Clinic No-Shows

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Game Plan

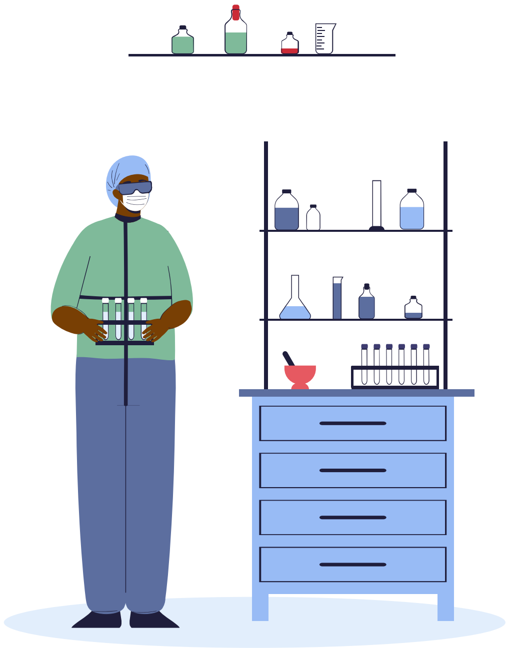
An exciting look ahead at what we'll cover:

01	**Problem**	What's the goal and why is this important?
02	**Data**	What's the data like? How was it processed?
03	**Models**	Probability models used and why they work?
04	**Evaluation**	How did we evaluate the models? Priors/Posteriors/Predictive evaluations?
05	**Results**	What were our findings?
06	**Conclusion**	What did we achieve? What limited us?

01

What’s the problem?

And why do we care?



No-Shows Hurt both Clinics and Patients!

No-Shows waste resources and time in the scheduling process, leading to delayed medical care that could impact health outcomes!

Identifying patients prone to “no-showing” could allow for interventions:

more frequent reminders

coordinating transportation

allocating home-health resources

02

Data

And what we did to it!

Data and Processing

Gender	M/F
Age	0–115
Neighborhood	Location of appointment
Scholarship	0/1
Hypertension	0/1
Diabetes	0/1
Alcoholism	0/1
Handicap	0–4
SMSRecieved	0/1
ScheduledDay	Date of scheduling
AppointmentDay	Date of appointment
NoShow	Yes/No

Preprocessing steps

- Converted categorical variables into numerical
- Corrected spelling of variable names
- Removed negative data and DateTime variables

New Variables Created

1. App_weekday: Generated from original appointment date variable
2. Days_between: Date of appointment – Date appointment was scheduled
3. Days_between_log: Log transformation of the Days_between variable

03

Modeling

And why we chose these models!

Models we attempted:

Hierarchical Model

Used 81 Neighborhoods as groups.

$$ln\left(\frac{P_{NoShow}}{1-P_{NoShow}}\right) = \alpha_{j,i} + \beta_{j,i}x_i + \epsilon_i$$

Full GLM

Included all predictors in the model except 'Neighborhood' variable.

Reduced GLM

Included only significant predictors in the model.

$$ln\left(\frac{P_{NoShow}}{1-P_{NoShow}}\right) = \alpha + \beta x_i$$

Resampled GLM (Reduced)

Under-sampled from majority class to improve performance.

Transformed Predictors GLM (Reduced)

Log transformed days_between variable to improve performance.

Priors

We were fairly uninformed:

$$\alpha \sim N(0, 1) \qquad\qquad \beta \sim N(\vec{0}_k, \vec{1}_k)$$

- After research into this topic area and little experience, we weren’t able to make a strong judgment on the shape of our parameter distribution.
- Normal priors were chosen due to the fact we had either scaled or and binary encoded data as we know that the data could possibly look Gaussian after transformations.

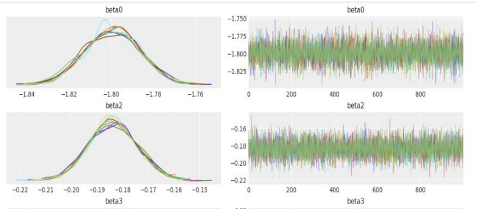
04

Evaluation

Prior, Posterior, and Predictive Evals!

Full/Reduced Model Prior Eval

	rank	elpd_waic	p_waic	elpd_diff	weight	se	dse	warning	scale
reduced_glm	0	-40165.529339	7.177396	0.000000	0.555282	159.600184	0.000000	False	log
full_glm	1	-40165.936794	11.299102	0.407455	0.444718	159.611291	2.717845	False	log

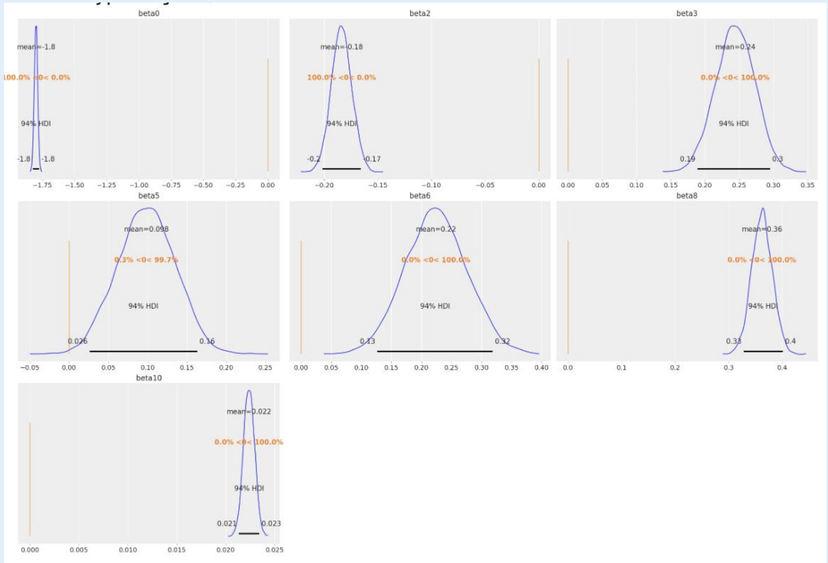


		mean	sd	hdi_3%	hdi_97%	mcse_mean	mcse_sd	ess_bulk	ess_tail	r_hat
Intercept →	**beta0**	-1.799	0.013	-1.824	-1.775	0.0	0.0	9862.0	5971.0	1.0
Scaled Age →	**beta2**	-0.184	0.009	-0.201	-0.166	0.0	0.0	10837.0	6876.0	1.0
Scholarship →	**beta3**	0.244	0.028	0.189	0.295	0.0	0.0	11267.0	6579.0	1.0
Diabetes →	**beta5**	0.098	0.037	0.026	0.163	0.0	0.0	10737.0	5343.0	1.0
Alcoholism →	**beta6**	0.224	0.051	0.126	0.319	0.0	0.0	12794.0	6274.0	1.0
SMSRecieved →	**beta8**	0.362	0.019	0.328	0.401	0.0	0.0	10617.0	6211.0	1.0
Days_between →	**beta10**	0.022	0.001	0.021	0.023	0.0	0.0	10620.0	6300.0	1.0

↑ Uncertainty Range

↑ Convergence!

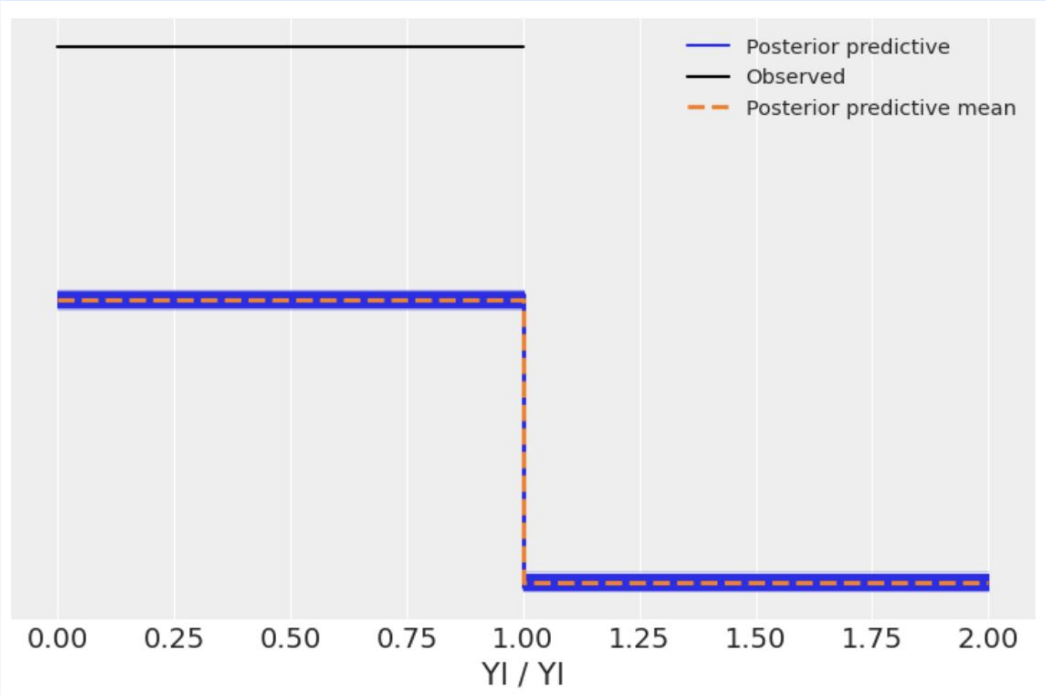
Full/Reduced Model Posterior Eval



Significant Predictors:

- Scaled-Age
- Scholarship
- Diabetes
- Alcoholism
- SMSreceived
- Days-Between

Predictive Eval with Uncertainty



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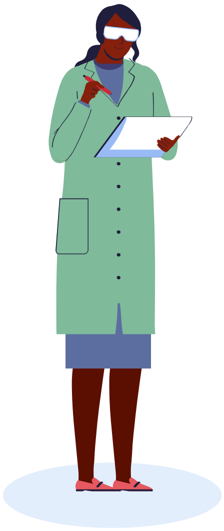
Results

What we found!



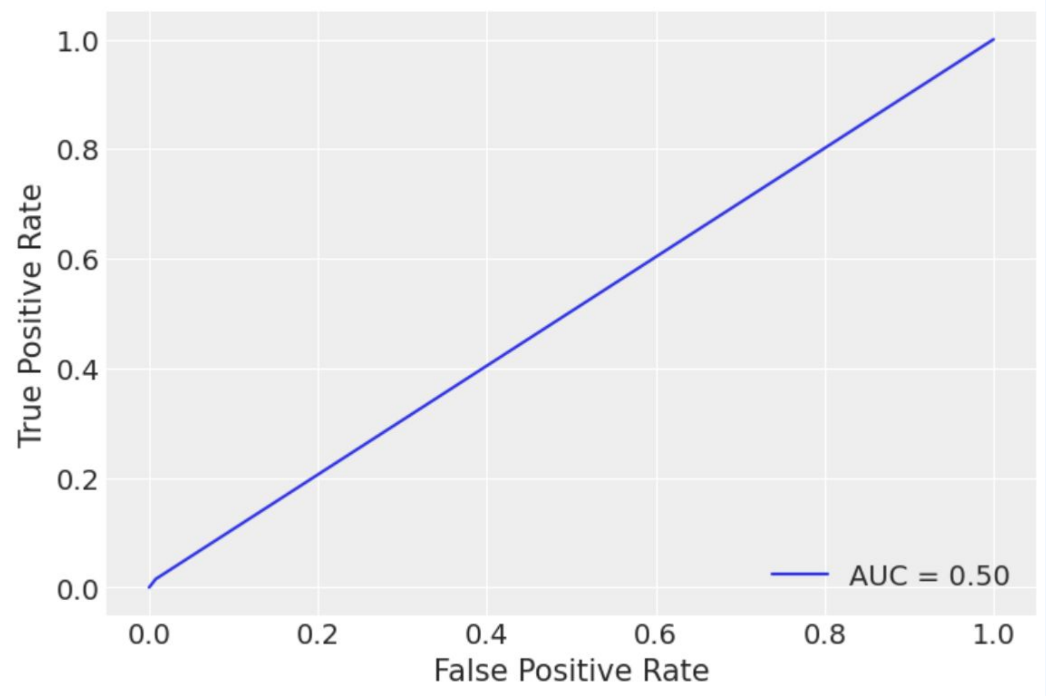
Model Results

Model	AUC	Precision
Hierarchical Model	None*	None*
Full GLM	0.503	1.52%
Reduced GLM	0.504	1.52%
Reduced GLM, Undersampled	0.558	23.18%
Reduced GLM, Undersampled, Transformed	0.612	56.49%

*Too many divergences

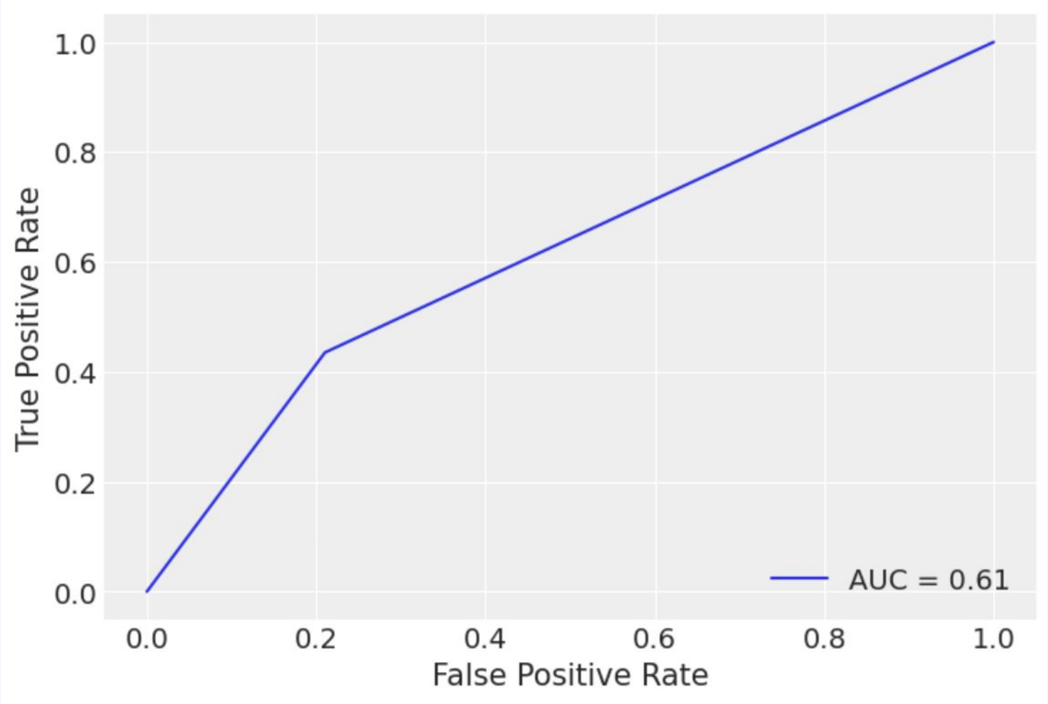
Full/Reduced Model Performance

	Show	No Show
Show	21918	170
No Show	5460	84



Undersampled Model Predictive Eval (Best Model)

	Show	No Show
Show	17443	4645
No Show	3132	2412



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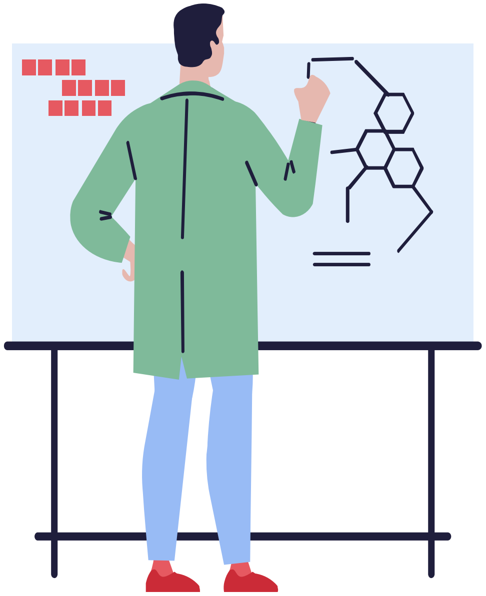
Conclusion

And limitations



Limitations we faced

Not Generalizable

Data only includes Brazilian clinic information

Imbalanced No-Show Ratio

Only 20% of patients classified as ‘no-show’

Wrong Data for Problem

Simple binary predictors about medical history could potentially not be appropriate for this problem

* Our last limitation was **time**. Given more time I’m sure we could have improved our predictive accuracy!

Conclusion
(We did not achieve our goal)

- Overall, we were **disappointed** by the predictive performance of our best model
- Although we attempted to predict whether a patient would be a “no-show”, **our best model only performed slightly better than random guessing**
- We would not recommend the utilization of this algorithm in the clinic setting to predict “no-shows”
- **Different patient characteristics** may better predict “no-shows”
- Given more time, we would try **interaction terms**, different preprocessing **regularization**, and finding **more quantitative predictors**!

Thanks!

Do you have any questions?

Resources

Special thanks to the resources below!

- Liu, D., Shin, W.-Y., Sprecher, E., Conroy, K., Santiago, O., Wachtel, G., & Santillana, M. (2022). Machine learning approaches to predicting no-shows in pediatric medical appointment. *Npj Digital Medicine*, *5*(1), Article 1. https://doi.org/10.1038/s41746-022-00594-w
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