Table 1: **Table: Summary Statistics by 30-Day Complication Status**

Variable	**No Complication** N = 927[1]	**Complication** N = 73[1]	**p-value**[2]
Age	59.22 (14.06)	65.99 (12.11)	<0.001
BMI	27.00 (4.69)	27.49 (5.11)	0.6
Surgery_Duration_Minutes	95.95 (39.79)	113.55 (47.64)	0.001
Estimated_Blood_Loss	126.47 (98.13)	143.85 (107.14)	0.2

[1] Mean (SD)

[2] Wilcoxon rank sum test

Complication Risk Model: SDSC Analytic Pitch

Walker Blackston, MSPH

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Background

To demonstrate how I think through surgical outcome prediction and statistical problems, I built a prototype risk model for 30-day complications based on simulated surgical data.

In this hypothetical dataset of 1,000 patients, we sought to compare predictors of complications at 30-days follow up from surgery. We simulated a variety of demographic and clinical variables based on seeds of real-world data and expected distributions in a random sample of patients. The following brief will highlight steps in the analysis, modeling and interpretation of findings. A full printout of code used to generate data and this document are available in the Github provided in my pitch.

Table 2: **Table: Procedure Type Distribution by 30-Day Complication Status**

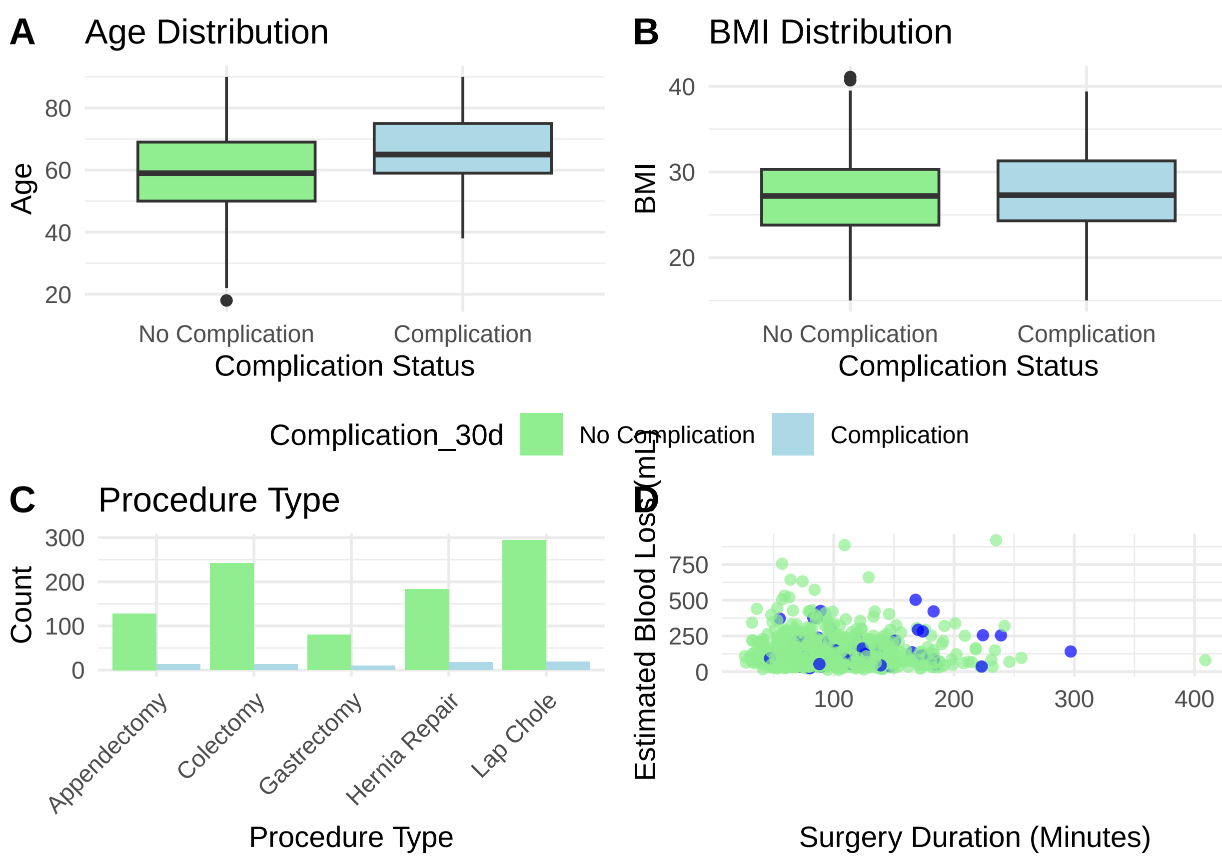
Procedure Type	**No Complication** N = 927[1]	**Complication** N = 73[1]	**p-value**[2]
Procedure_Type			0.2
Appendectomy	128 (14%)	13 (18%)	
Colectomy	242 (26%)	13 (18%)	
Gastrectomy	80 (8.6%)	10 (14%)	
Hernia Repair	183 (20%)	18 (25%)	
Lap Chole	294 (32%)	19 (26%)	
Intraoperative_Events	138 (15%)	21 (29%)	0.002
ASA_Class			0.039
1	83 (9.0%)	8 (11%)	
2	290 (31%)	18 (25%)	
3	352 (38%)	22 (30%)	
4	159 (17%)	16 (22%)	
5	43 (4.6%)	9 (12%)	

[1]n (%)

[2]Pearson's Chi-squared test; Fisher's exact test

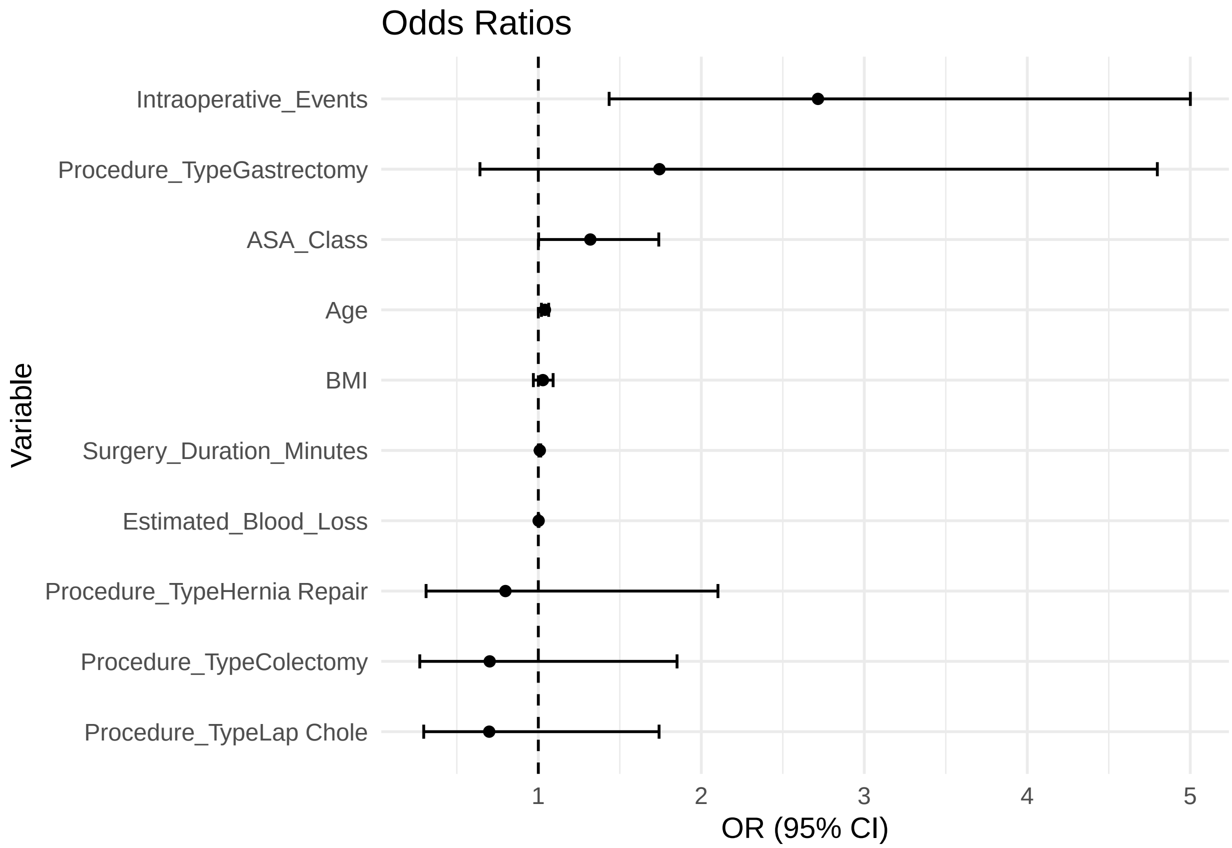
Data Summary

Exploring the data

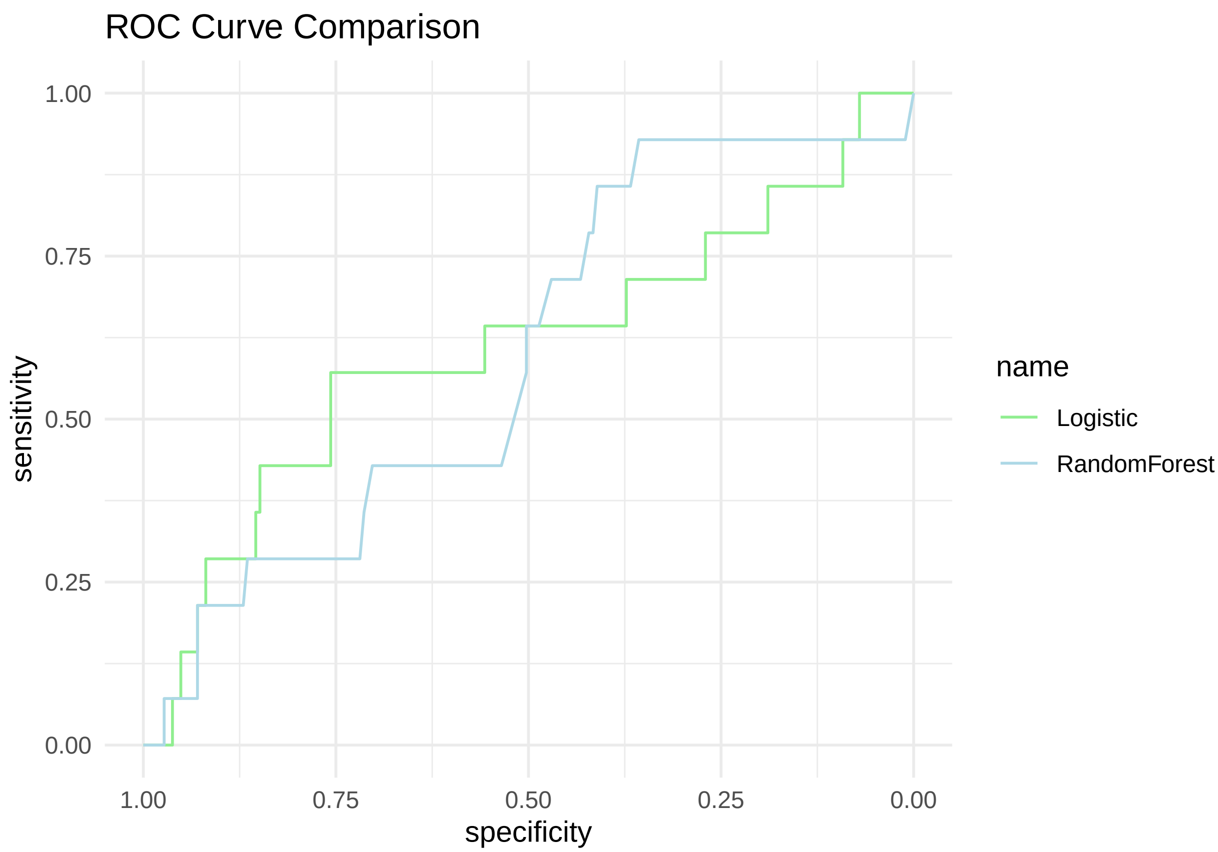


Predictive Modeling

Logistic Model



Machine Learning Model (Random Forest)



Results

The model achieved an AUC (Logistic): 0.61 and AUC(RandomForest): 0.6, respectively with higher odds of complication associated only with:

- Advanced age
- Intra-operative events

Accuracy and Interpretation

Table 3: Confusion Matrix (Logistic Regression)

Prediction \ Reference	No Complication	Complication
No Complication	185	14
Complication	0	0

Table 4: Overall Performance Metrics (Logistic Regression)

Accuracy	Kappa	AccuracyLower	AccuracyUpper	AccuracyNull	AccuracyPValue	McnemarPValue

0.93	0	0.88	0.96	0.93	0.57	0

Table 5: Class-Specific Performance Metrics (Logistic Regression)

Sensitivity	Specificity	Pos Pred Value	Neg Pred Value	Precision	Recall	F1	Prevalence	Detection Rate	D
1	0	0.93	NaN	0.93	1	0.96	0.93	0.93	

Table 6: Confusion Matrix (Random Forest)

Prediction \ Reference	No Complication	Complication
No Complication	185	14
Complication	0	0

Table 7: Overall Performance Metrics (Random Forest)

Accuracy	Kappa	AccuracyLower	AccuracyUpper	AccuracyNull	AccuracyPValue	McnemarPValue
0.93	0	0.88	0.96	0.93	0.57	0

Table 8: Class-Specific Performance Metrics (Random Forest)

Sensitivity	Specificity	Pos Pred Value	Neg Pred Value	Precision	Recall	F1	Prevalence	Detection Rate	D
1	0	0.93	NaN	0.93	1	0.96	0.93	0.93	

Next Steps

This model demonstrates early potential to extract explainable risk signals from surgical outcomes data. If advanced with real-world video and procedural metadata, the insights could power a live surgeon feedback loop or benchmark dashboard.