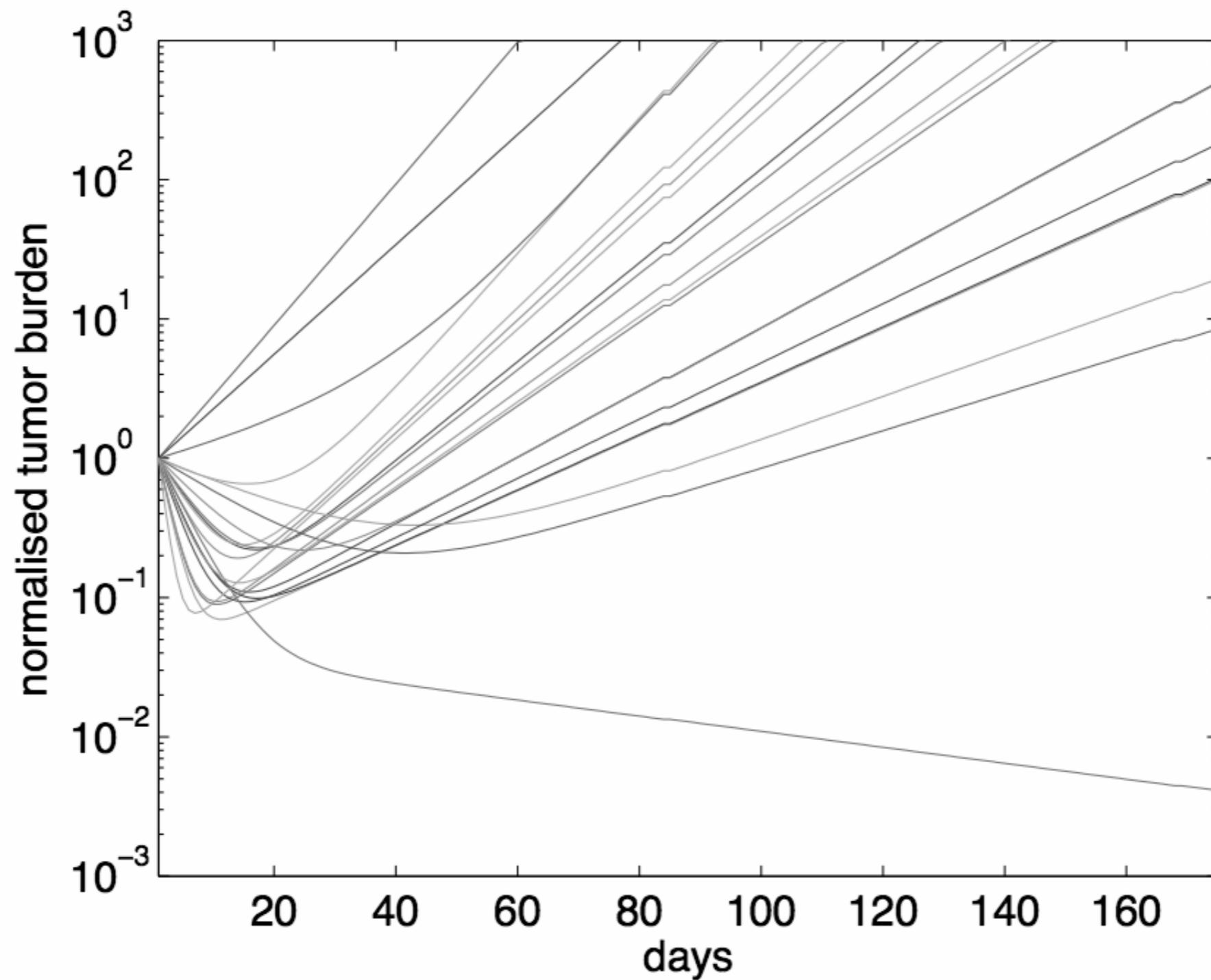
# estimated parameters

Parameter	Meaning	Value	Ref.
$\alpha_M$	growth from MET-overexpression	$\alpha_0/2 \text{ day}^{-1}$	Navab <i>et al.</i> Neoplasia 2009
$\alpha_H$	growth from HER2-overexpression	$\alpha_0/2 \text{ day}^{-1}$	Based on $\alpha_M$
$\mu$	mutation rate	$10^{-7} \text{ day}^{-1}$	Tomlinson <i>et. al</i> , PNAS, 1998
$\eta_M$	degree of MET-overexpression	10	Navab <i>et al.</i> Neoplasia 2009
$\gamma_M$	sensitivity to HGF	$10^{-2} \text{ cell}^{1/3} \text{ day}^{-1}$	-
$s_{4,5}$	synergism between MEK & PI3K	0.5	Jokinen <i>et al.</i> , 2012
$\sigma_\beta$	std. of drug sensitivity	$\alpha_0/2$	model specific
$\kappa$	decay of toxicity	2.0	model specific
$\alpha_0$	baseline growth rate	$0.2 \log 2 \text{ day}^{-1}$	-
$\tau$	surface/volume ratio	2/3	-
$\beta_E$	sensitivity to EGFR-inhibitor	$0.53 \text{ day}^{-1}$	Rosell <i>et al.</i> , 2012
$\beta_{MET}$	sensitivity to MET-inhibitor	$0.18 \text{ day}^{-1}$	Landi <i>et al.</i> , 2013
$\beta_H$	sensitivity to HER2-inhibitor	$0.21 \text{ day}^{-1}$	Greve, J.D., 2012
$\beta_P$	sensitivity to PI3K-inhibitor	$0.1 \text{ day}^{-1}$	Besse <i>et al.</i> , 2011
$\beta_{MEK}$	sensitivity to MEK-inhibitor	$0.038 \text{ day}^{-1}$	Jokinen <i>et al.</i> , 2012

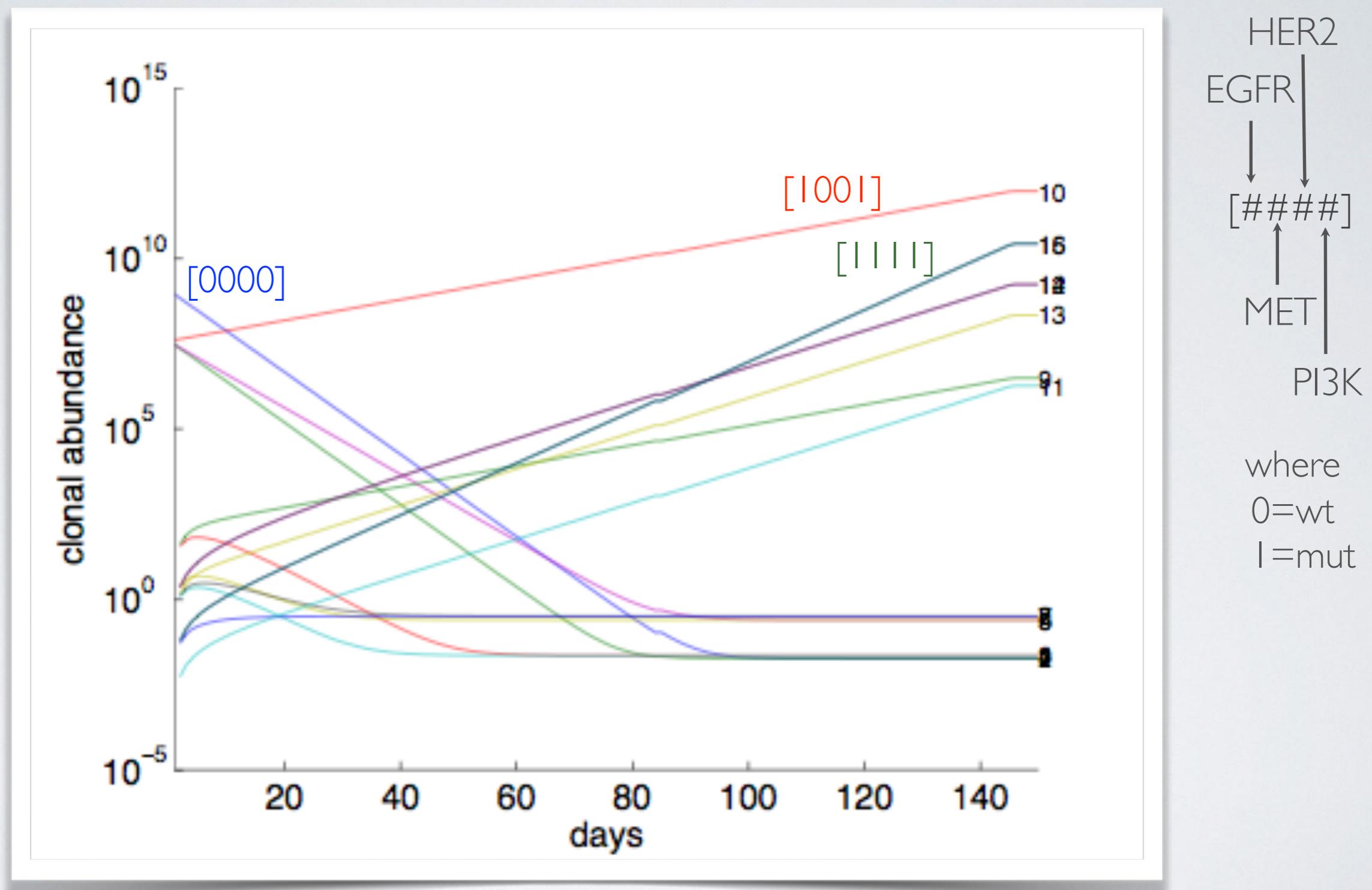
# response rates

Targeted gene	Drug	Clinical Benefit	$\beta$ -value	Ref.
EGFR	Erlotinib	85–90%	0.53	Rosell <i>et al.</i> , 2012
EGFR-T790M	Erlotinib	0%	0	Yang <i>et al.</i> , 2012
MET-amp	MetMAb (+ erlotinib)	55%	0.18	Landi <i>et al.</i> , 2013
HER2-amp	Afatinib	60–70%	0.21	Greve <i>et al.</i> , 2012
PI3Kwt	GDC-0941	44%	0.1	Besse <i>et al.</i> , 2011

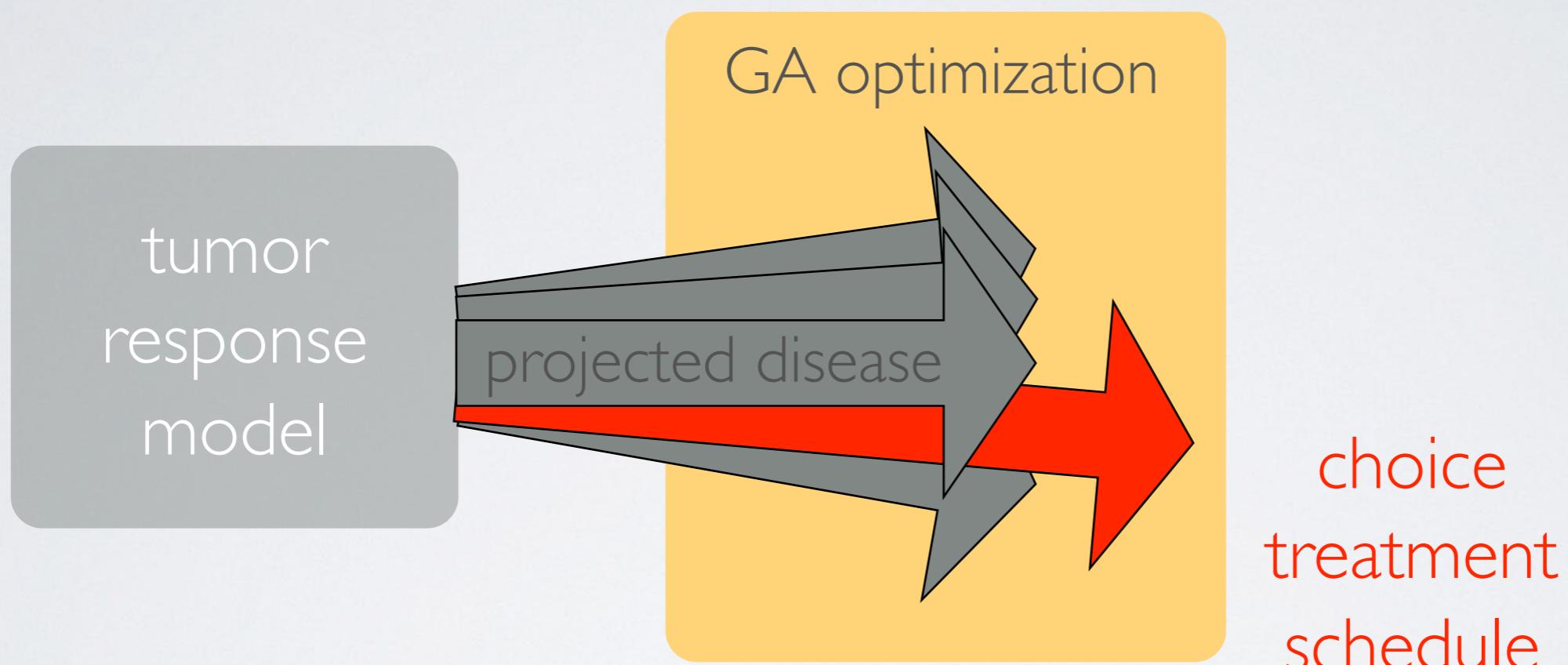
# VIRTUAL PATIENT COHORT: RESPONSE TO ERLOTINIB (SOC)



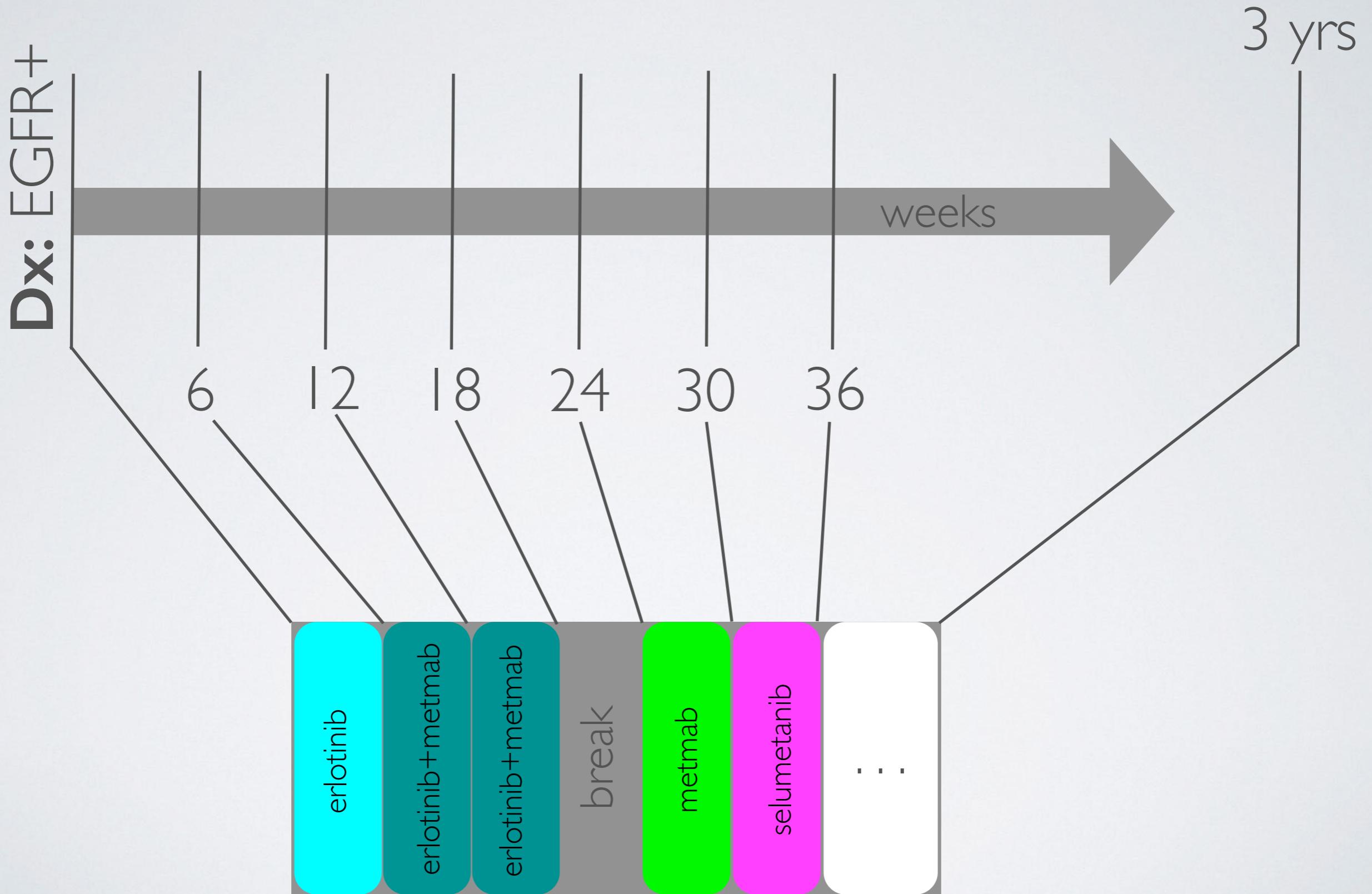
# ERLOTINIB (SOC) CLONAL EVOLUTION

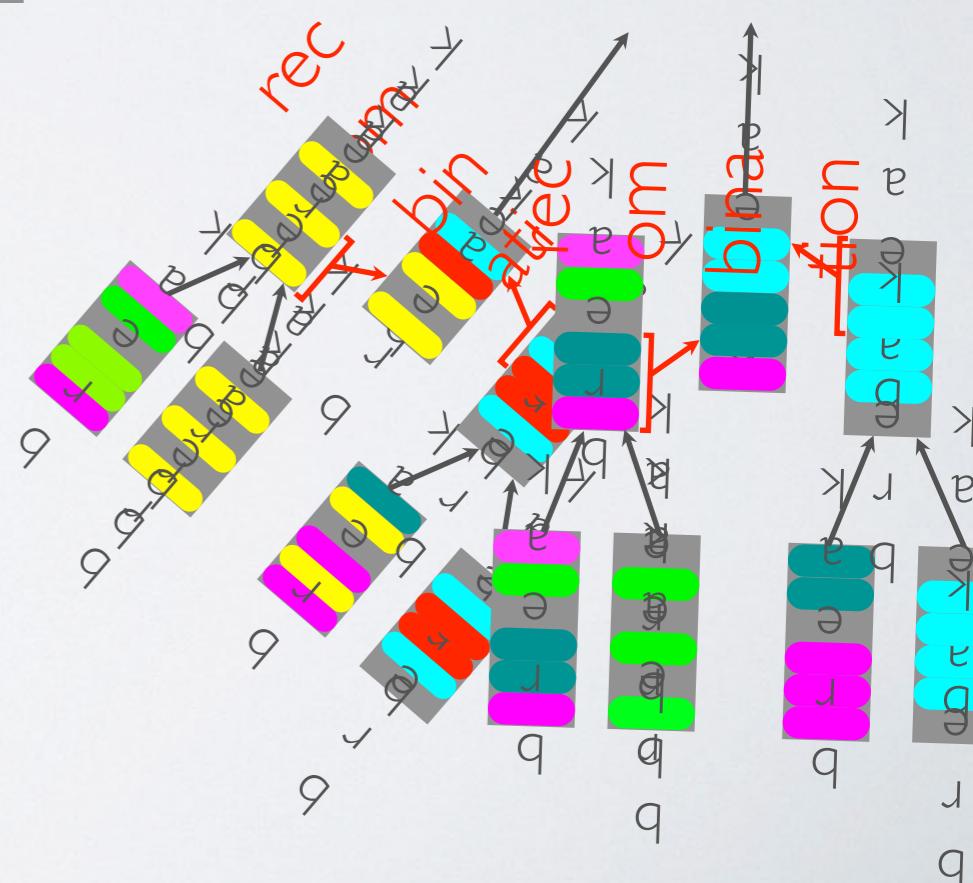
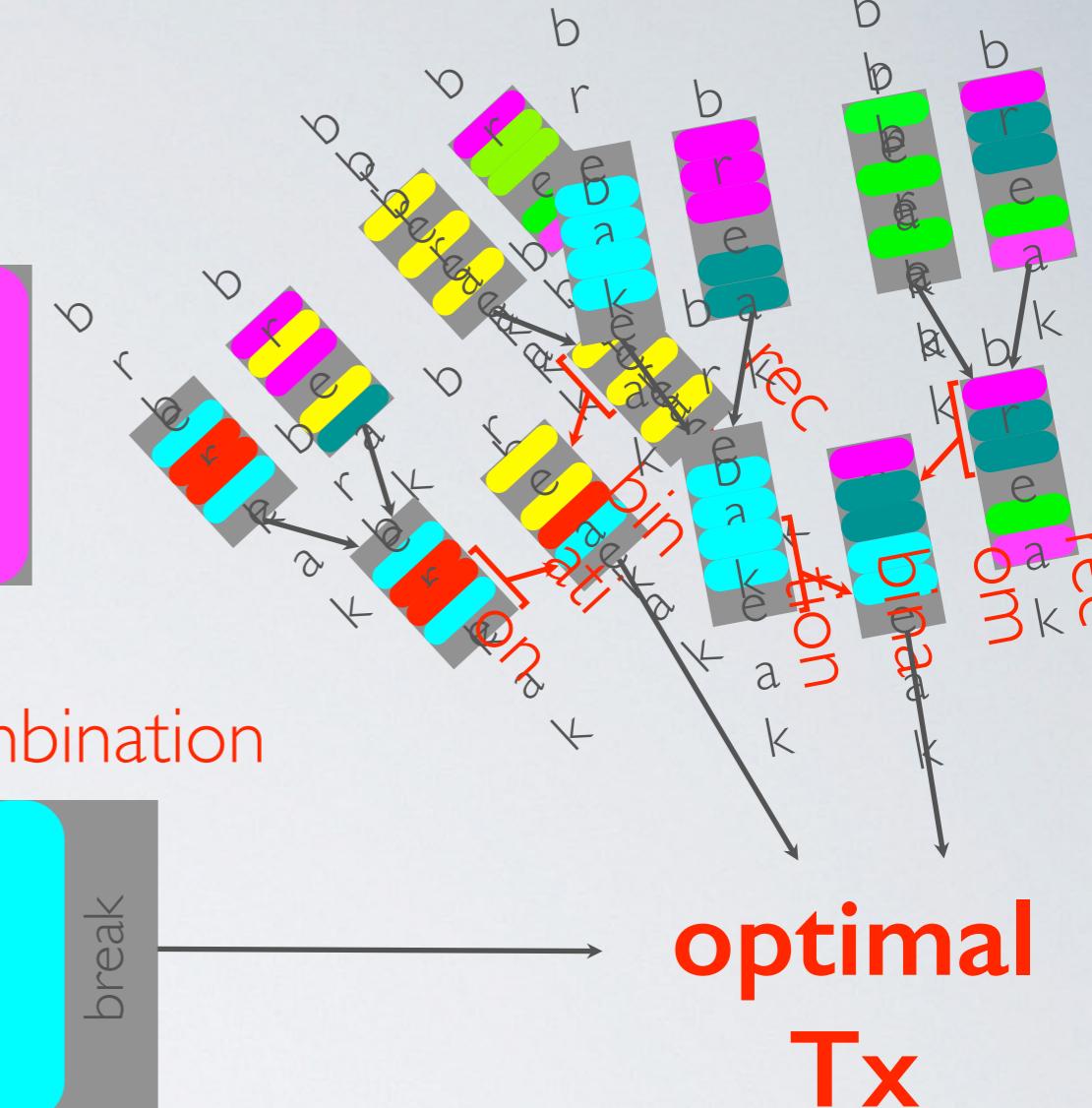
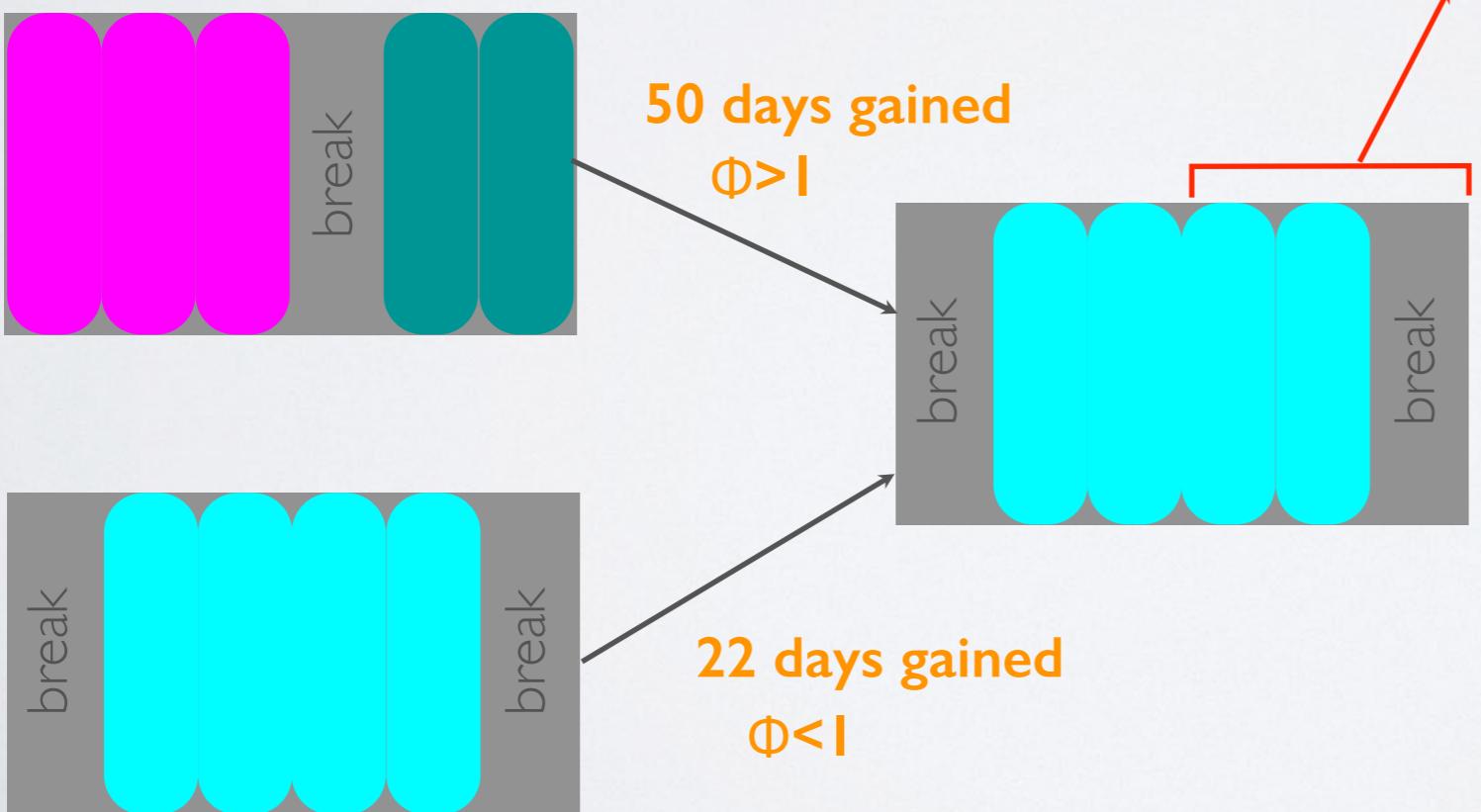
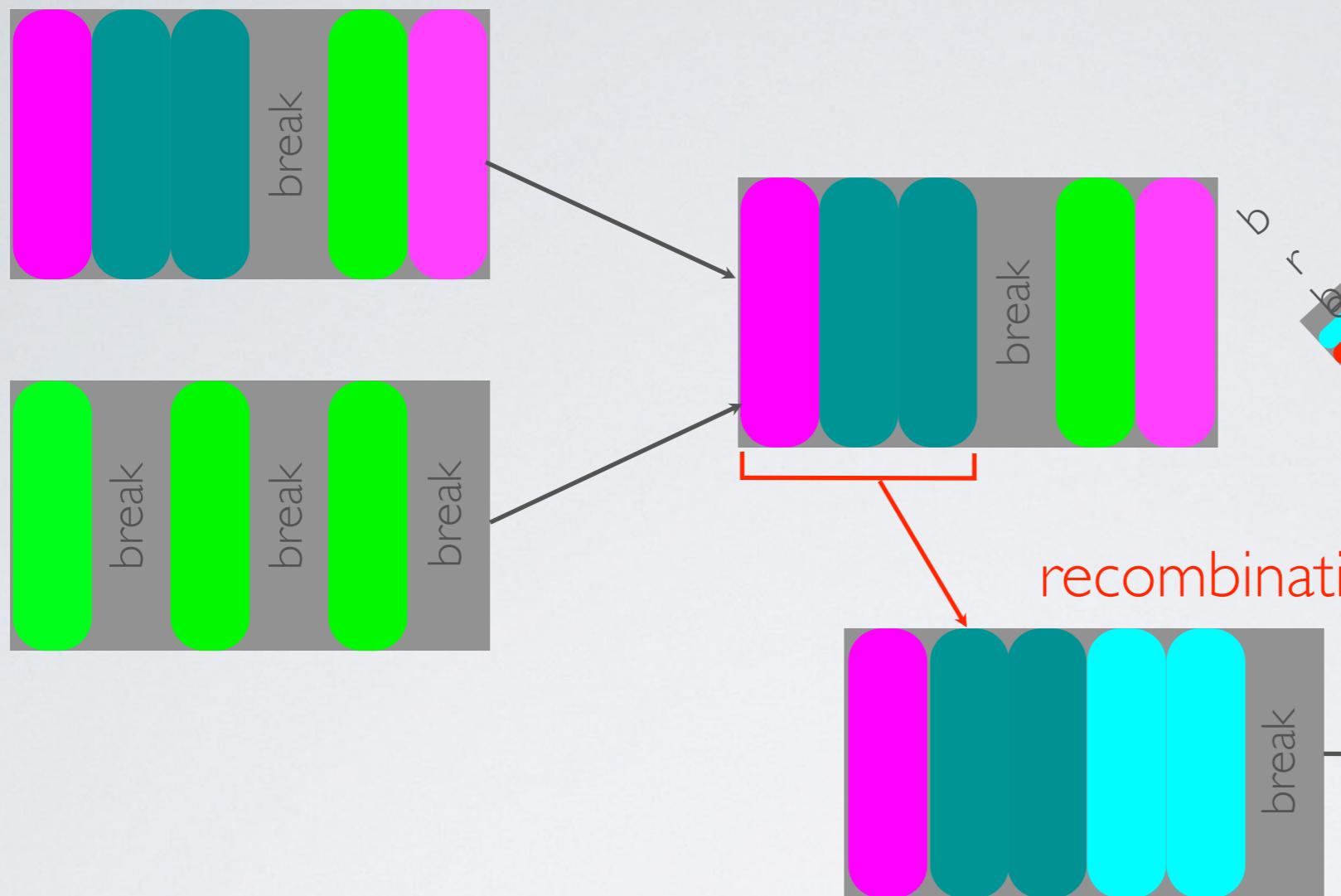


# More is more.

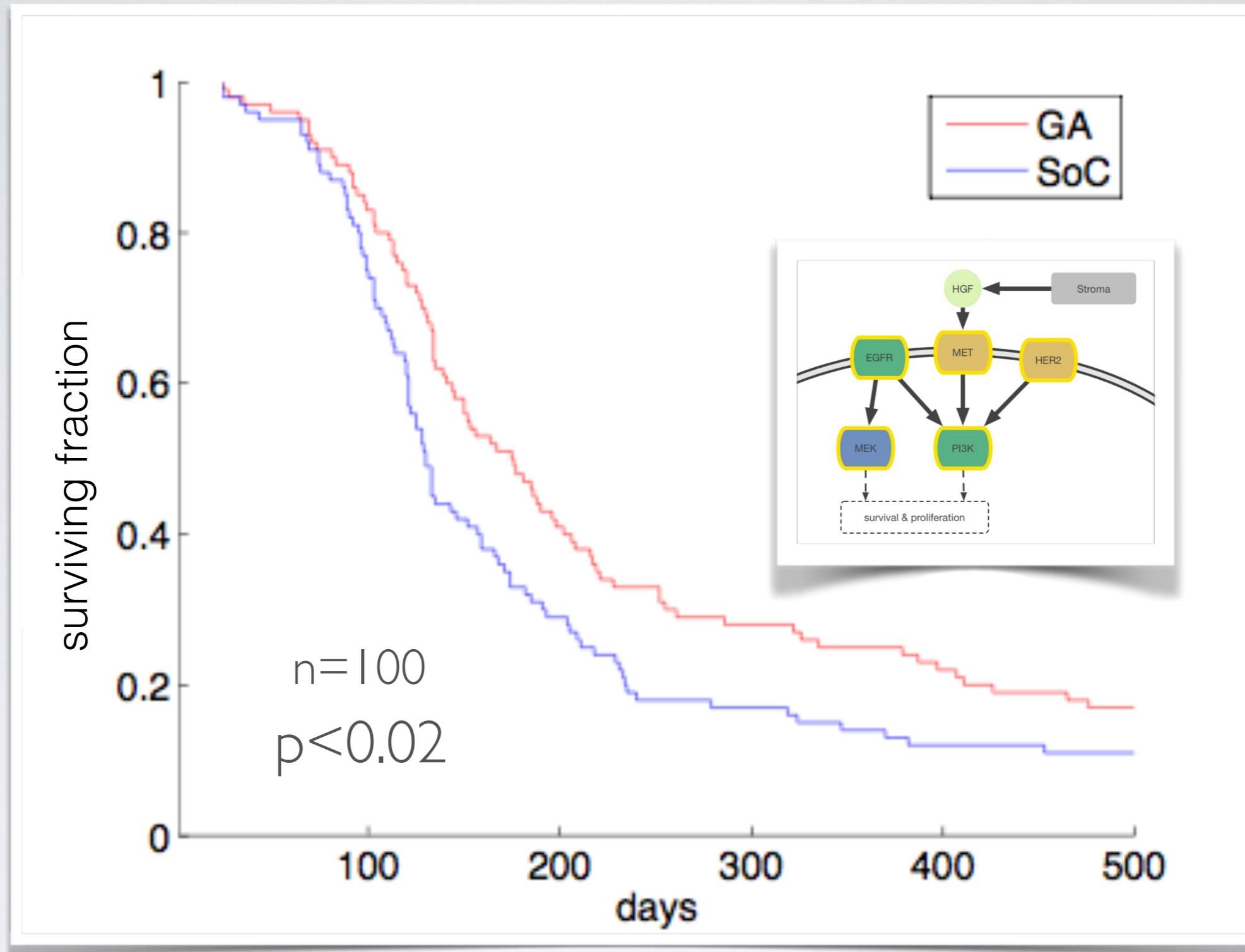


# possible patient timeline





# SOC VS. GA-DERIVED TX SCHEDULE



SOC: erlotinib

GA: erlotinib+everolimus → metmab+everolimus → erlotinib+metmab → erlotinib+everolimus

# FEEDBACK & REFINEMENT

Tx strategy response

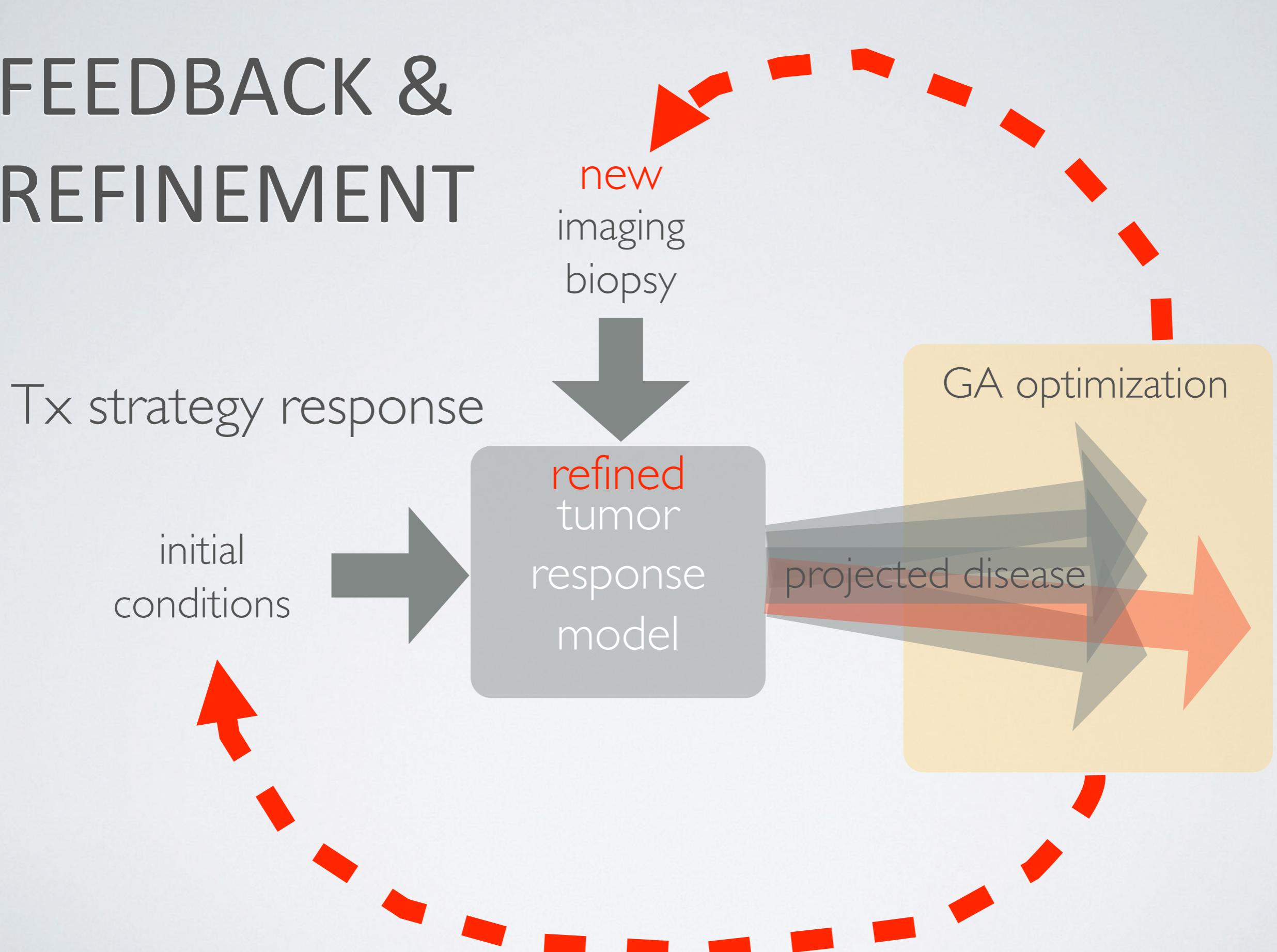
initial conditions

refined tumor response model

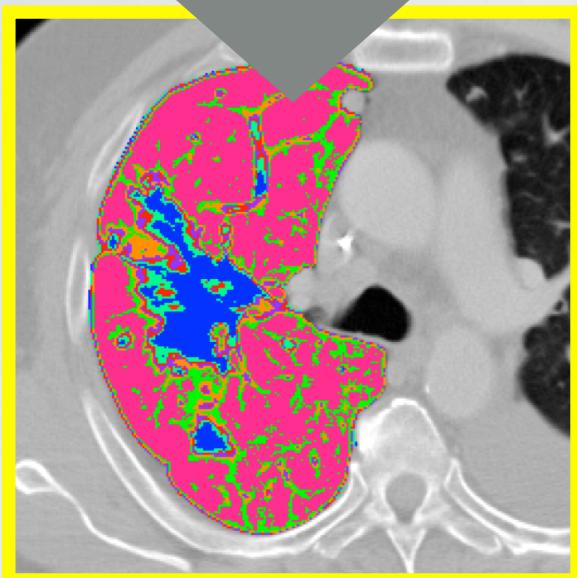
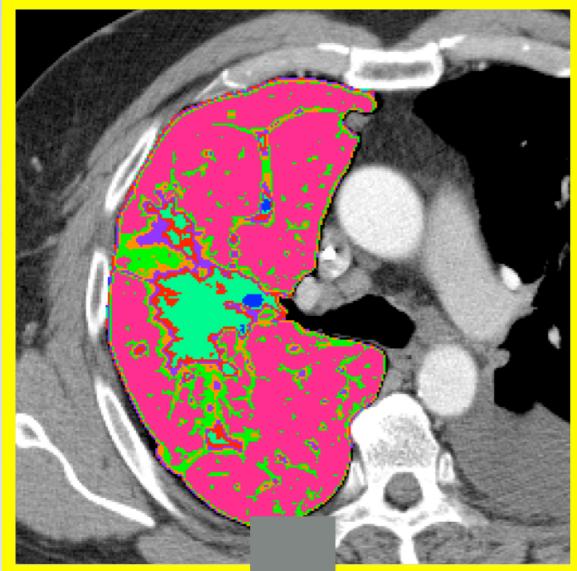
new imaging biopsy

GA optimization

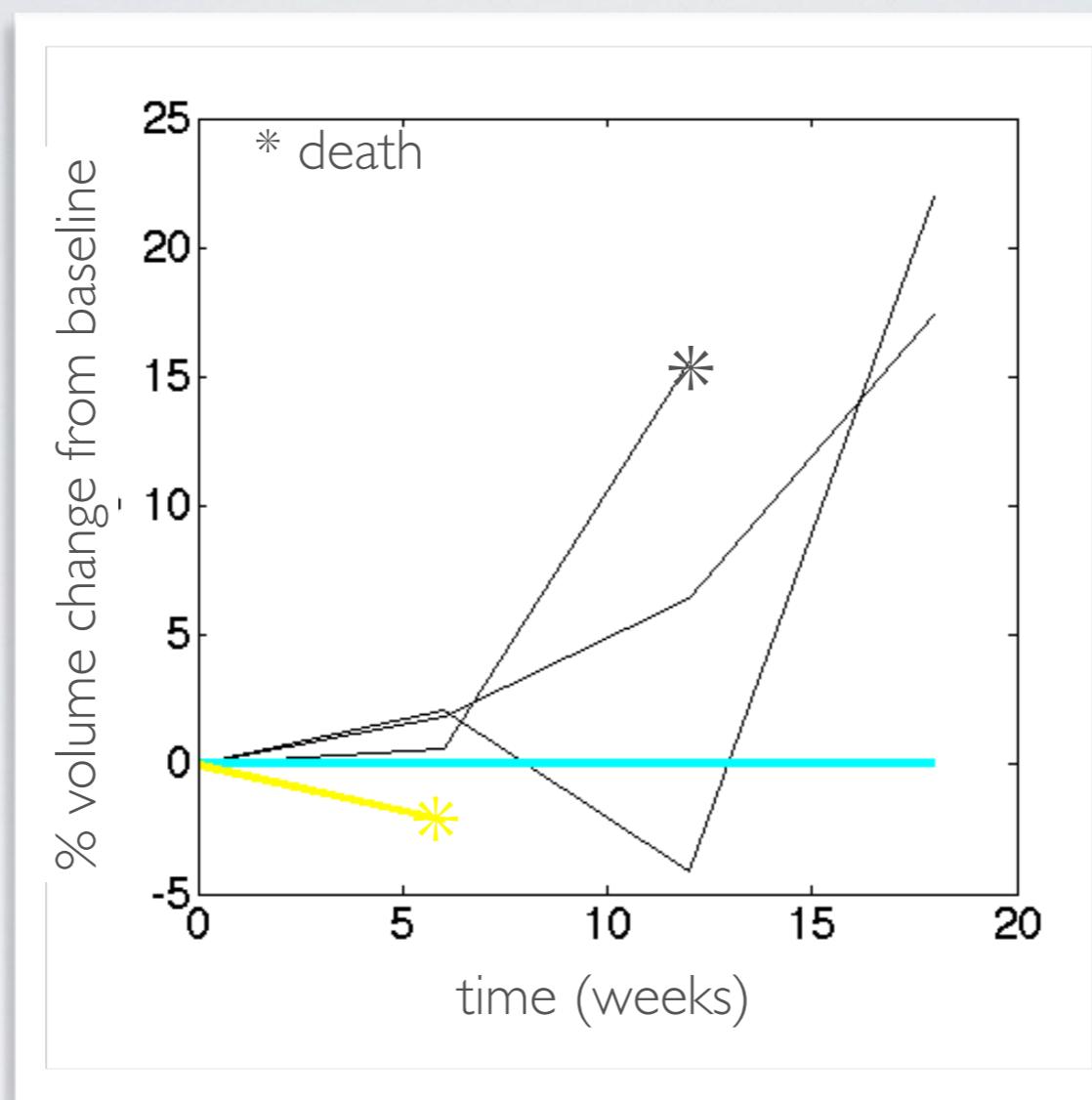
projected disease



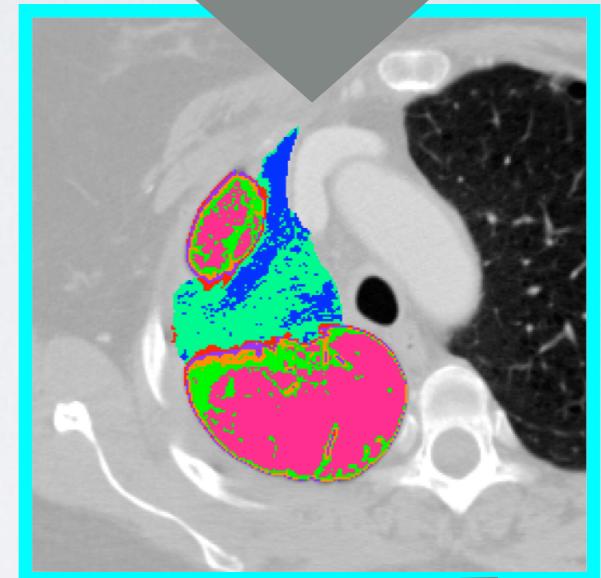
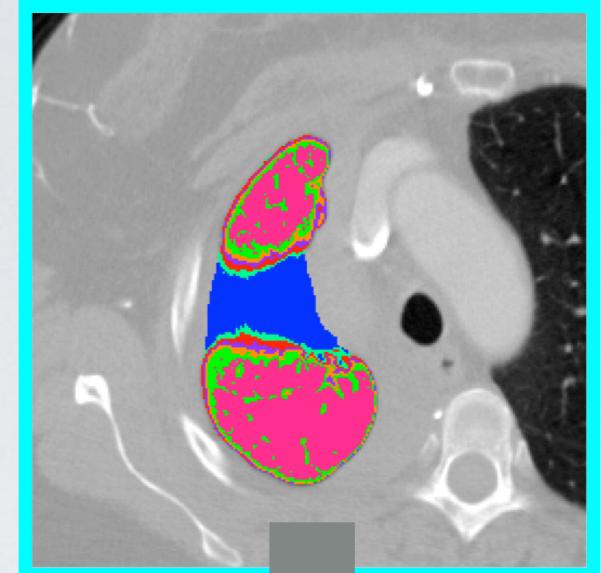
worst case



new patient data



Best case

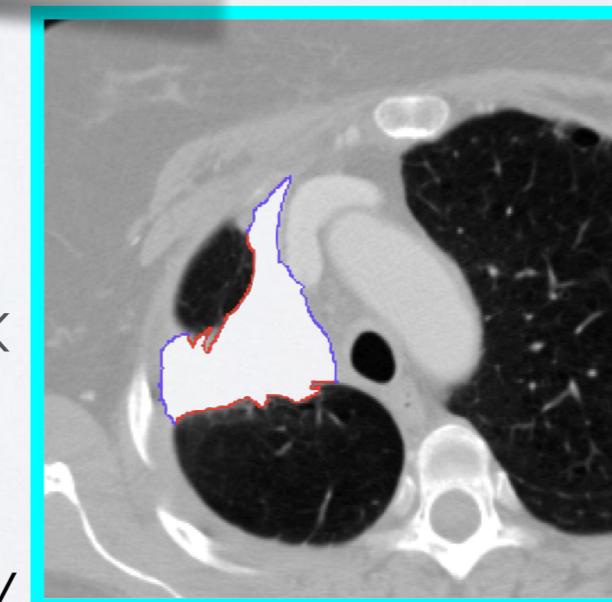
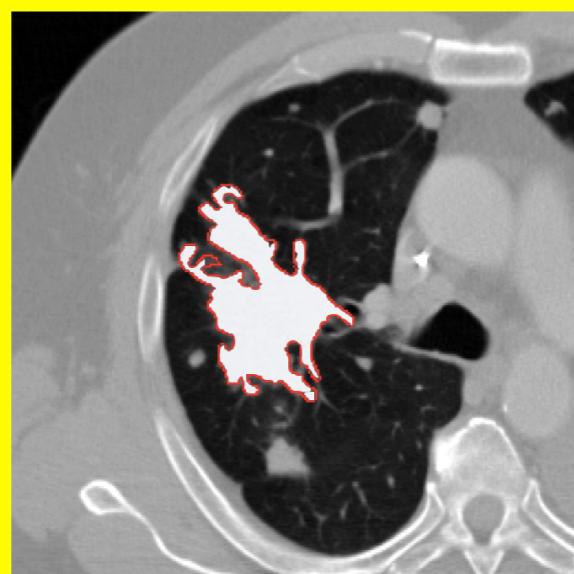


change in stromal  
component

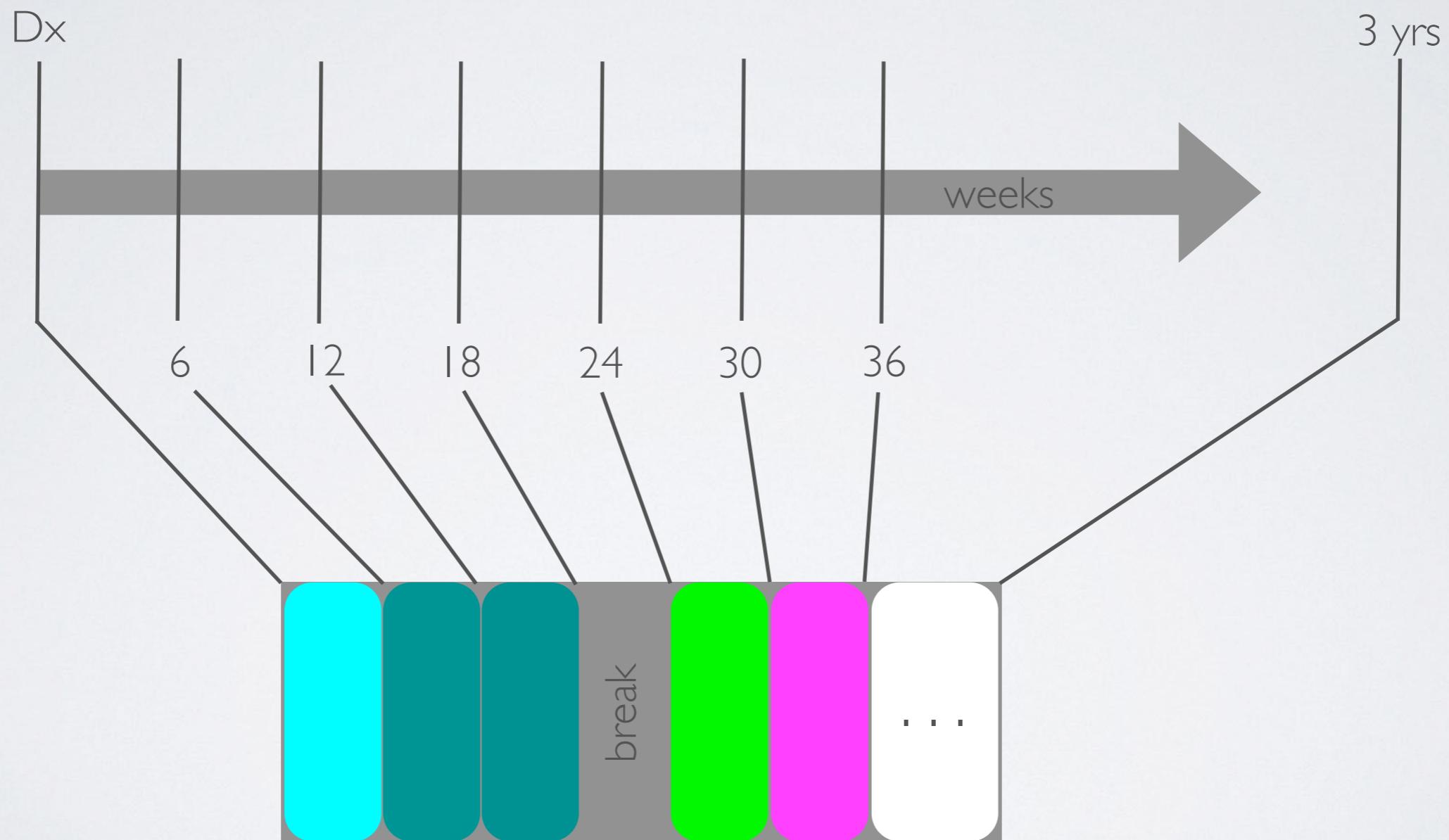
160 px

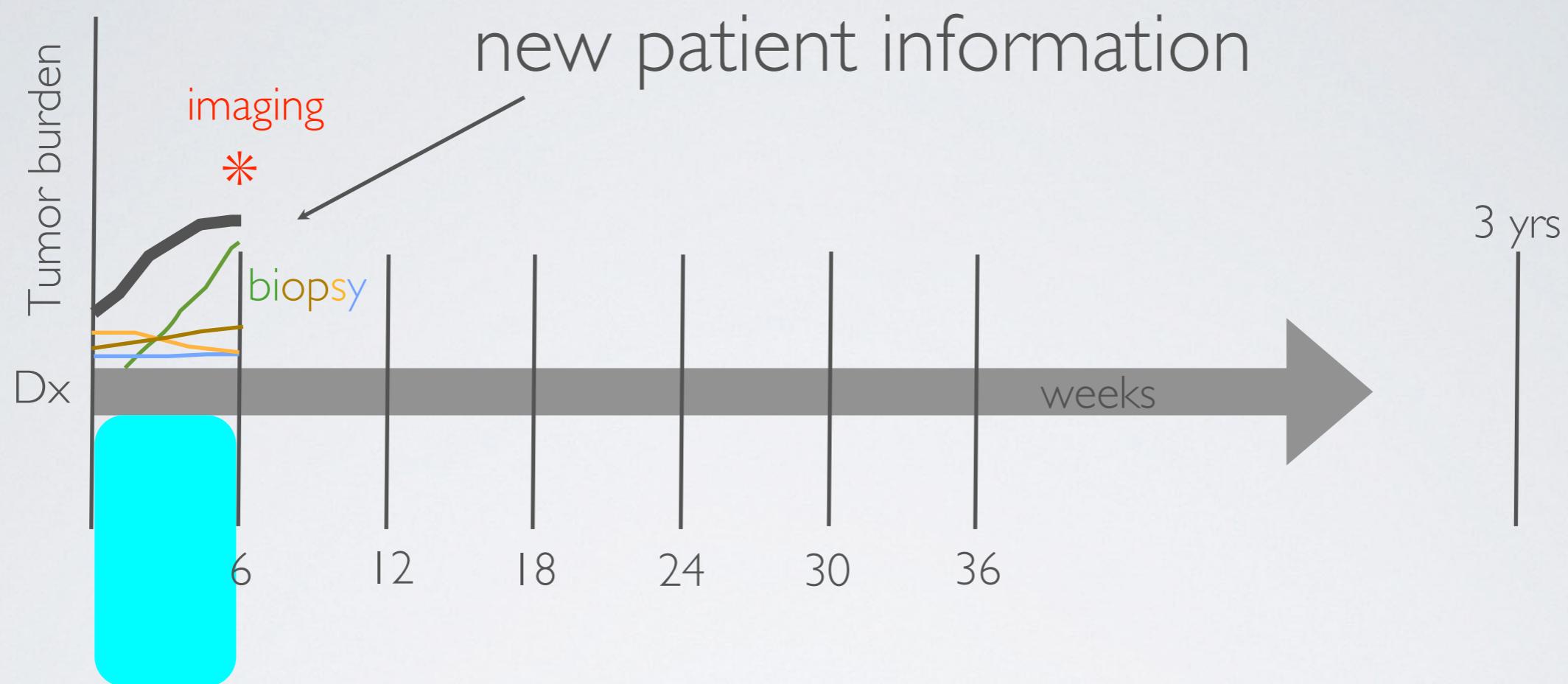
18 px

serum HGF & biopsy

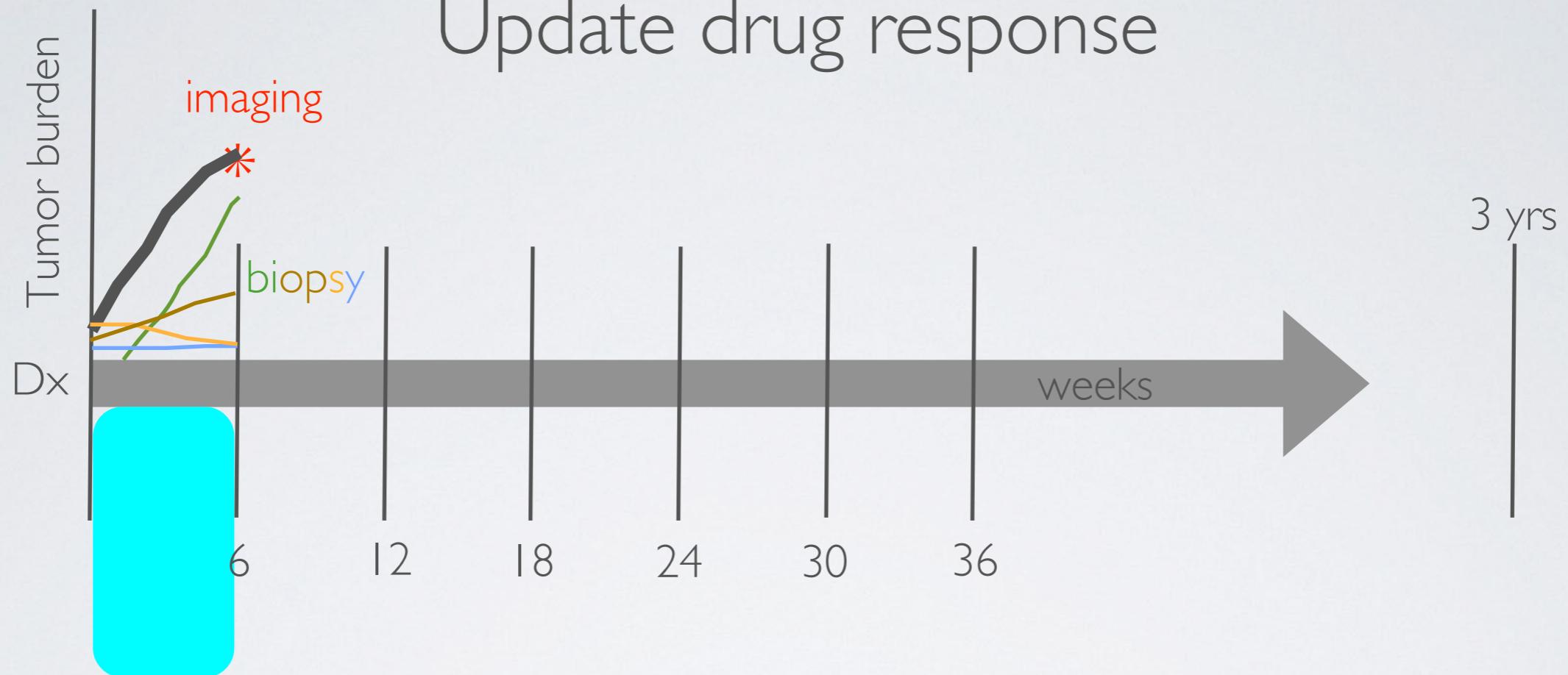


GA finds optimal treatment schedule at Dx

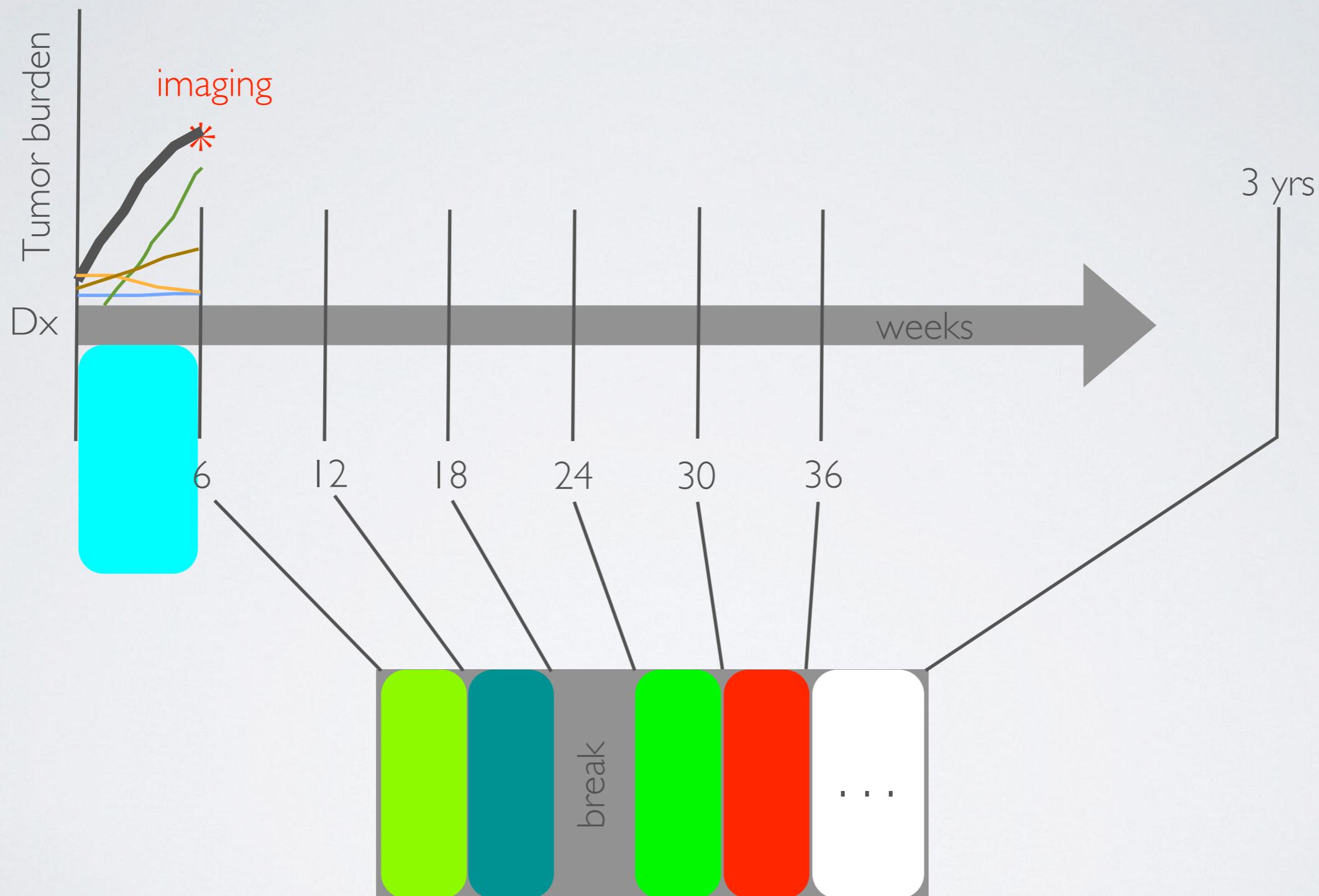


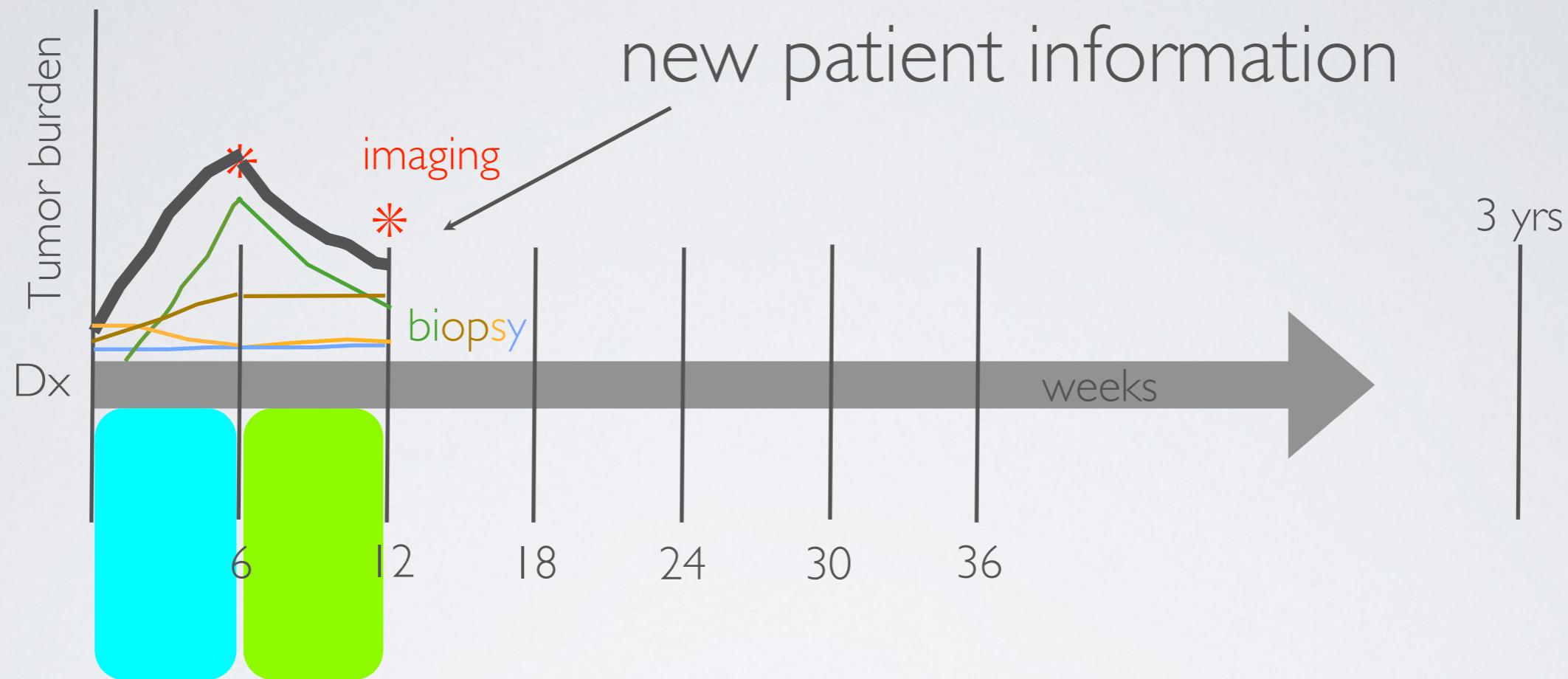


# Update drug response

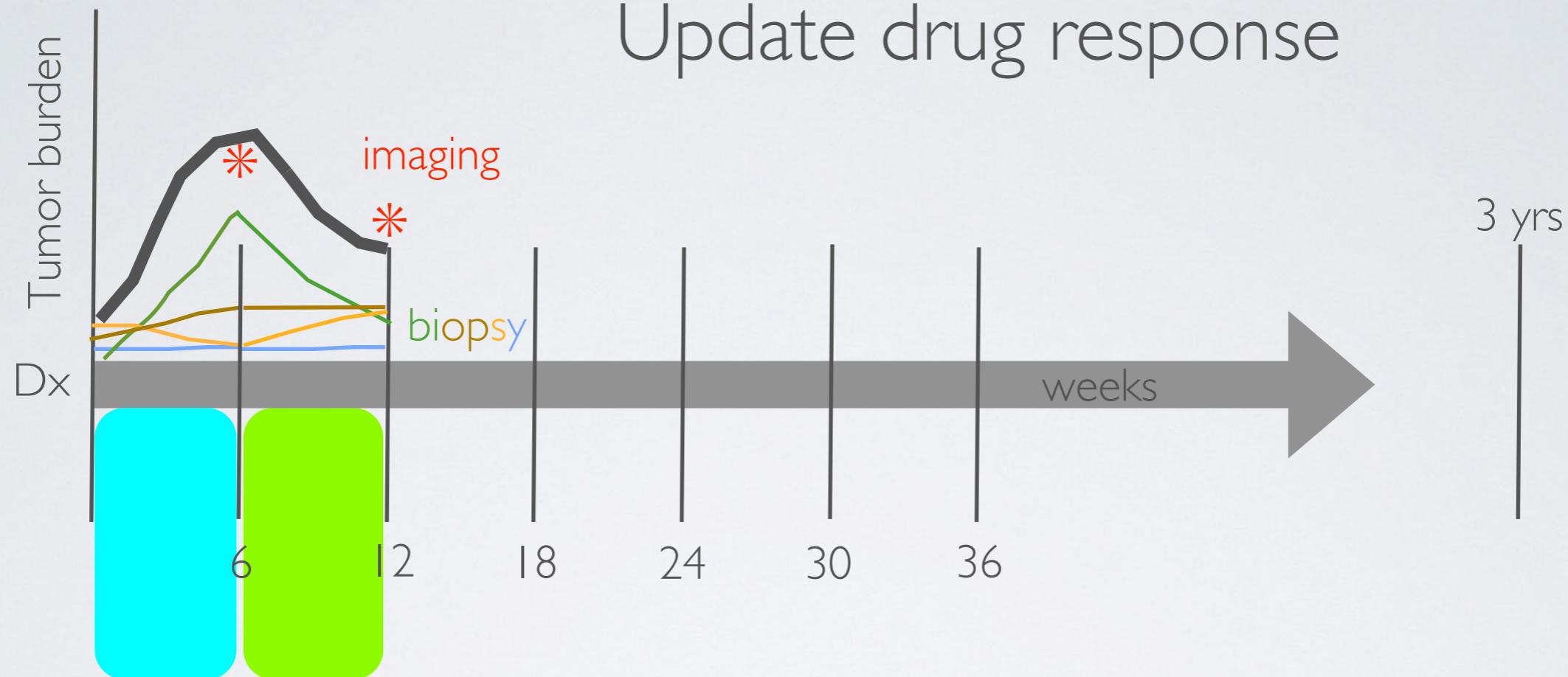


# New optimal Tx schedule

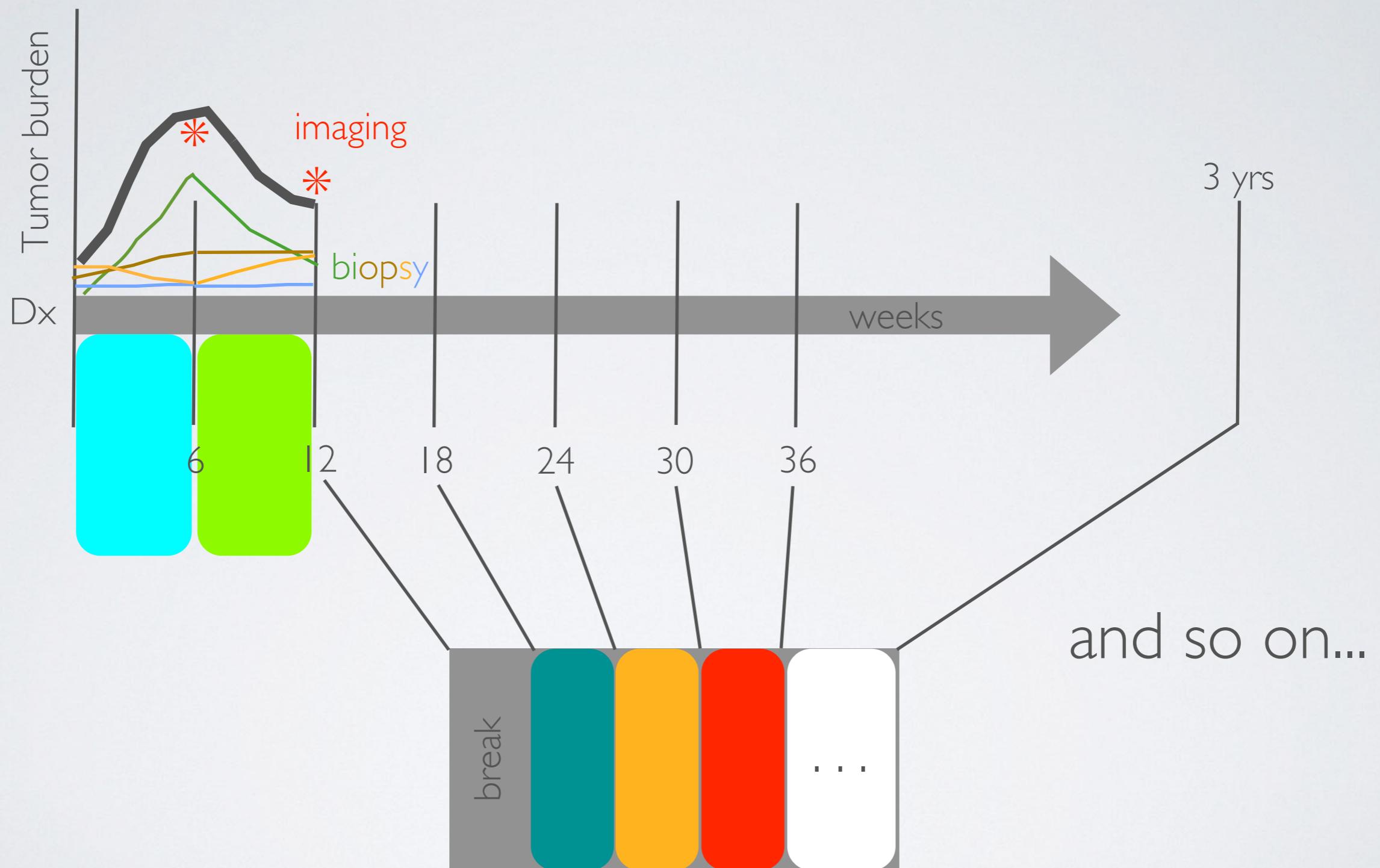




## Update drug response

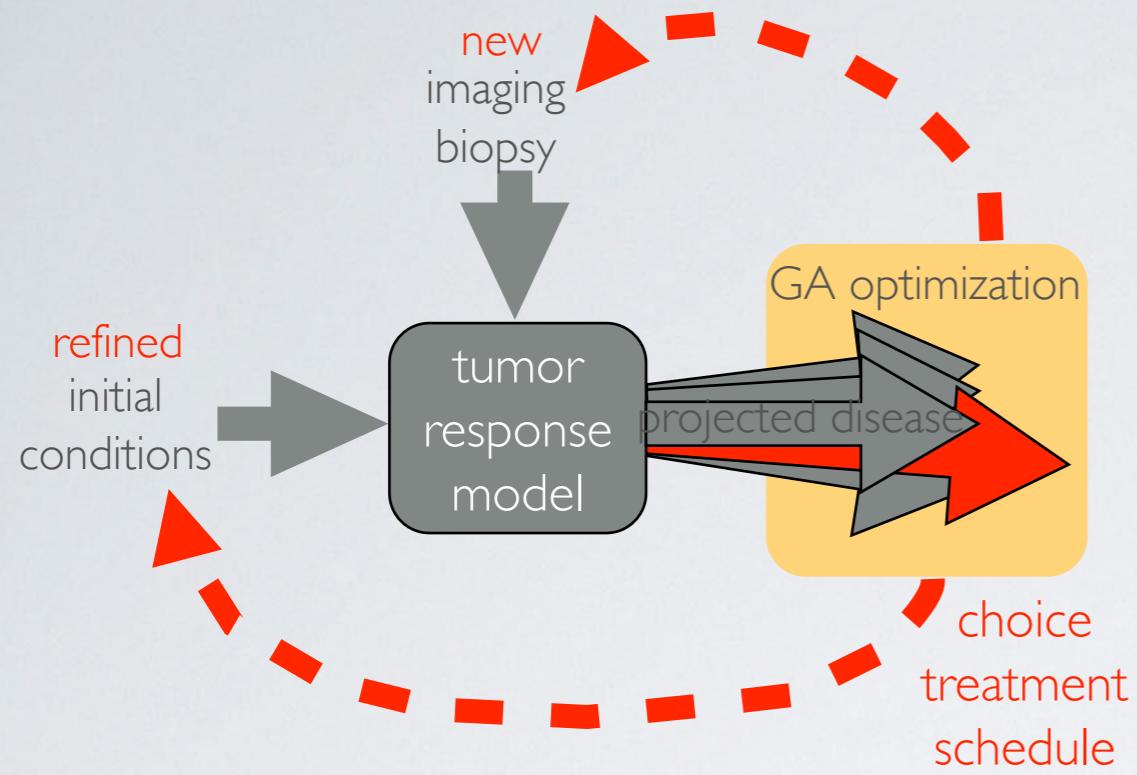


# New optimal Tx schedule



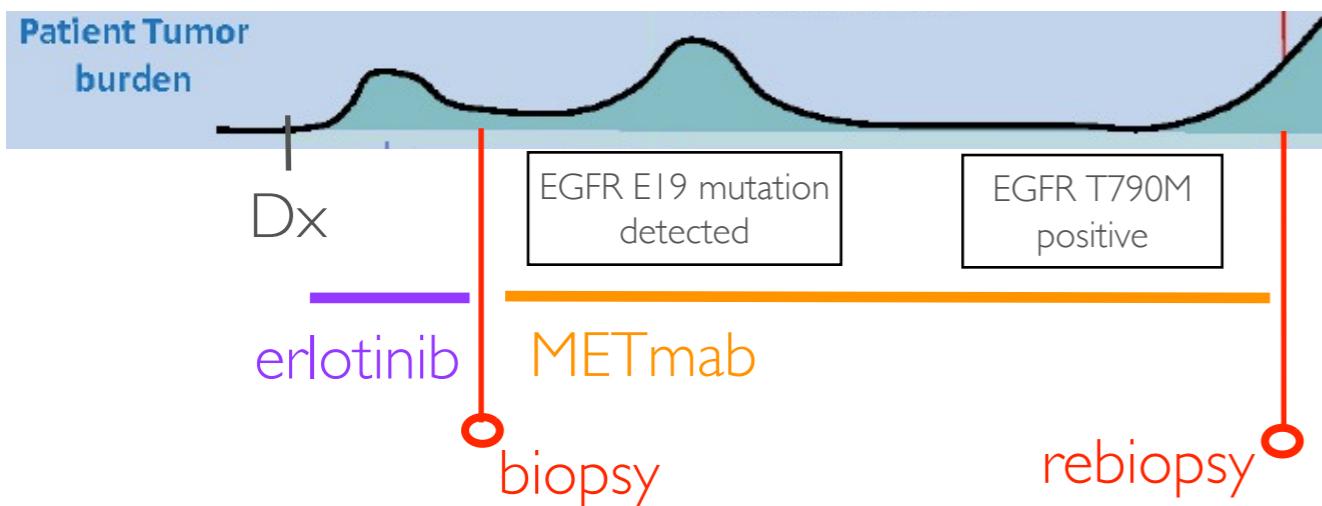
# Conclusions

- 1) We have built a model that captures clonal dynamics of EGFR driven lung cancers.
- 2) Using a GA to optimize treatment scheduling of combinations of known drugs, the model predicts a treatment schedule that prolongs survival (45 days past that of standard of care).
- 3) Periodic updating and refinement of the model from patient-specific data should improve the model and the prediction of the treatment by the GA.

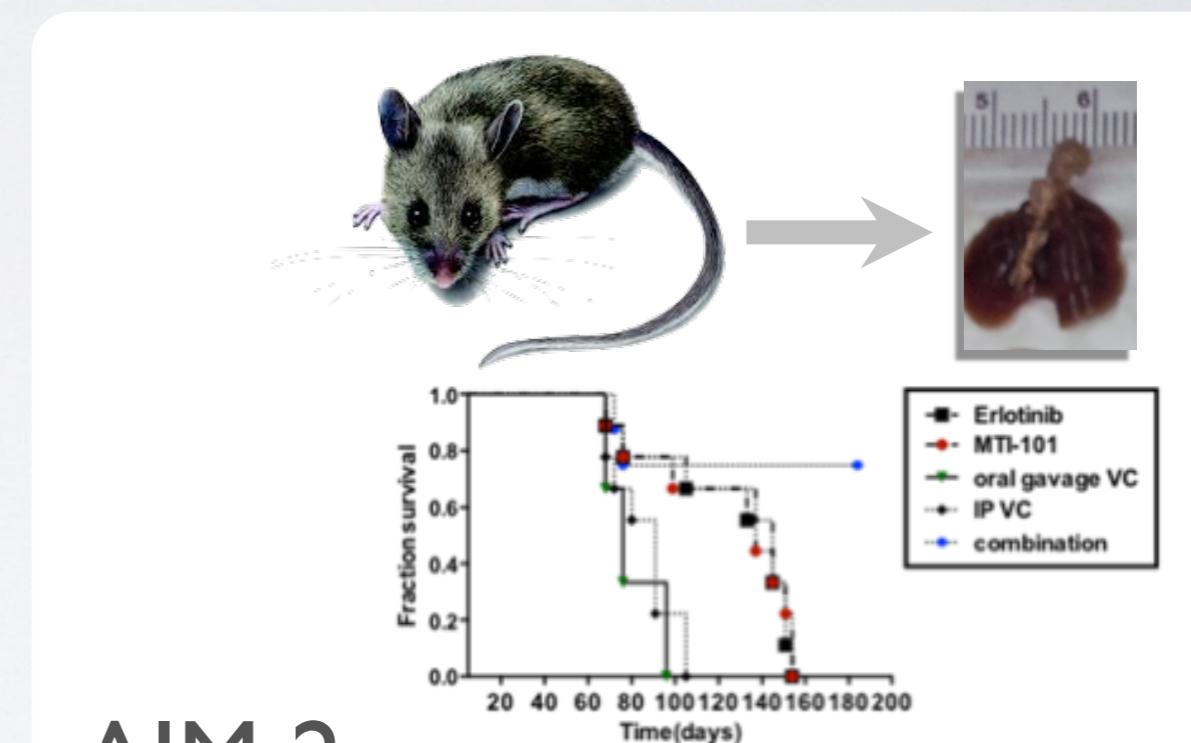


## AIM 1:

Refine the mathematical model using clinical data from a retrospective institutional cohort of advanced EGFR+ lung cancer patients.



**HYPOTHESIS:** Pretreatment molecular phenotypes with real-time clinical variables obtained from plasma and imaging can be used to predict optimal drug sequence and thereby extend progression free survival.



## AIM 2:

Utilize model-derived novel drug combination schedules and compare with standard of care using a metastatic EGFR driven *in vivo* model.

# TEAM LUNG

