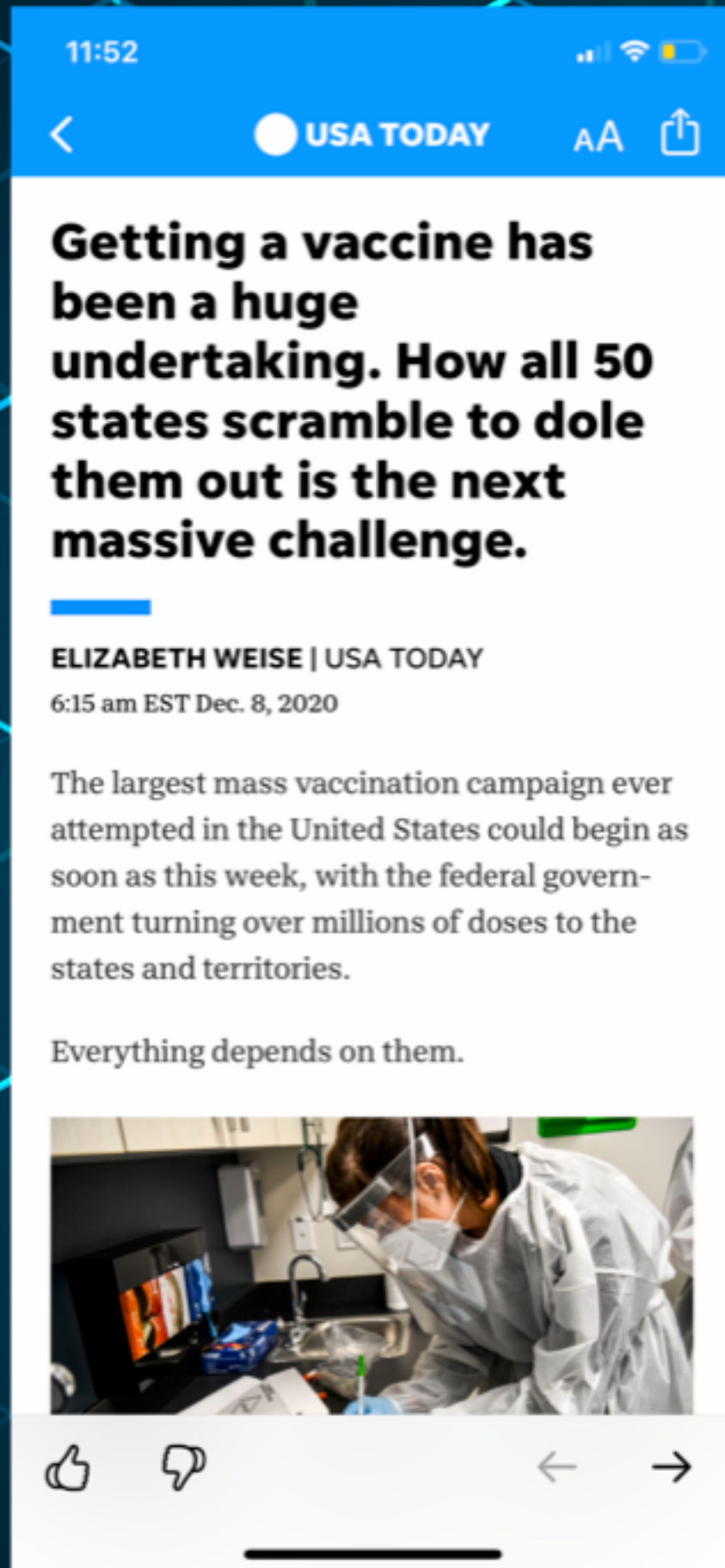


H1N1 Vaccine Prediction

Group 10

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Introduction

- Using National 2009 H1N1 Flu Survey to predict vaccine demand in the United States
- Focusing on quantity of production

Business Problem

Why is this important?

- Pharmaceutical companies need an estimate as to not overproduce or underproduce
- Would benefit agencies like the World Health Organization and healthcare providers to plan distribution and receipt of large quantities of vaccines

Methodology

**Exploratory Data
Analysis**



Data Cleaning



Model Building



Preprocessing



Model Evaluation



Conclusion

Dataset Details

DRIVENDATA

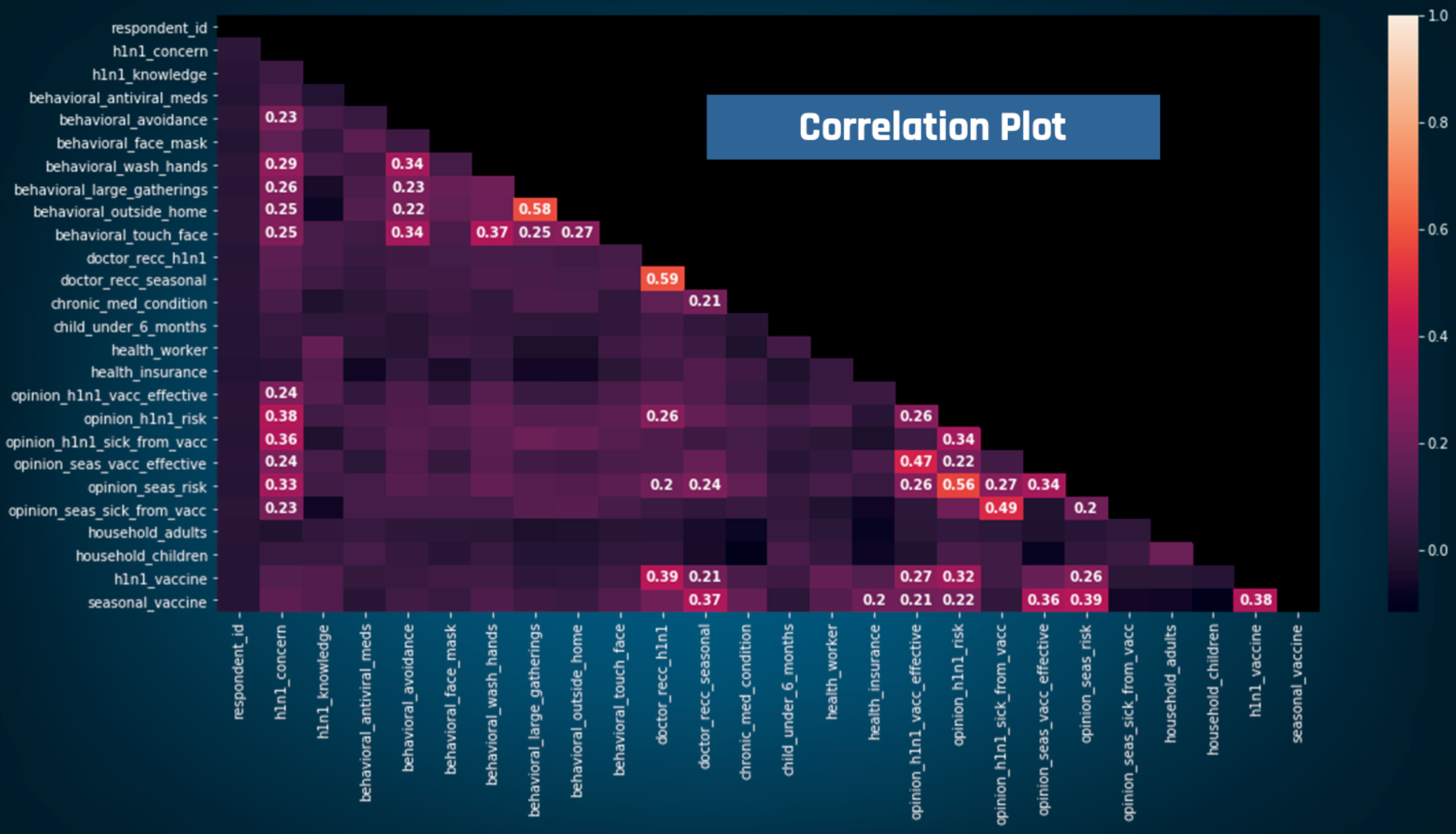
Number of attributes: 38

Number of Instances: 26706

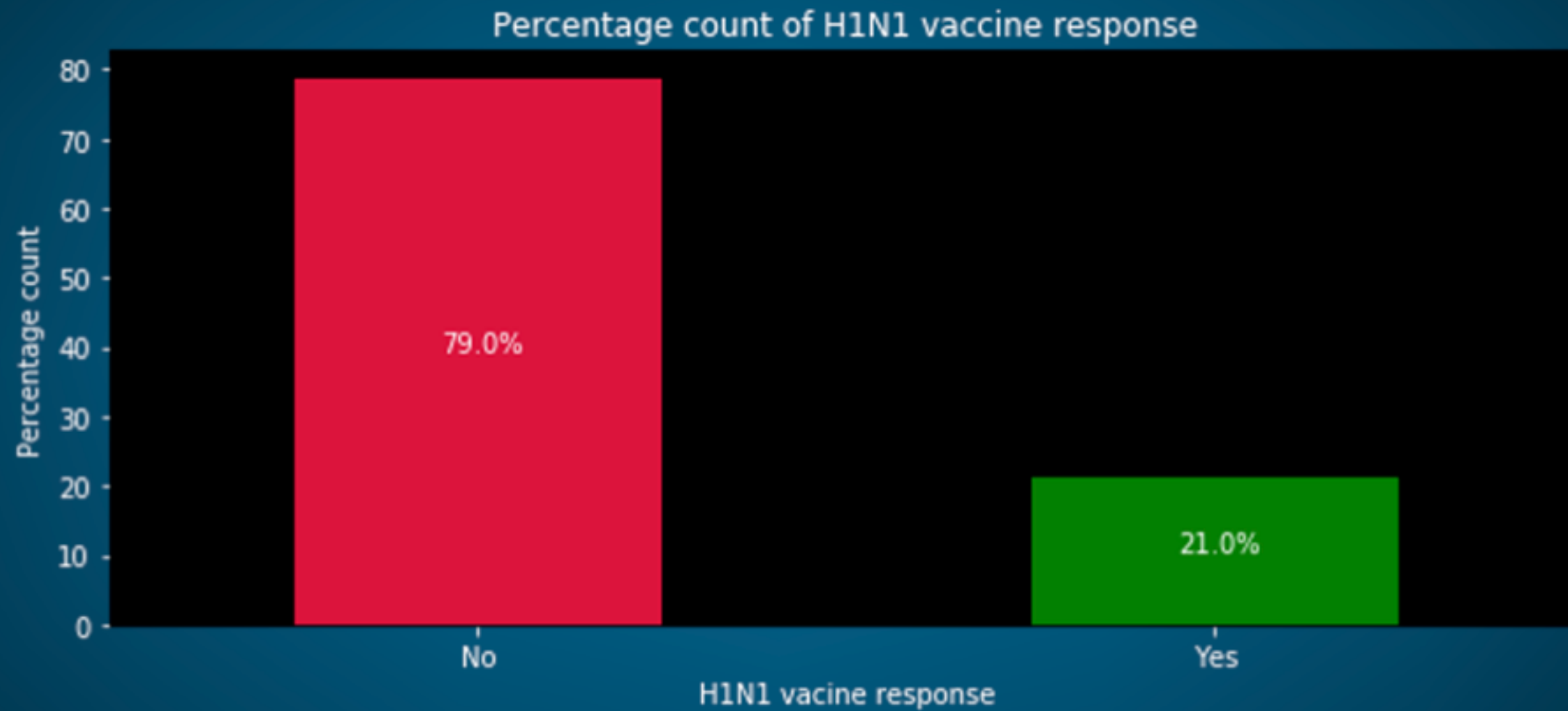
Behavioural	Opinion	Demographic	Others
- antiviral_meds - avoidance - face_mask - wash_hands - large_gatherings - outside_home - touch_face	- h1n1_vacc_effctive - h1n1_risk - h1n1_sick_from_vacc - seas_vacc_effective - seas_risk - seas_sick_from_vacc - h1n1_concern	- age_group - education - race - sex - income_poverty - marital_status - rent_or_own - household_adults - household_children - employment_status - census_msa	- h1n1_knowledge - doctor_recc_h1n1 - doctor_recc_seasonal - chronic_med_condition - child_under_6_months - health_worker - health_insurance - h1n1_vaccine - employment_industry - employment_occuption - hhs_geo_region



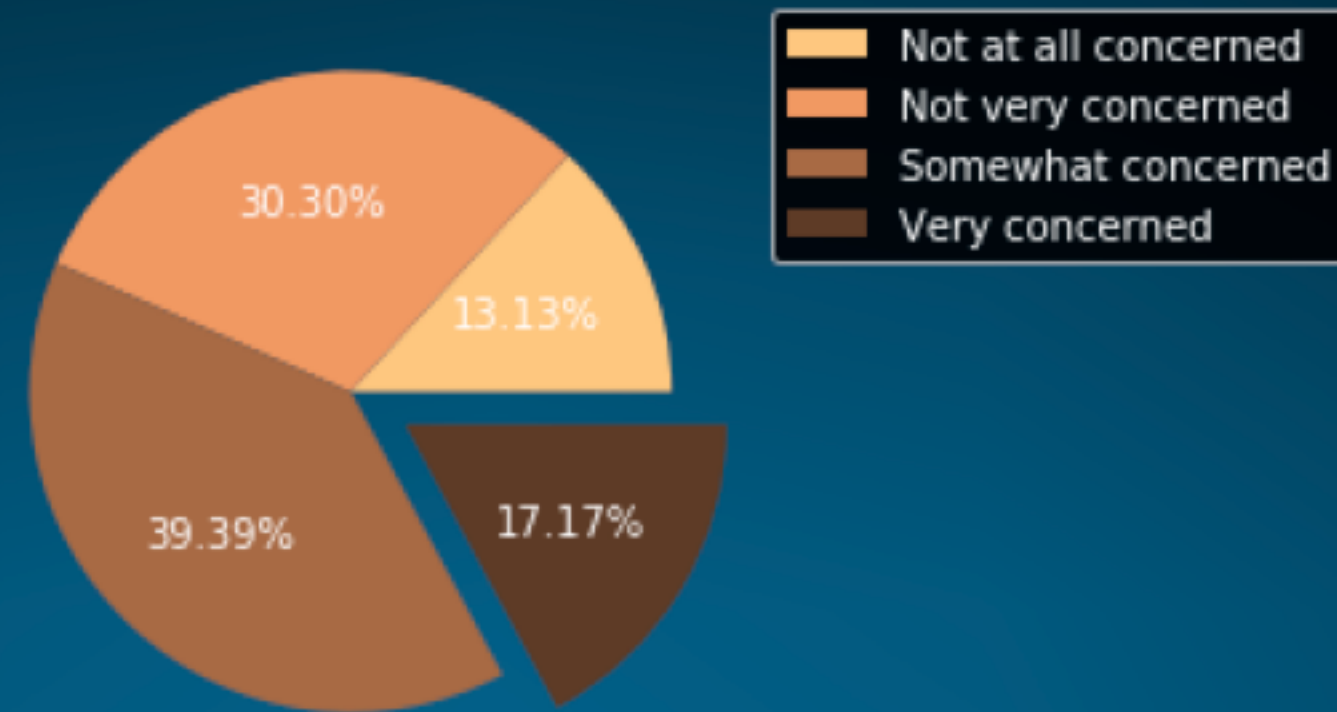
Exploratory Data Analysis



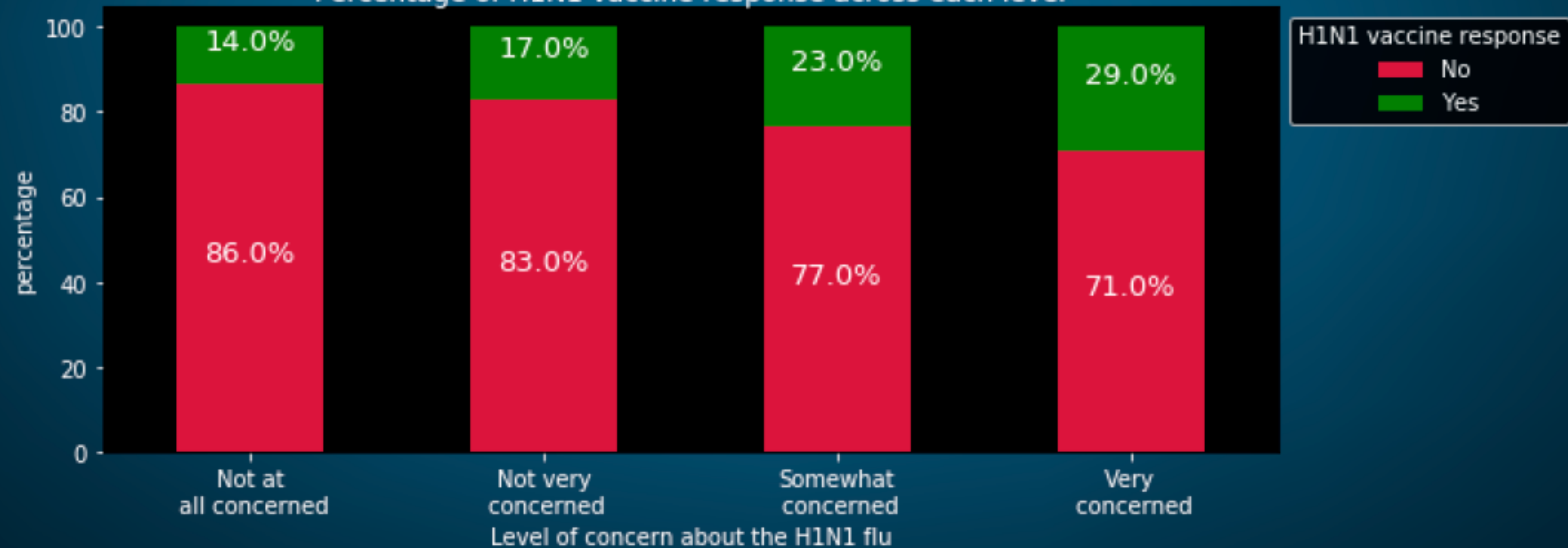
Class Imbalance



Percentage count of H1N1 concern level



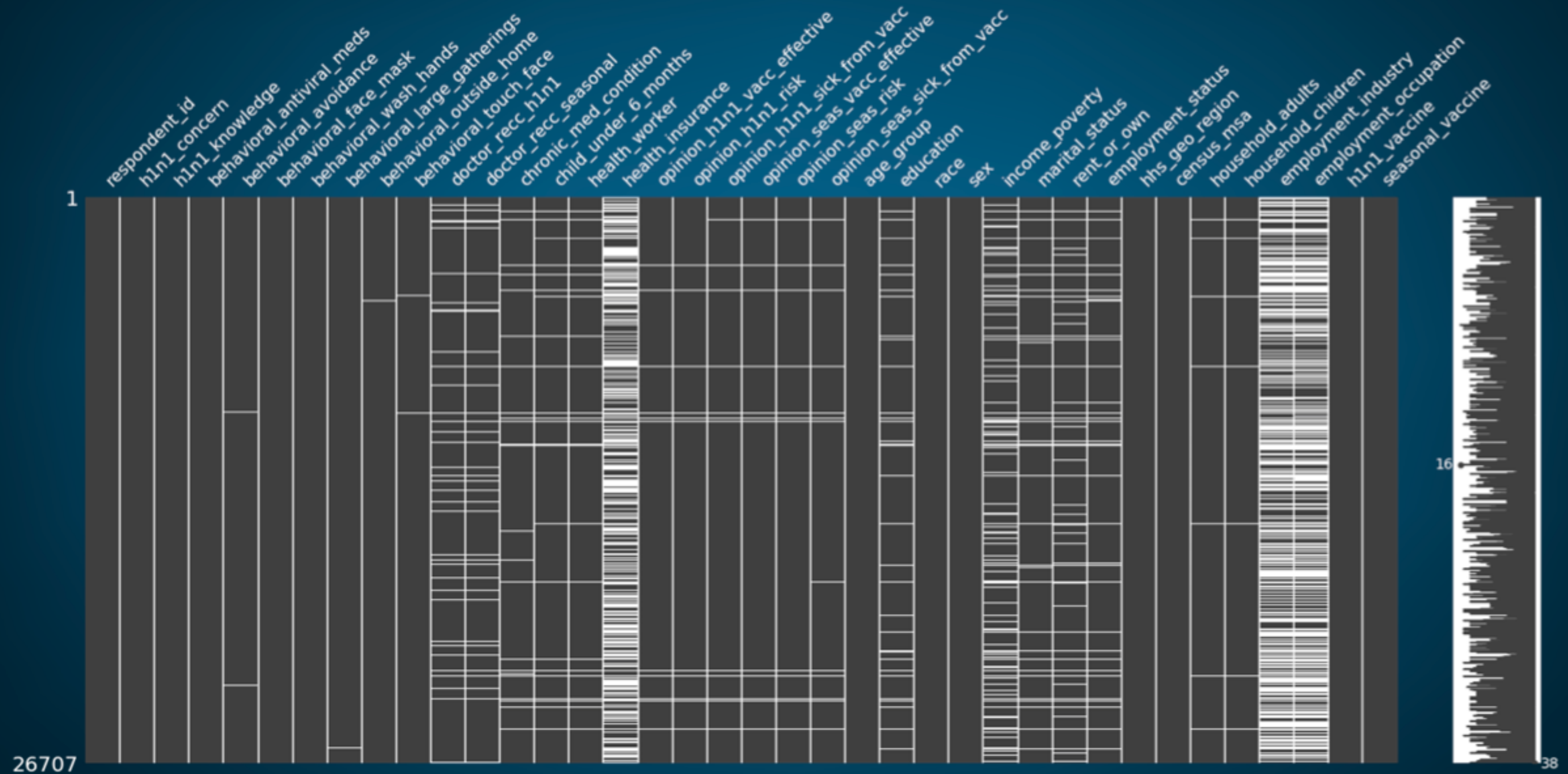
Percentage of H1N1 vaccine response across each level





Data Cleaning

Missing Value in Data



Missing Value Imputation

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Naïve Bayes

Imputed attribute
by prediction



Null Pattern

Imputed attribute
based on the Null
value pattern



Median/Mode

Imputed attribute
based on central
measure



Model Building

Machine Learning Models

Model 1

**Naïve
Bayes**

Model 2

**Decision
Tree**

Model 3

**Random
Forest**

Several versions of each model were built

- Forward feature selection
- Oversampling
- 10-fold cross validation

Performance measure

Precision Recall Fscore

Prediction

Actual	Prediction	
	Positive	Negative
	Positive	FN
Negative	FP	TN

$$\uparrow \text{Precision} = \frac{TP}{TP+FP} \downarrow$$

$$\uparrow \text{Recall} = \frac{TP}{TP+FN} \downarrow$$

$$\uparrow \text{Fscore} = \frac{2 * \text{Precision} \uparrow * \text{Recall} \uparrow}{\text{Precision} + \text{Recall}}$$

Model Performance

Naïve Bayes	Accuracy	Class 1 Precision	Class 1 Recall	Class 1 F1-Score	Class 1 ROC_AUC
Benchmark	79.99%	0.526	0.633	0.574	0.828
Forward Selection	84.35%	0.692	0.474	0.563	0.849
Oversampling	73.97%	0.740	0.740	0.740	0.822
Oversampling Forward Select	78.25%	0.793	0.769	0.781	0.856

Decision Tree	Accuracy	Class 1 Precision	Class 1 Recall	Class 1 F1-Score	Class 1 ROC_AUC
Benchmark	84.31%	0.670	0.521	0.586	0.798
Forward Selection	85.01%	0.693	0.533	0.602	0.839
Oversampling	83.83%	0.827	0.855	0.841	0.863
Oversampling Forward Select	83.91%	0.830	0.825	0.861	0.860

Random Forest	Accuracy	Class 1 Precision	Class 1 Recall	Class 1 F1-Score	Class 1 ROC_AUC
Benchmark	84.69%	0.721	0.460	0.562	0.868
Forward Selection	84.78%	0.671	0.554	0.607	0.637
Oversampling	91.23%	0.893	0.937	0.914	0.974
Oversampling Forward Select	91.48%	0.896	0.939	0.917	0.974



Model Evaluation

Model	Process
Naïve Bayes	Oversampling Forward Select
Decision Tree	Oversampling
Random Forest	Oversampling Forward Select

Training Set Performance

Accuracy	Class 1 Precision	Class 1 Recall	Class 1 F1-Score	Class 1 ROC_AUC
79.25%	0.800	0.780	0.790	0.865
85.00%	0.836	0.871	0.853	0.870
91.74%	0.903	0.935	0.919	0.974

Testing Set Performance

Accuracy	Class 1 Precision	Class 1 Recall	Class 1 F1-Score	Class 1 ROC_AUC
79.56%	0.519	0.777	0.612	0.868
77.70%	0.491	0.747	0.592	0.758
81.20%	0.552	0.713	0.622	0.864

Conclusion

- Naïve Bayes was the best performing model in terms of minimizing potential loss in sales/revenue
- Using the confusion matrix we estimate 107.1 million doses will be needed



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Thank you

Do you have any questions?

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