

Designing Evolutionary Treatment for Metastatic Non-Small Cell Lung Cancer

Virginia Ardévol Martínez & Kateřina Staňková

Dynamic Game Theory Team

Department of Data Science & Knowledge Engineering, Maastricht University

Joint work with:

Jakob Nikolas Kather, Rachel Cavill, Monica Salvioli, Frank Thuijsman, Joel S. Brown

CATMo 2020



Outline

- 1 Cancer Treatment as a Stackelberg Evolutionary Game (SEG)
- 2 SEG Application to Treatment of Metastatic Non-Small Cell Lung Cancer with Immune Checkpoint Inhibition
 - Data
 - Questions
 - Approach to Address One of These Questions
 - Interesting Observations
 - Results
- 3 Conclusions & Future Research
- 4 Discussion Points

1. Cancer Treatment as a Stackelberg Evolutionary Game

players	physician (leader)	patients' cancer cells (followers)
strategies	therapy options	effective strategies of therapy resistance
objectives	patients' quality of life	fitness

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Salvioli, PhD thesis 2020; Salvioli et al, PLOS One, in press; Cunningham et al, JTB 2018, PLOS One 2020, Stankova et al, JAMA Onc 2019...

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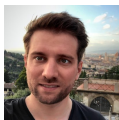
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What is the minimal knowledge necessary?

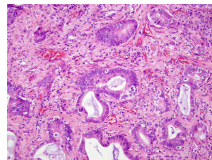
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Data on NSCLC treated with Immune Checkpoint Inhibition:

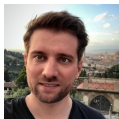


- Stage 4, anti-PD1 drug Atezolizumab (MPDL3280A)
- Tumor diameter over time, typically few time points
- In our dataset typically 2 or 3 metastases per patient

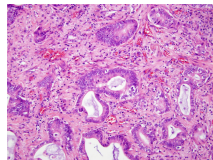


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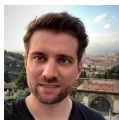


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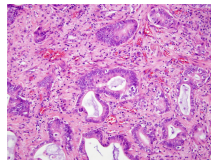


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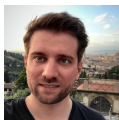
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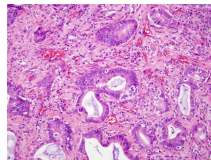
- 1 Based on the initial tumor volume proxy and its trend, can we predict how its volume will change in the future?
- 2 Would adaptive immunotherapy work in cases where tumor keeps growing when treated in the standard way?

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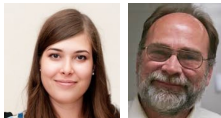


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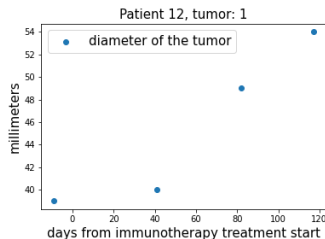
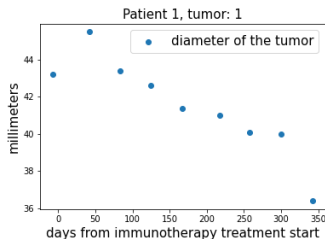
Our modelling approach to answer question 2:



- Fitting the data into minimalistic G-function model
- Optimizing the treatment for cases with tumor growing

2. SEG Application to Treatment of Metastatic NSCLC

Example of data:



- All patients treated with the same immune checkpoint inhibition
- Treatment starts between the first and second data points

Are these different trends a result of treatment-induced resistance and other patient- and tumor-specific factors?

2. SEG Application to Treatment of Metastatic NSCLC

NSCLC model details (Vincent and Brown (2005)):

$$\dot{x} = x G(m, u, x)$$

$$\dot{u} = \sigma \frac{\partial G(m, u, x)}{\partial u}$$

$$G(m, u, x) = r(u) \left(1 - \frac{x}{K}\right) - \frac{m}{k + b u} - d$$

symbol & range	meaning
$m \in \{0, 1\}$	treatment (on or off)
$u \in [0, 1]$	rate of treatment-induced resistance
$K > 0$	carrying capacity
$x \in [0, K]$	cancer cell population
$G(m, u, x)$	fitness-generating function
$r_{\max} > 0$	maximal growth rate
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Three different forms of $r(u)$ considered:

- Quadratic cost of resistance: $r(u) = r_{\max}(1 - u^2)$
- Linear cost of resistance: $r(u) = r_{\max}(1 - u)$
- No cost of resistance : $r(u) = r_{\max}$

2. SEG Application to Treatment of Metastatic NSCLC

Fitting the model (also for predictions):

- The population of cancer cells is estimated from the diameter.
- Distinguishing 6 groups of tumors: 3 according to initial volume and 2 according to initial trend.
- Fix K , b and σ per group, estimate r_{\max} , k and $u(0)$ per patient, d fixed to 0.01.

	Small	Medium	Large
Increasing	$K = 0.1$ $b = 100$ $\sigma = 0.01$	$K = 2$ $b = 150$ $\sigma = 0.01$	$K = 2$ $b = 0.9$ $\sigma = 0.05$
Decreasing	$K = 1000$ $b = 5$ $\sigma = 0.05$	$K = 0.5$ $b = 2$ $\sigma = 0.01$	$K = 1000$ $b = 10$ $\sigma = 0.01$

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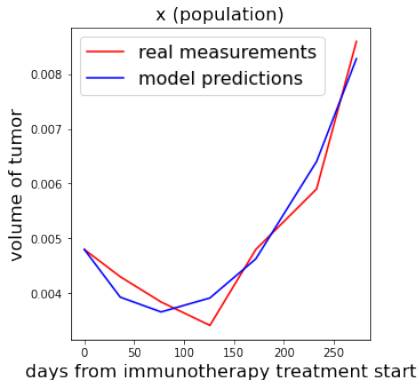
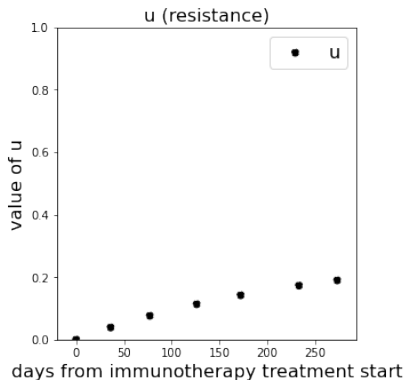
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Jakob Nikolas Kather: "There is no cost of resistance or carrying capacity in cancers I am dealing with"

2. SEG Application to Treatment of Metastatic NSCLC

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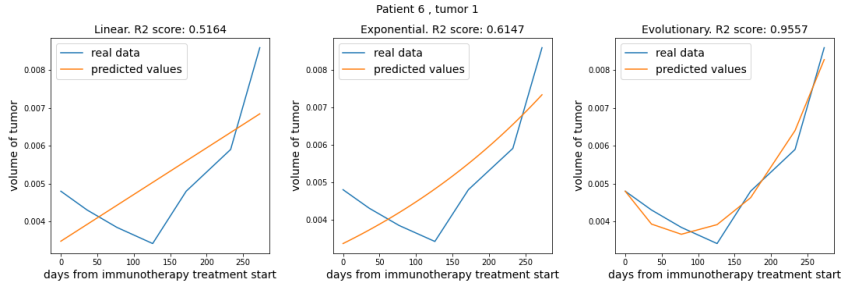
Patient 6, tumor: 1



2. SEG Application to Treatment of Metastatic NSCLC

Comparison with linear and exponential models:

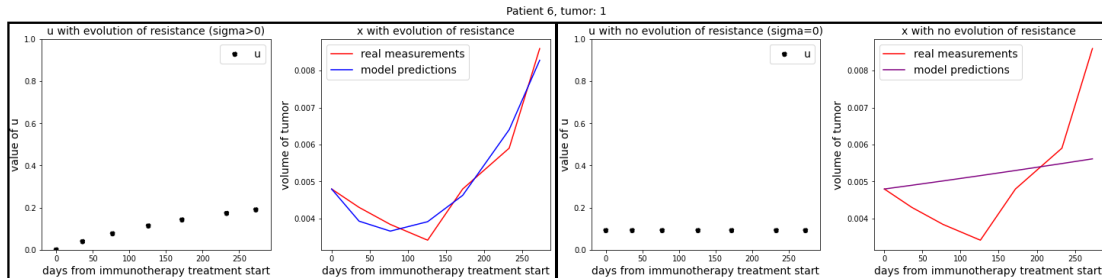
- Mean of the R2-scores: 0.59, 0.72, 0.80 for linear, exponential and evolutionary models, respectively.



Linear, exponential and evolutionary model with quadratic cost of resistance

2. SEG Application to Treatment of Metastatic NSCLC

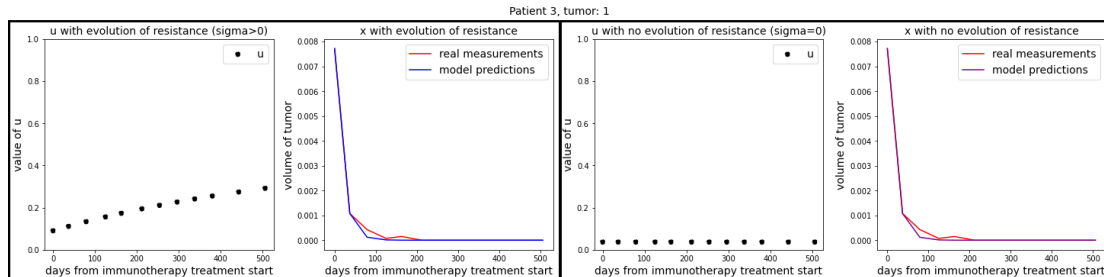
Evolution of treatment-induced resistance only plays an important role in tumors that exhibit a rapid change of trend.



Evolutionary model with quadratic cost of resistance with and without evolution of resistance

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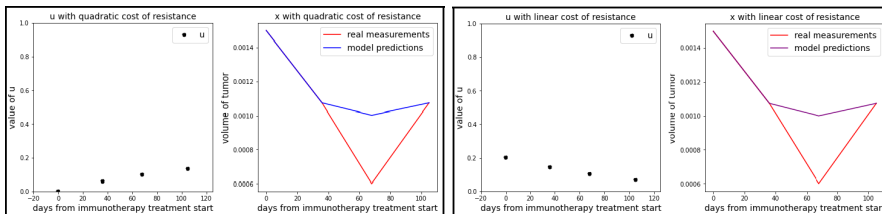
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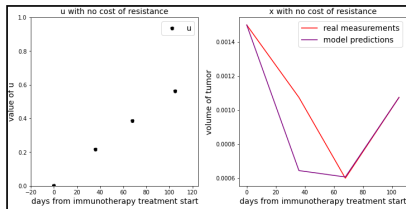
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2. SEG Application to Treatment of Metastatic NSCLC

Comparison of the different forms of $r(u)$:



Quadratic and linear cost of resistance



No cost of resistance

2. SEG Application to Treatment of Metastatic NSCLC

Optimization

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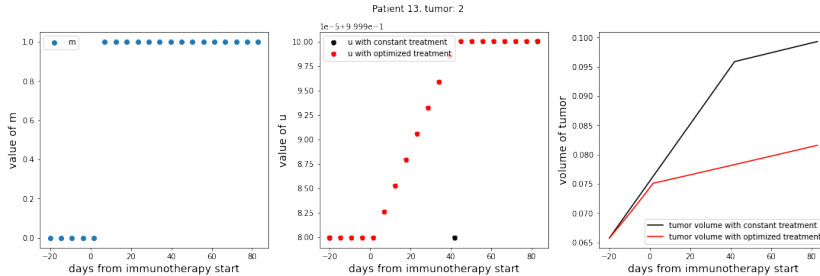
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Preliminary results:

- With linear and/or quadratic cost of resistance, the best is to always treat or not treat at all
- With no cost of resistance, sometimes it is the best to switch between no and standard treatment. We do not understand yet when precisely.
- With the objective $\min x(T)$, we can never stop the growth, we can only slow it down

2. SEG Application to Treatment of Metastatic NSCLC

Optimization - preliminary results:



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- For tumors that change diameter rapidly, evolution of treatment-induced resistance plays a role
- For small tumors the error in estimating tumor volume may cause issues with the best fit; it may be that our conclusion would change with better tumor proxy
- Our model has better predictive capabilities than linear/exponential models used until now

4. Discussion Points/Questions for You

- Does resistance to immune checkpoint inhibition in NSCLC carry a cost?
- If yes, is there any way how to estimate it from other measurements (For other projects/cancers, we are exploring whether genomics and histopathology can help us to answer such questions, but here we know too little)?
- What other information can be useful here?
- Would a model with immune cells as active players be a better choice here?

Thank you !

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