

Problem Statement

Introduction

- Virtual patients (VPs) are used within QSP modeling to explore the impact of variability and uncertainty on clinical response
- Combinations of parameter values that produce physiological solutions, i.e., valid VPs, are difficult to determine a priori, because of complex interdependencies in QSP models
- Sampling parameters, simulating protocols of interest, and then filtering out any non-physiological solutions is a common approach
 - Number of plausible VPs may be only a fraction of the generated VPs (<5%)
 - Requires time-consuming simulations to build a cohort of VPs that fully characterizes variability
- Machine learning (ML) surrogate models are a promising approach for improving efficiency of VP generation
 - Infers valid parameter combinations from preliminary QSP model simulations and "pre-filters" parameter sets based on predicted response values

Objectives

• Use machine learning surrogate models to improve efficiency of VP cohort generation in a psoriasis QSP model

Conclusion

Use of surrogate models significantly increases efficiency over random parameter sampling for generation of VP cohorts with no loss of diversity.

Design

- Use existing psoriasis QSP model constructed in MATLAB[®]SimBiology[®]
 - 11 constrained model species, 5 varied parameters
- Use Gaussian Process Regression (GPR) as regression function to generate surrogate models
 - Evaluated several ML models using MATLAB[®] Regression Learner app; compared Root Mean Squared Error (RMSE) for each model type
- Train surrogate models with data (10,000 simulations) at a 70/30 partitioned split
 - Use QSP model to generate data for the regression function

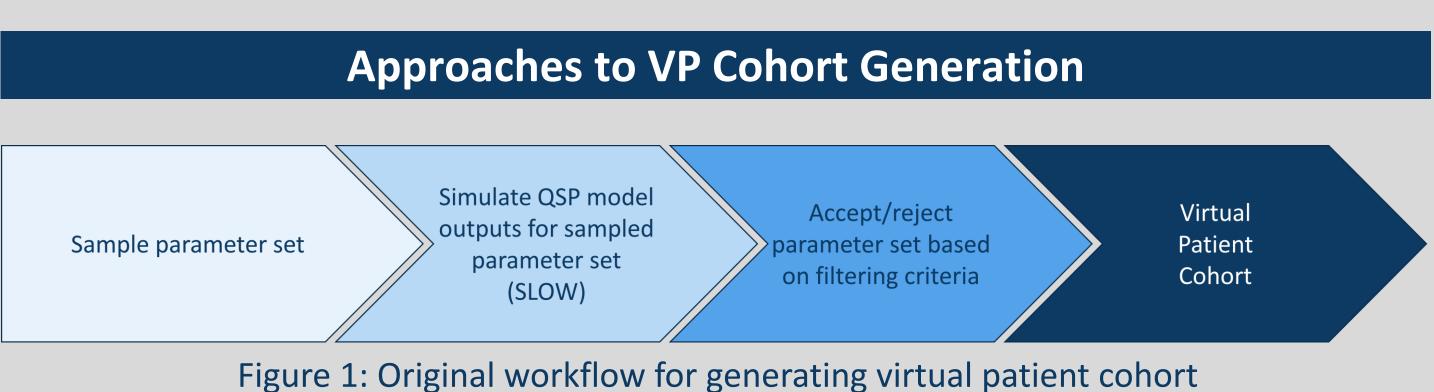
Surrogate Modeling with Machine Learning for Faster Virtual Patient Cohort Generation in QSP Models

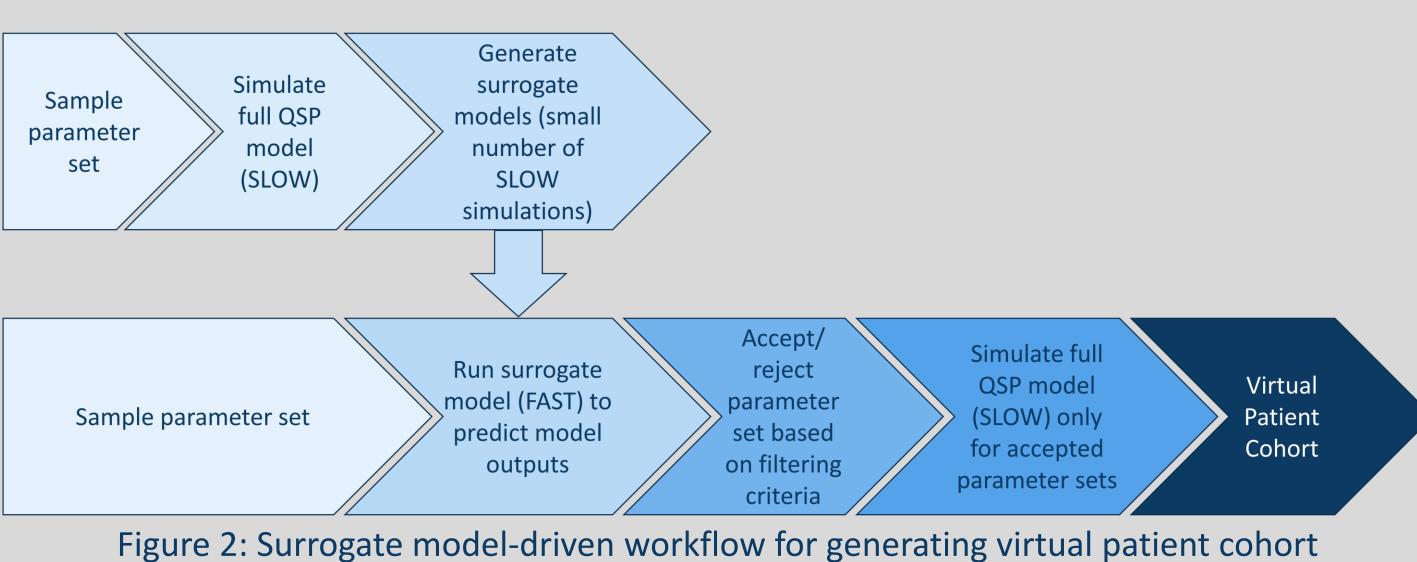
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Methods

Surrogate Modeling

- Surrogate model: Statistical model that approximates a complex, higher order model
 - Surrogate model is trained using input/output data obtained through simulation of the original model
- Surrogate models can be used to "replace" a mechanistic model that might be slow to simulate, yielding very fast predictions
- Surrogate models are a smarter approach to VP cohort generation • Simulation of QSP models: Computationally expensive; potential for many parameter sets to be rejected after filtering
 - Surrogate modeling approach: Instantaneously predict model output for a parameter set, accept/reject parameter sets based on filtering criteria





Efficiency of Method

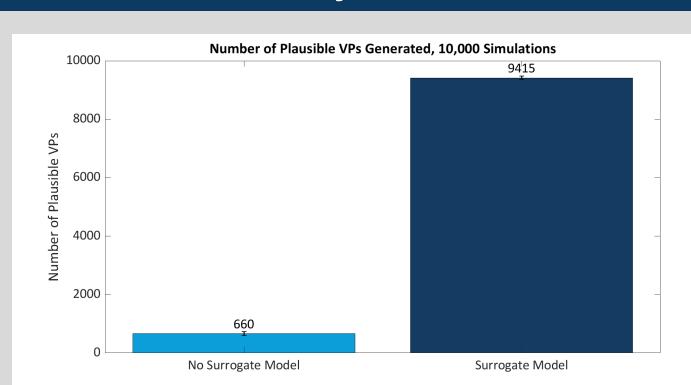
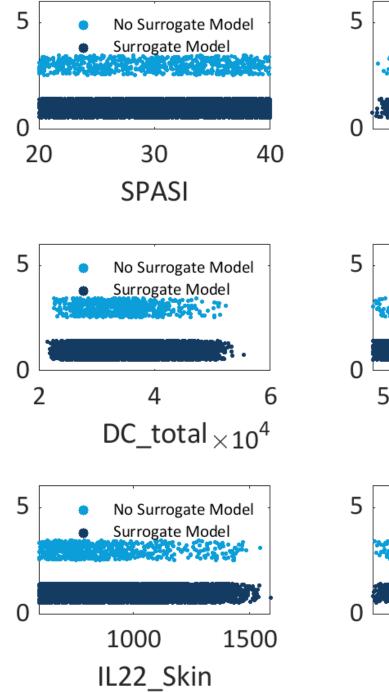


Figure 3: Number of plausible VPs generated by both the original and surrogate modeling approaches. Error bars represent standard deviation from 5 trials of 10,000 simulations each.

Result: Surrogate modeling approach generated **14x** as many plausible VPs as the original approach for the same amount of computational time once the surrogate models were constructed





Distribution of Sampled Parameters

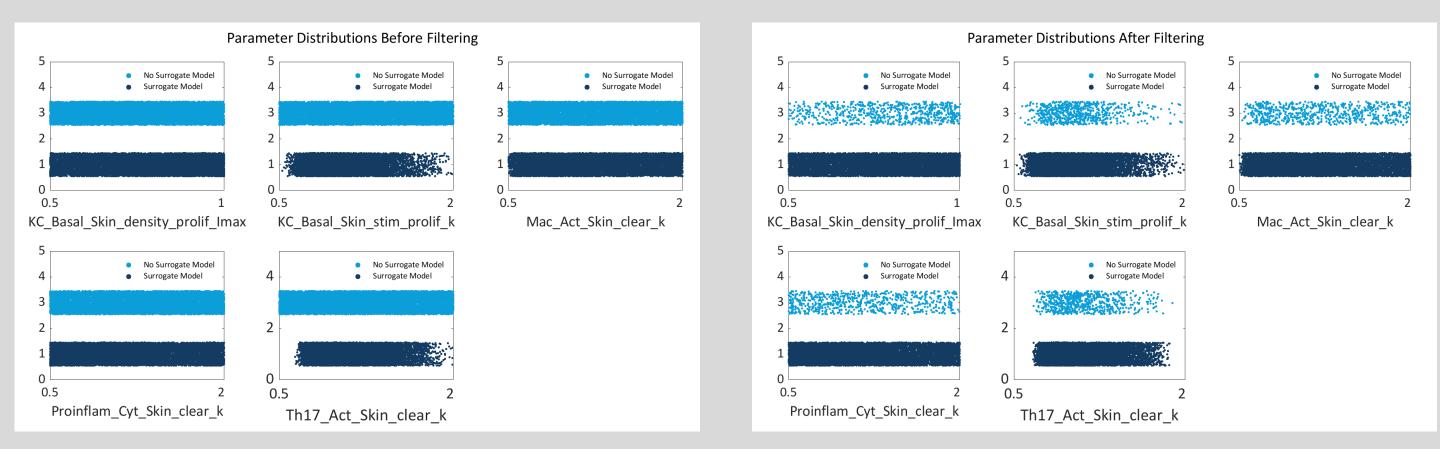


Figure 5: Distribution of sampled parameters before filtering (left) and after filtering (right) for both the original and surrogate modeling approaches.

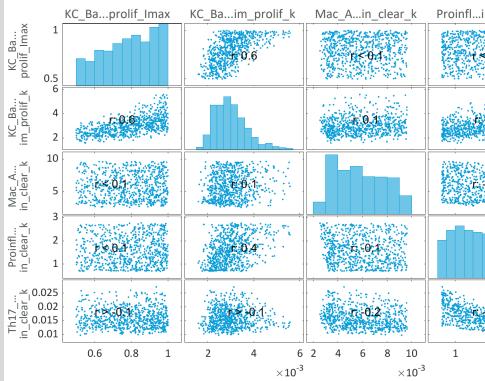


Figure 6: Correlation matrix for sampled parameters after final filtering step for (left) virtual cohort created using original workflow and (right) parameters sampled using surrogate modeling approach.

- preserved.



Results

Distribution of Model Observables Observables Distributions No Surrogate Mode No Surrogate Model No Surrogate Model Surrogate Model Surrogate Mode KC_Basal_Skin_0⁴ KC_Diff_Skip₁₀² CC_Skin $\times 10^4$ No Surrogate Mode No Surrogate Mode No Surrogate Mode Surrogate Mode Surrogate Model 10000 10 Th17_total IL17 Skin $Treg_total_{\times 10}^4$ No Surrogate Model No Surrogate Model Surrogate Model Surrogate Model 100 150 200 60 IL23_Skin TNF_Skin

Figure 4: Distribution of model observables after filtering at steady state (60 weeks).

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• **Results:** Model outcomes and parameters were similarly distributed in both methods. Relationships between parameters were also

• **Significance:** The use of surrogate models does not diminish sampling or outcome variability, and recapitulates relationships between parameters consistent with the full QSP model.