

Data-driven design of targeted gene panels for estimating immunotherapy biomarkers

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January 2021



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Abstract

- ❶ Exome-wide biomarkers such as tumour mutation burden (TMB) are useful predictors of response to immunotherapy.
- ❷ While whole-exome sequencing directly measures TMB, its cost prevents it from being standard-of-care.
- ❸ We develop a data-driven framework both for selecting targeted gene panels and for using them to intelligently estimate immunotherapy biomarkers.
- ❹ To do this, we utilise an exome-wide generative model of mutation, whose structure can be chosen to reflect biological assumptions.

Outline

1 Biological/Clinical Background

- Cancer and immunotherapy
- Exome-wide biomarkers
- Targeted gene panels

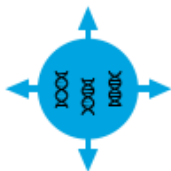
2 Generative/predictive modelling framework

- Generative models: what and why?
- From generative models to predictive models

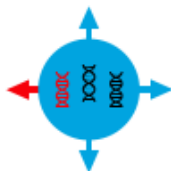
3 Application to non-small cell lung cancer

Cancer is a disease of the genome

Cancer arises when DNA in cells changes (mutates).



(a) Non-cancer cell: Normal DNA.



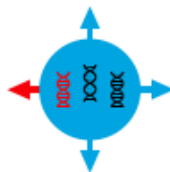
(b) Cancer cell: Mutated DNA.

Immunotherapy enables the immune system

Immunotherapy 'releases the brakes' on the immune system in order for it to attack tumours.



(a) Low-damage cell: **unrecognisable** to immune system.



(b) High-damage cell: **recognisable** to the immune system.

However, the immune system can only attack tumours that it recognises!

Tumour mutation burden stratifies patients for immunotherapy response

As a simple proxy for likelihood of immune response, we can use **tumour mutation burden**: the total count of non-synonymous mutations throughout the tumour exome.

Advantages:

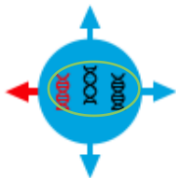
- ❶ Calculated from DNA sequencing only (compatible with liquid biopsy).
- ❷ Relevant across cancer types.

Disadvantages:

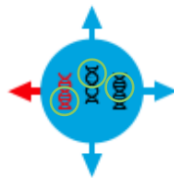
- ❶ Requires Whole-Exome Sequencing (WES) to measure directly.
- ❷ Fails to incorporate other features of the immune environment.

Targeted panels make genomic biomarkers viable

Rather than the entire exome/genome, targeted gene panels sequence a **subset** of genes.



(a) Whole-exome sequencing: **all genes** sequenced.



(b) Targeted panel sequencing: **subset** of genes sequenced.

Problem Statement

Aims:

- 1 Select a discrete set of genes to form a panel (of pre-specified cost).
- 2 Estimate TMB from panel sequencing data.

Mutations and biomarkers: some notation

We'll use i , g , and s to refer to:

- 1 A sample i (ranging from $i = 1$ to $i = N$),
- 2 A gene g (belonging to some index set G),
- 3 A variant type s (for example synonymous/non-synonymous).

Finally, we write:

- 4 M_{igs} , to refer to a mutation count of a particular sample, gene, and mutation type.

We then can define the TMB of the i th sample via:

$$T_i = \sum_{\substack{g \in G \\ s: \text{non-synonymous}}} M_{igs}.$$

What is a generative model of mutation?

A generative model of mutation attempts to capture the **underlying distribution** of variants across the entire exome/genome.

A simple example (Poisson):

$$M_{igs} \sim \text{Poisson}(\lambda_{gs}) \quad (1)$$

Why use generative models of mutation?

- ❶ Utilise known biology to inform the structure of the model.
- ❷ (Sometimes) make interpretable inferences.
- ❸ Generate trust that we've thought about it!

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Choice of distribution, exome organisation, parameter space.

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Parameter estimates, post-model inference.

- ❸ Generate trust that we've thought about it!

Generative models to predictive models

Aims:

- 1 Select a discrete set of genes to form a panel (of pre-specified cost).
- 2 A mechanism for estimating TMB from panel sequencing data.

Proposed mechanism: Linear estimator.

$$\hat{T} = \sum_{g,s} w_{gs} M_{igs} \quad (2)$$

Optimisation procedure:

$$\hat{w} := \arg \min_w \{ \mathbb{E}[(\hat{T}_i - T_i)^2] + \lambda |w| \}, \quad (3)$$

where λ is a penalty specifying panel cost, and the expectation \mathbb{E} is over the distribution learned by our generative model.

NSCLC: Poisson-based generative model fit

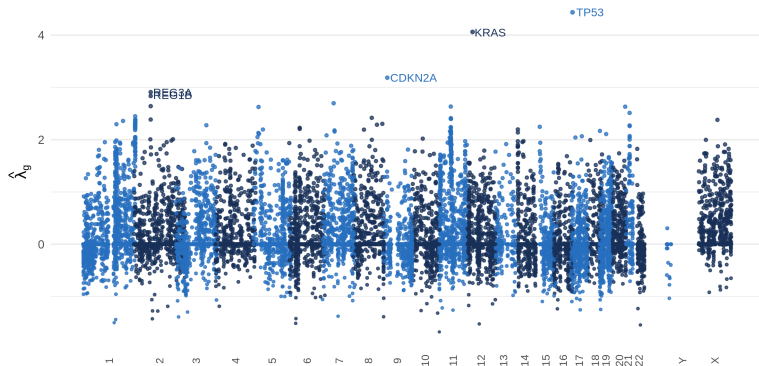


Figure: Generative model parameters.

NSCLC: Poisson-based generative model fit

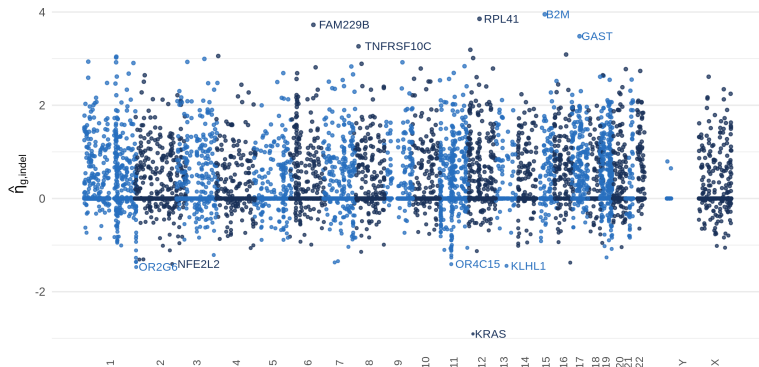


Figure: Generative model parameters (indel-specific).

NSCLC: Estimation performance

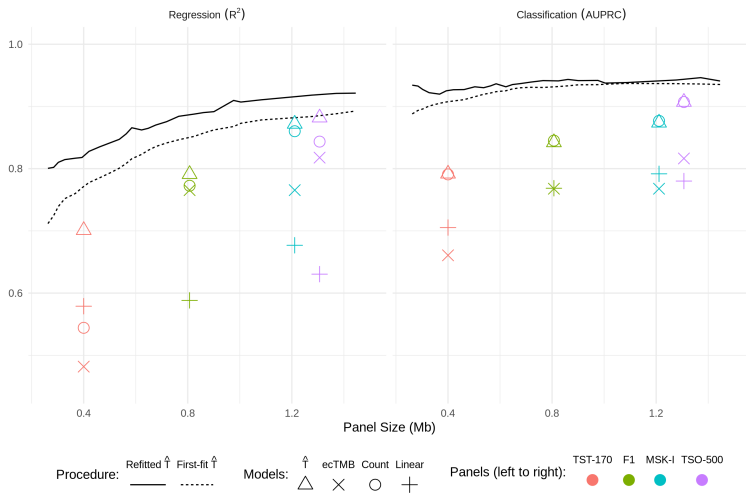


Figure: Predictive model performance: comparison with commercial panels and other predictive methods.