

VIRGO: Variational Inference Bayesian machine learning model for Risk adjustment of General Outcome indicators

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INTRODUCTION

- Audit and feedback is a crucial part of improving healthcare quality.
- Comprehensive risk adjustment that consider patient risks is needed to facilitate fair benchmarking of outcome indicators.
- Current methods do not comprehensively account for the interactions between diagnosis and procedures.
- We aim to create an explainable Bayesian machine learning model that **facilitates risk adjustment and explanation** for better audit and feedback.
- We present **VIRGO**: Variational Inference Bayesian machine learning of General Outcome indicators.

METHODS

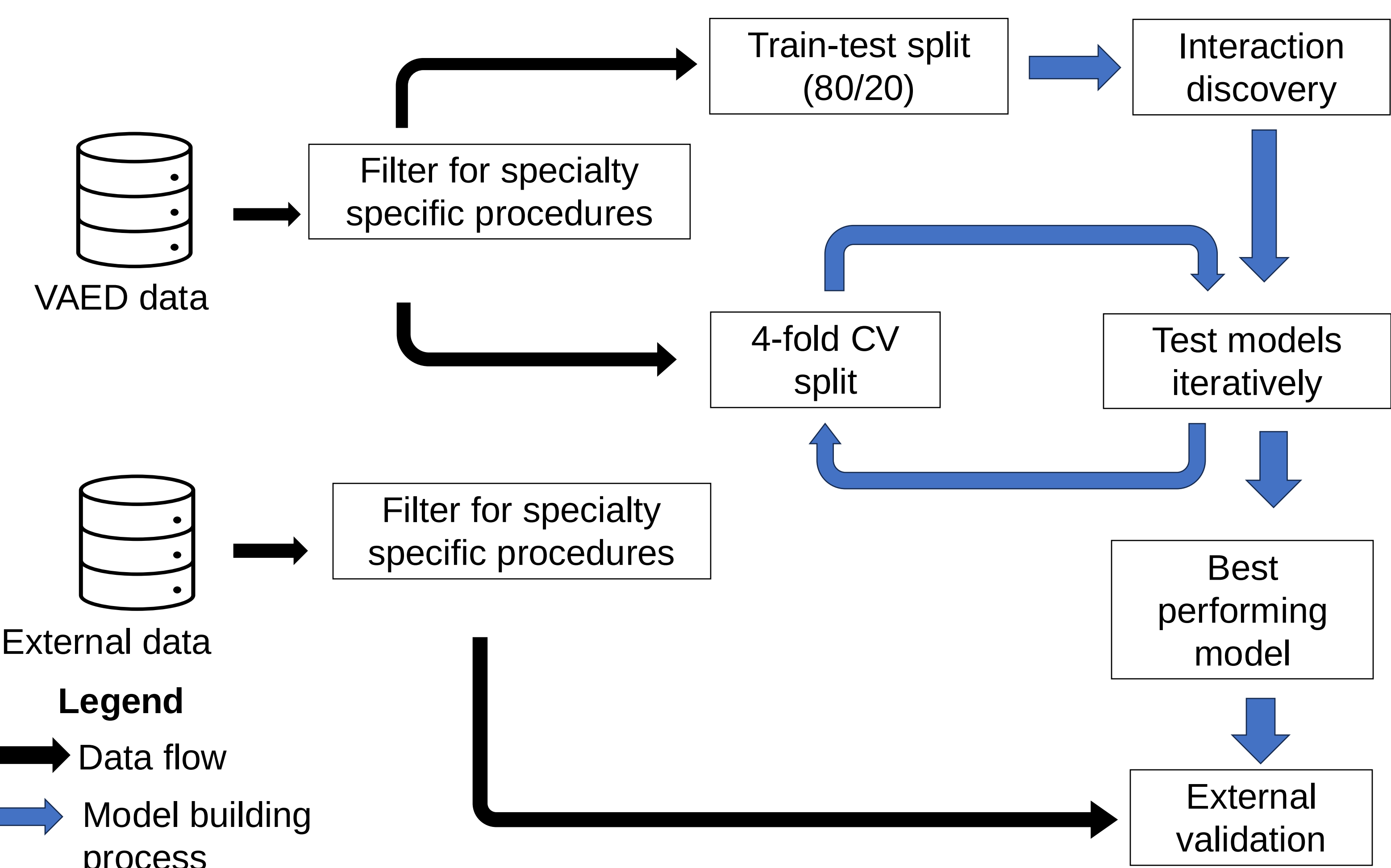


Figure 1: Data pre-processing and validation steps.

- We model length of stay (LOS) and hospital acquired complications (HACs) rate using zero-inflated negative binomial (ZINB), facilitating **true to distribution modelling**.
- We use cross-validation to train our model, using data from all patients in Victoria.
- After training, we tested on external datasets provided by partner hospitals.
- We compare our prediction using RMSE against XGBoost and LightGBM, two state of the art machine learning (ML) algorithms and other common ML algorithms.

RESULTS

Risk Adjustment Capabilities

Case study of patient with longer than expected LOS

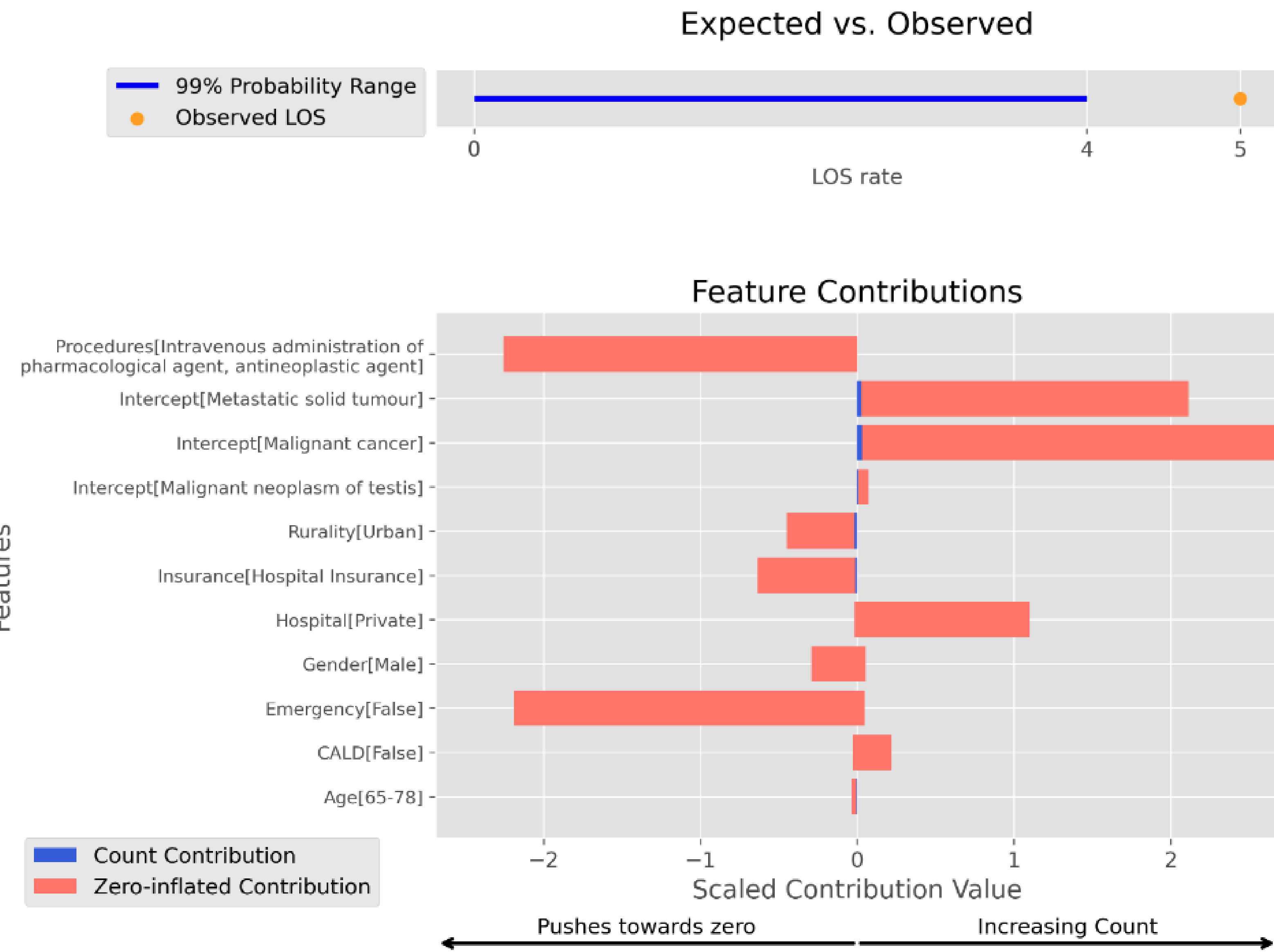


Figure 2: Case study of a patient with longer than expected LOS. The top subplot compares the predicted length of stay (LOS) within a 99% probability range against the observed LOS rate. The bottom subplot elucidates the contribution of individual model variables. By adjusting for patient risk factors, procedures and diagnosis, VIRGO can provide feedback and indicate potential outliers for further investigation.

RESULTS

Predictive Capabilities

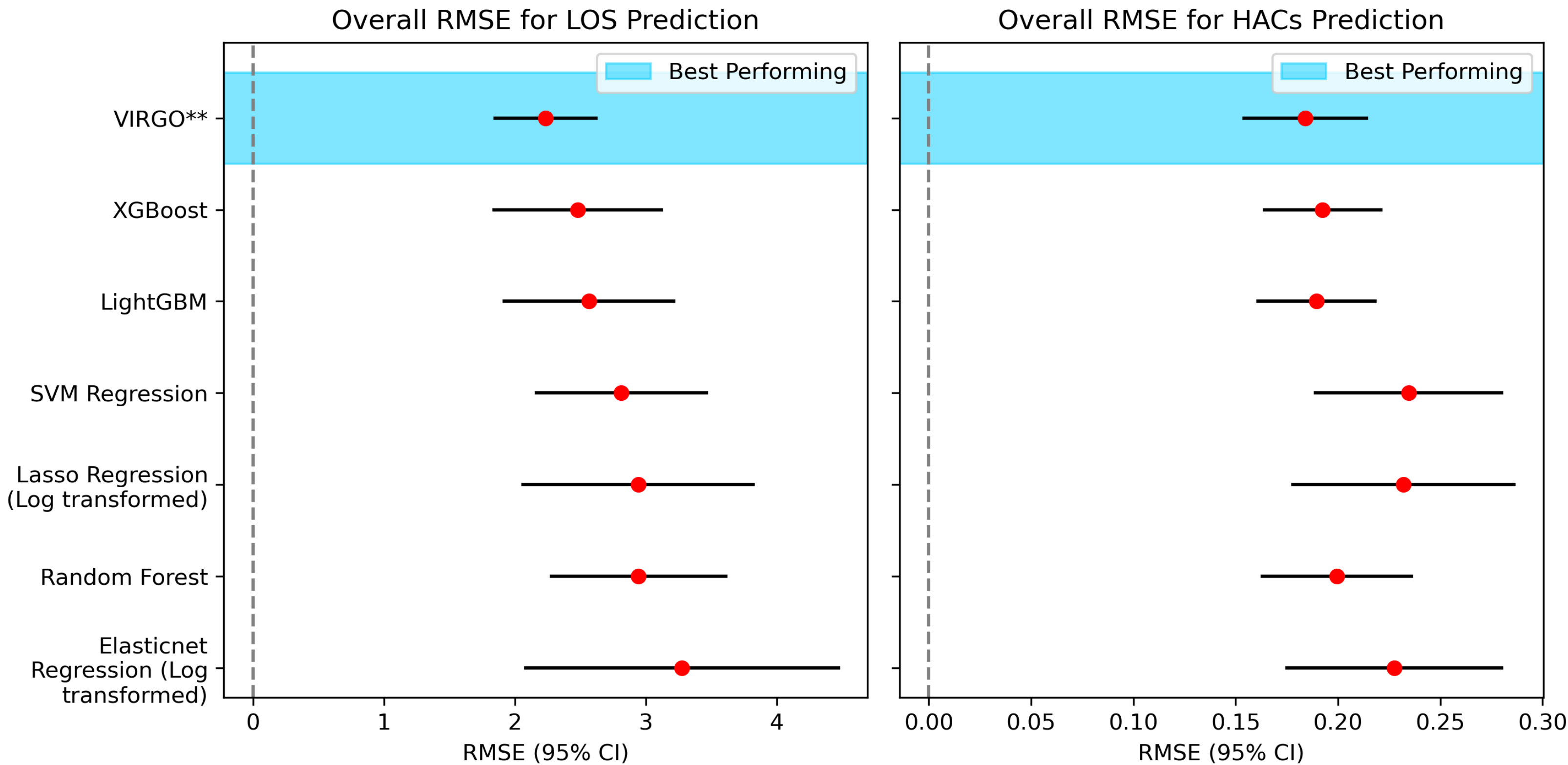


Figure 3: Prediction capabilities of VIRGO.

- Our model performed the best in predicting both LOS and HACs against state-of-the-art ML algorithms. (Figure 3)

Explanation Capabilities

Figure 4.1

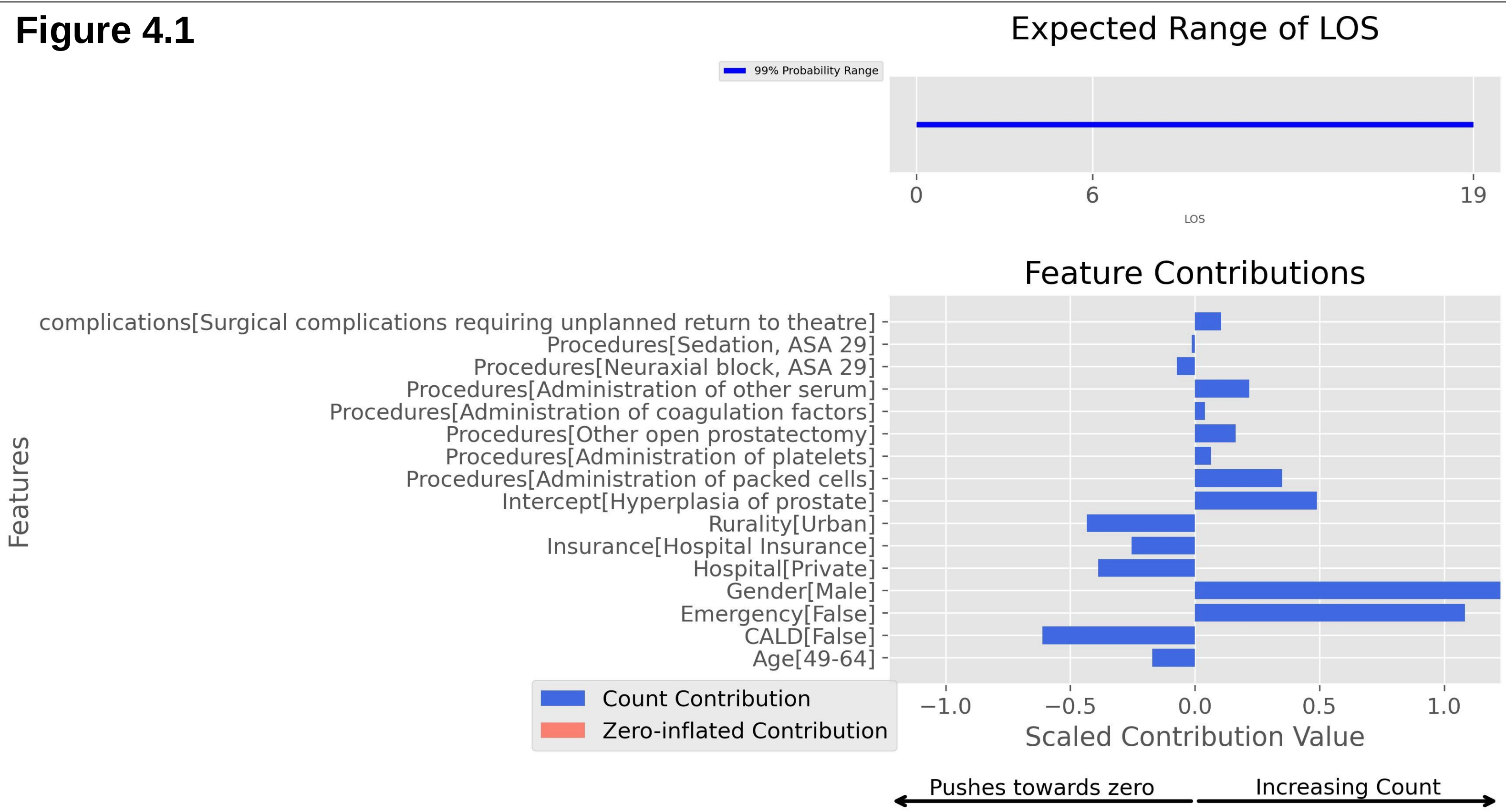


Figure 4.2

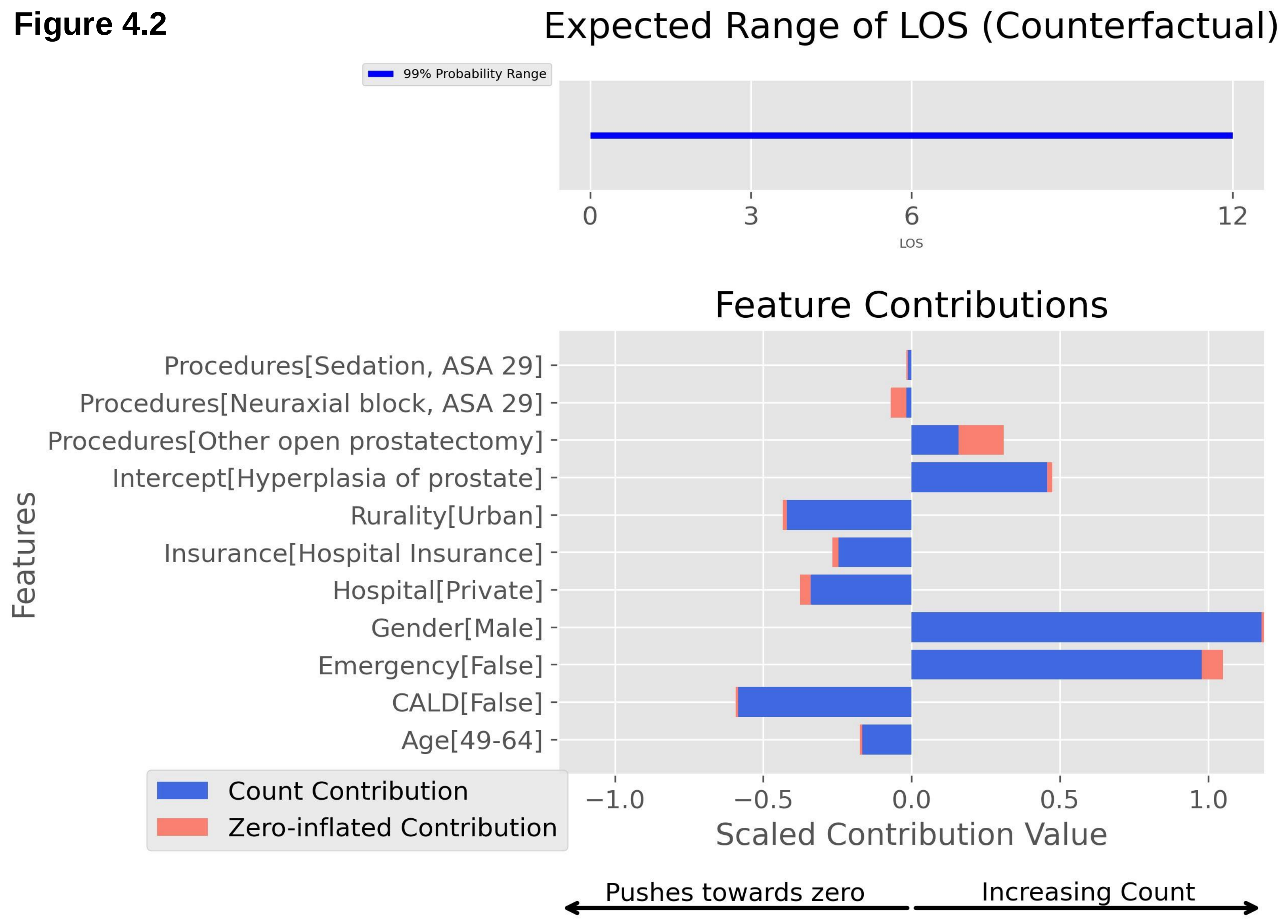


Figure 4: Counterfactual analysis of a patient with surgical complications developed during open prostatectomy for prostate hyperplasia (Figure 4.1). We simulate expected outcomes *if the patient* did not have surgical complications and require blood transfusions. The model predicts that within 99% probability that expected LOS drops from 0 – 19 days to 0 – 12 days (Figure 4.2).

CONCLUSIONS

- By risk-adjusting patient risk factors, diagnosis and procedures, VIRGO can be used to provide clinically relevant feedback to healthcare professionals **using only hospital administrative data**.
- Furthermore, given the accurate predictions of LOS, hospital administrators can allocate hospital resources efficiently.



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Contact Harvey!

