



# Seer Project

Team 9

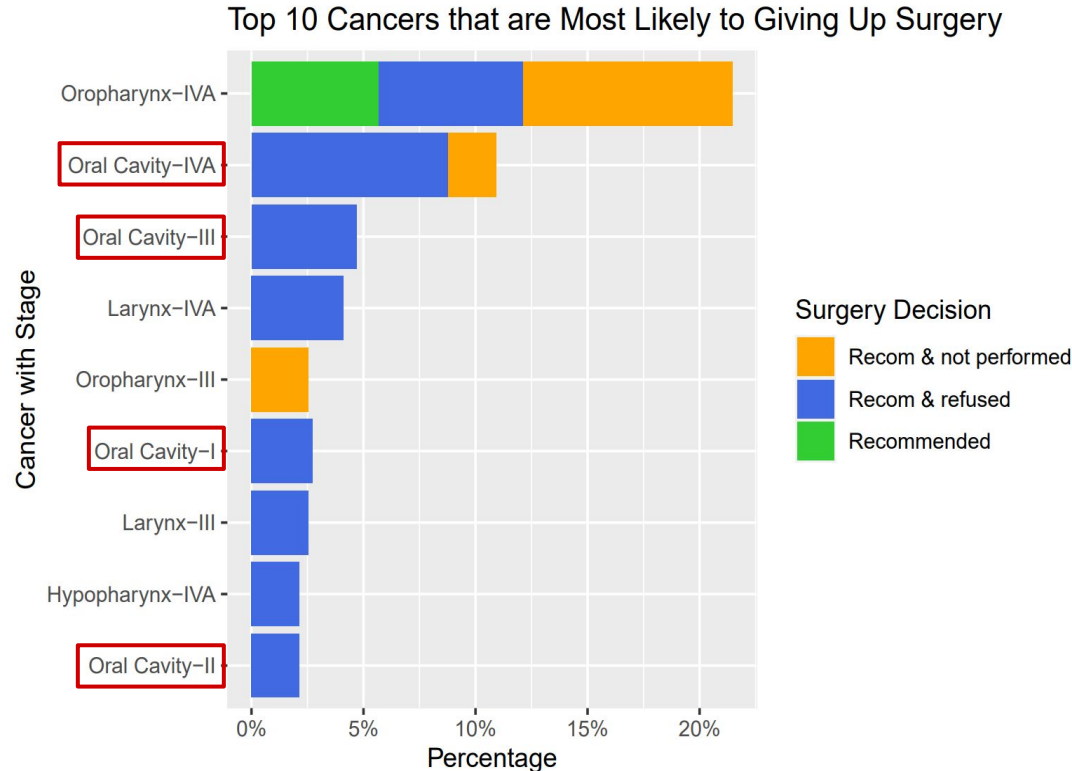


## Team goal

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Our main goal of the project is to explore how biases (race, gender, education level and other factors including) will affect the matching of recommended and actual therapy of patients.

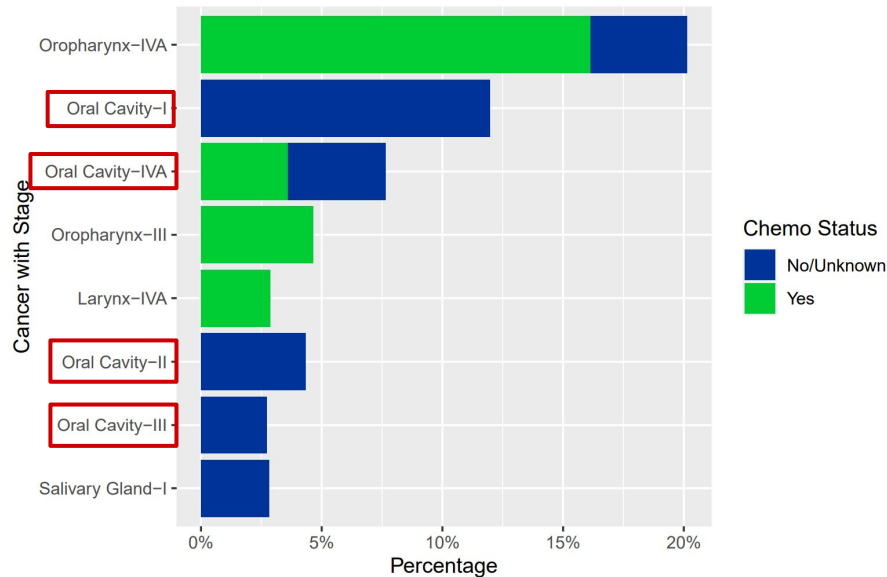
# Exploratory Data Analysis



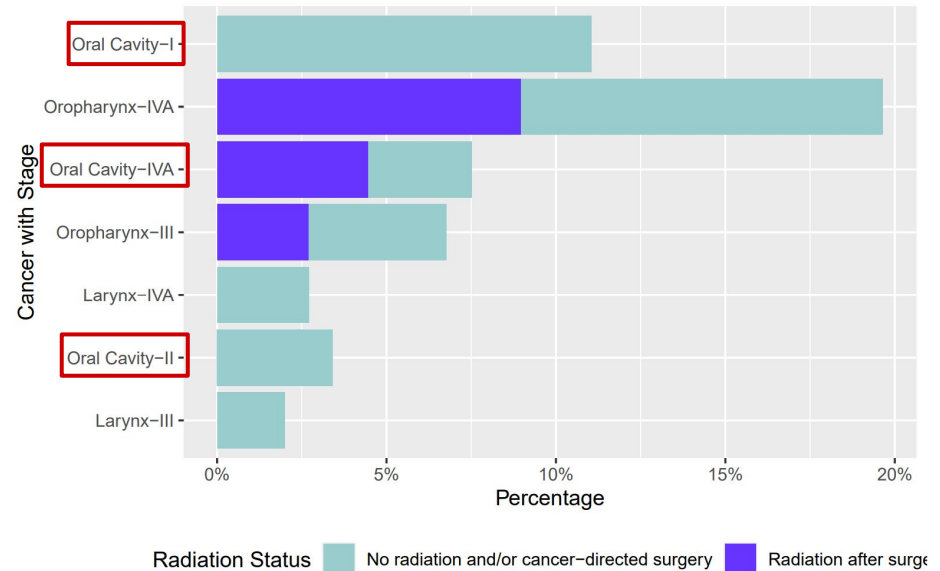
- to simplify our research, we would like to choose only one kind of cancer to analyze
- we firstly explore the top 10 cancers that the patients are most likely to give up the surgery

# Exploratory Data Analysis

Top 10 Cancers by Chemo Status

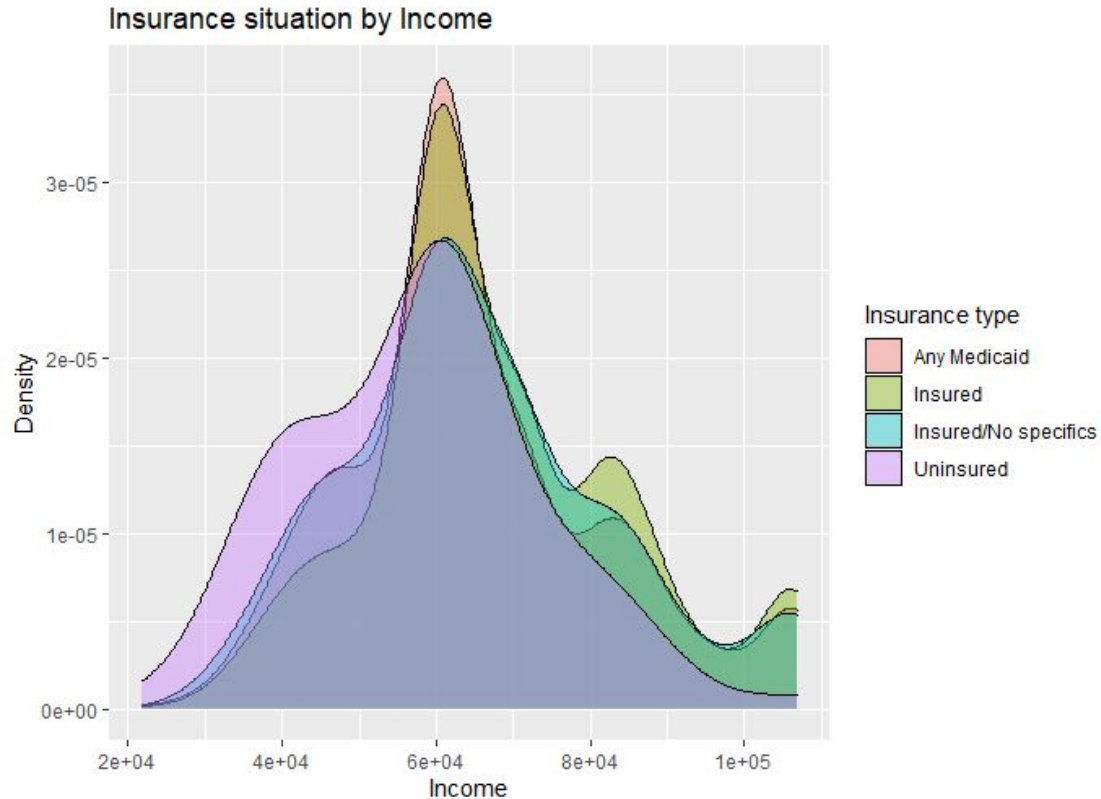


Top 10 Cancers by Radiation Status



- combining the information given by the status of chemo and radiation therapy, we would like to choose oral cavity cancer as our research direction

# Exploratory Data Analysis

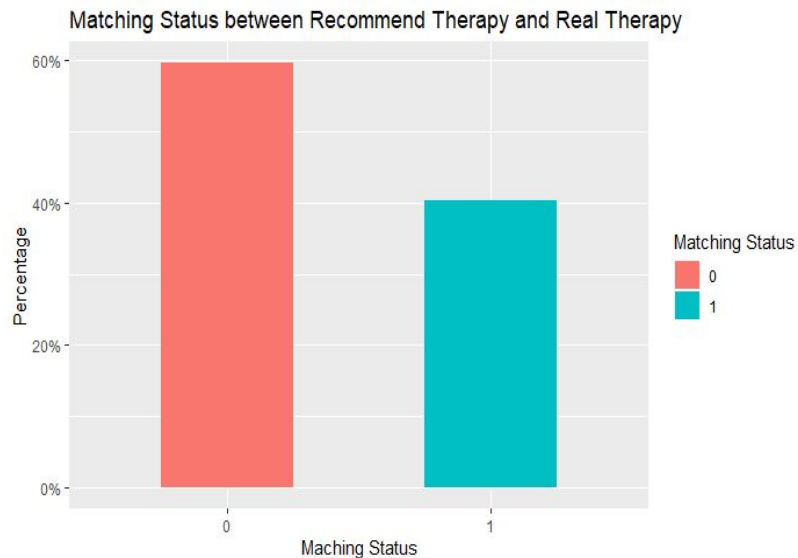
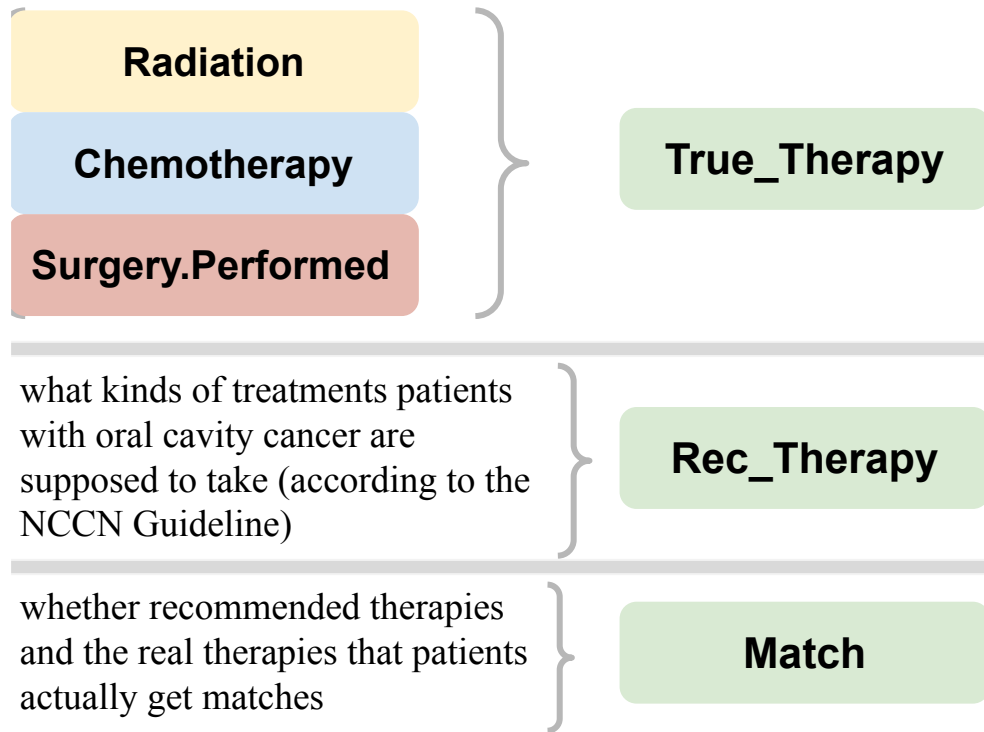


- The overlap of insurance status become more serious as the income increase

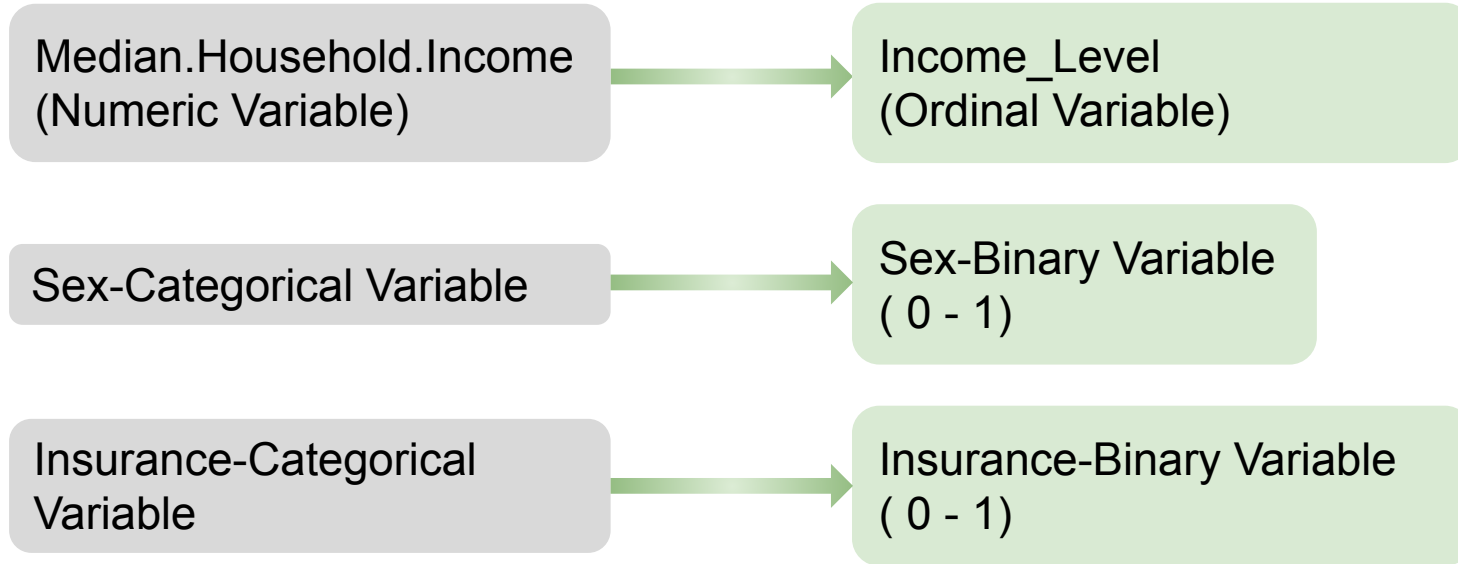
# Feature Engineering: Establishment

Known information

Created new variable

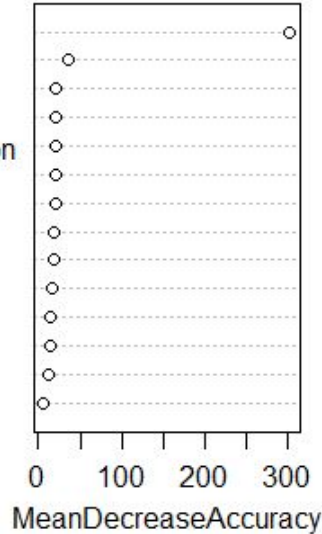


# Feature Engineering: Transformation

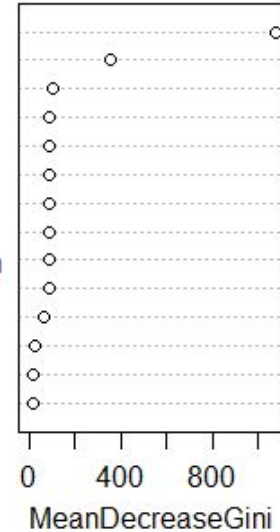


# Feature Selection

Cancer\_Stage  
Cause.of.Death  
Language.Isolation  
X9th.Education  
Bachelors.Education  
Unemployed  
HS.Education  
Below.Poverty  
Insurance  
Race  
SEER.Registry  
Age.at.Diagnosis  
Income\_Level  
Sex



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Sex  
Insurance  
SEER.Registry  
Income\_Level



- use Random Forest method to select the variables for modeling
- besides, we add Race, Sex and Race:Sex to our model



# Model: Logistic Regression

```
m1 <- glm(Match ~ Cancer_Stage + Language.Isolation +  
X9th.Education + Bachelors.Education + Unemployed + Age.at.Diagnosis  
+ Below.Poverty + Race + Sex + Race:Sex + Insurance, data =  
trainset, family = binomial(link = "logit"))
```

# Model: Logistic Regression

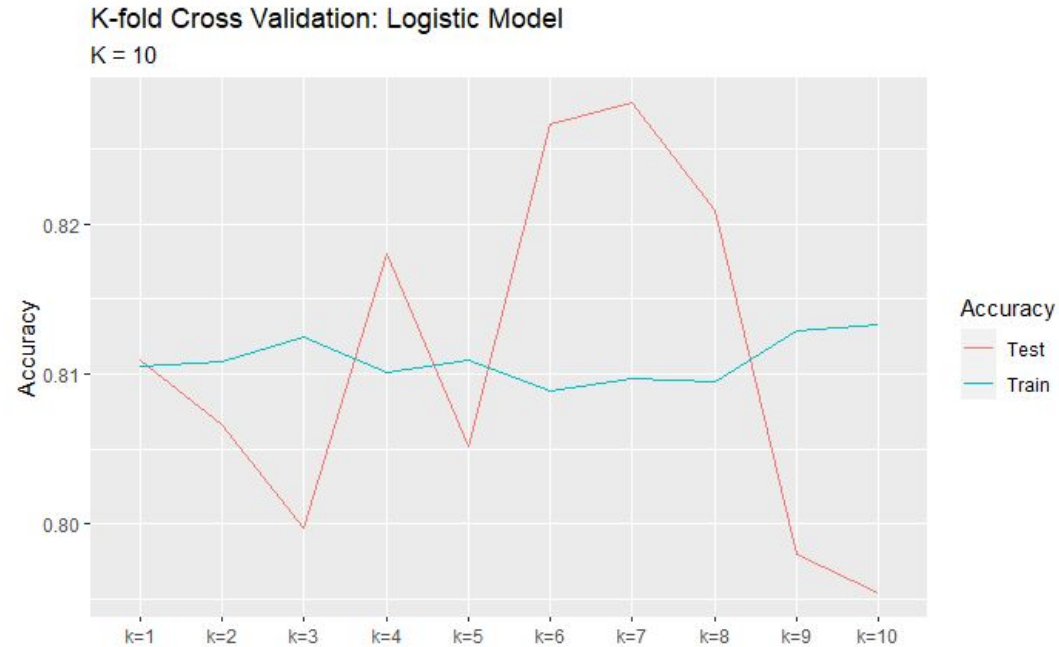
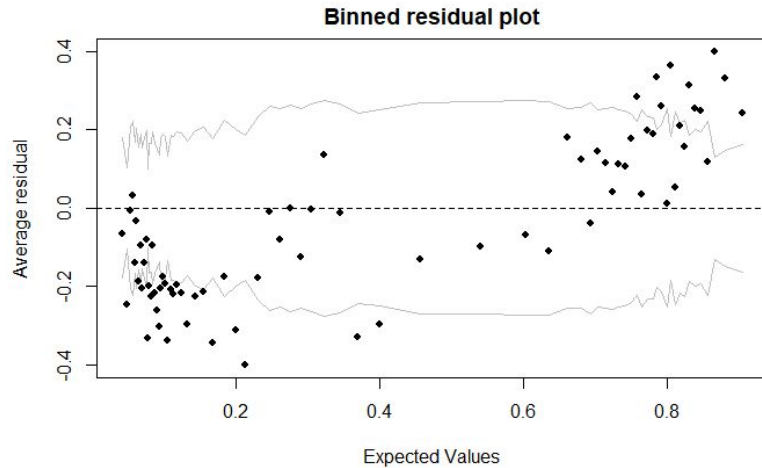
Coefficients:

	Estimate	Std. Error	z value	Pr(> z )
(Intercept)	-0.551067	0.463549	-1.189	0.23452
Cancer_StageOral Cavity-II	1.469965	0.105471	13.937	< 2e-16 ***
Cancer_StageOral Cavity-III	3.839796	0.122130	31.440	< 2e-16 ***
Cancer_StageOral Cavity-IVA	3.555869	0.099432	35.762	< 2e-16 ***
Cancer_StageOral Cavity-IVB	2.677457	0.190496	14.055	< 2e-16 ***
Cancer_StageOral Cavity-IVC	1.464121	0.242658	6.034	1.60e-09 ***
Cancer_StageOral Cavity-IVNOS	1.806551	0.358426	5.040	4.65e-07 ***
Language.Isolation	0.003538	0.024995	0.142	0.88742
x9th.Education	-0.025723	0.028146	-0.914	0.36077
Bachelors.Education	-0.007626	0.006961	-1.096	0.27329
Unemployed	-0.008275	0.027486	-0.301	0.76338
Age.at.Diagnosis	-0.024195	0.002570	-9.414	< 2e-16 ***
Below.Poverty	-0.012761	0.011773	-1.084	0.27842
RaceAsian or Pacific Islander	0.088143	0.194500	0.453	0.65042
RaceBlack	-0.530187	0.209907	-2.526	0.01154 *
RaceHispanic	-0.155889	0.174066	-0.896	0.37048
RaceAmerican Indian/Alaska Native	-0.232158	0.595413	-0.390	0.69660
Sex	-0.176231	0.089030	-1.979	0.04776 *
Insurance	0.520147	0.178509	2.914	0.00357 **
RaceAsian or Pacific Islander:Sex	0.287099	0.255635	1.123	0.26140
RaceBlack:Sex	0.049180	0.263059	0.187	0.85170
RaceHispanic:Sex	0.537039	0.220622	2.434	0.01492 *
RaceAmerican Indian/Alaska Native:Sex	0.076711	0.826572	0.093	0.92606

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- For equity issue, we find that the coefficients of **Age**, **RaceBlack**, **Sex**, **Insurance** and **RaceHispanic:Sex** are significant

# Model: Logistic Regression



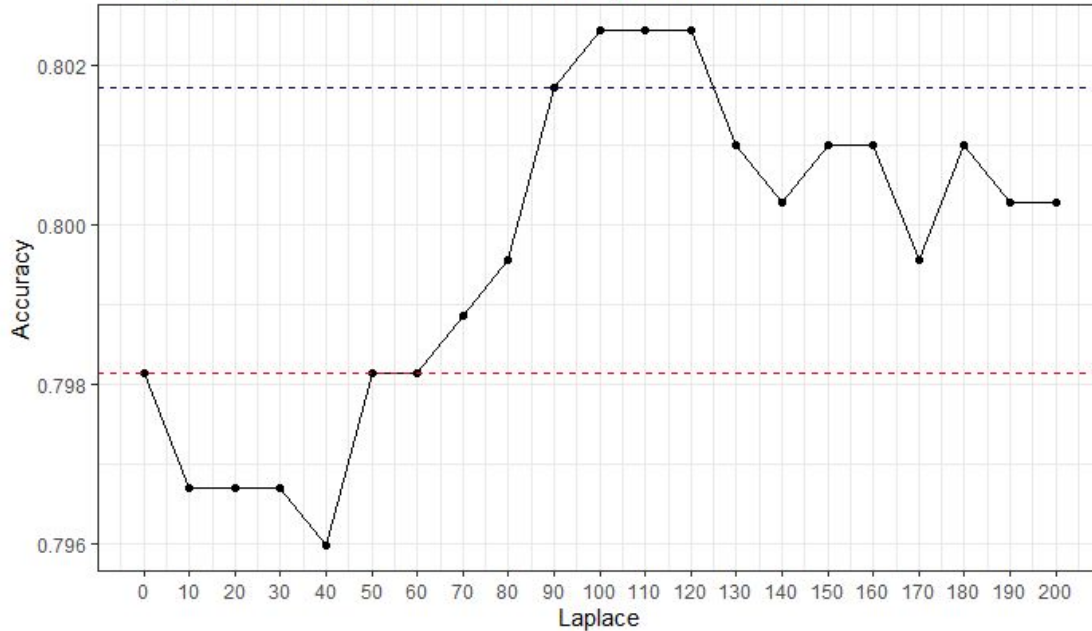
# Model: Naive Bayes

```
m2 <- naiveBayes(as.factor(Match) ~ Cancer_Stage +  
Language.Isolation + X9th.Education + Bachelors.Education +  
Unemployed + Age.at.Diagnosis + Below.Poverty + Race +  
as.factor(Sex) + as.factor(Insurance), data = trainset)
```

Match	White	Asian & PI	Black	Native
0	0.73	0.08	0.07	0.006
1	0.67	0.10	0.08	0.007

# Model: Naive Bayes

Tuning: Laplace parameter in Naive Bayes on Test Set



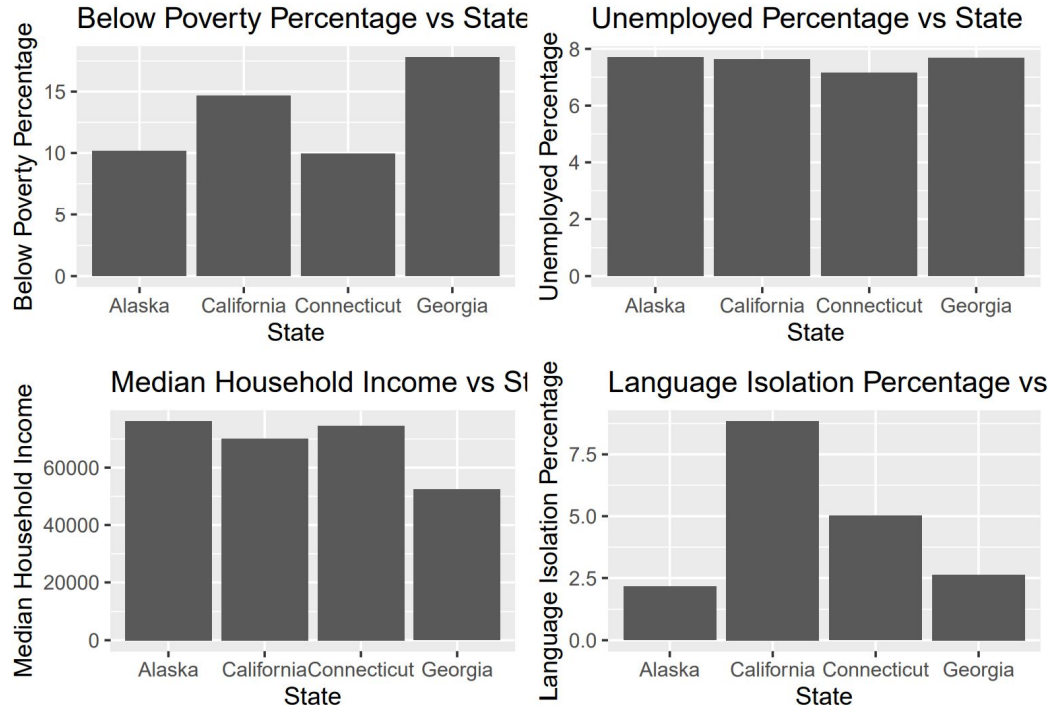
Blue Line: Logistic Model

Red Line: Naive Bayes Classifier,  
Untuned

# Conclusion

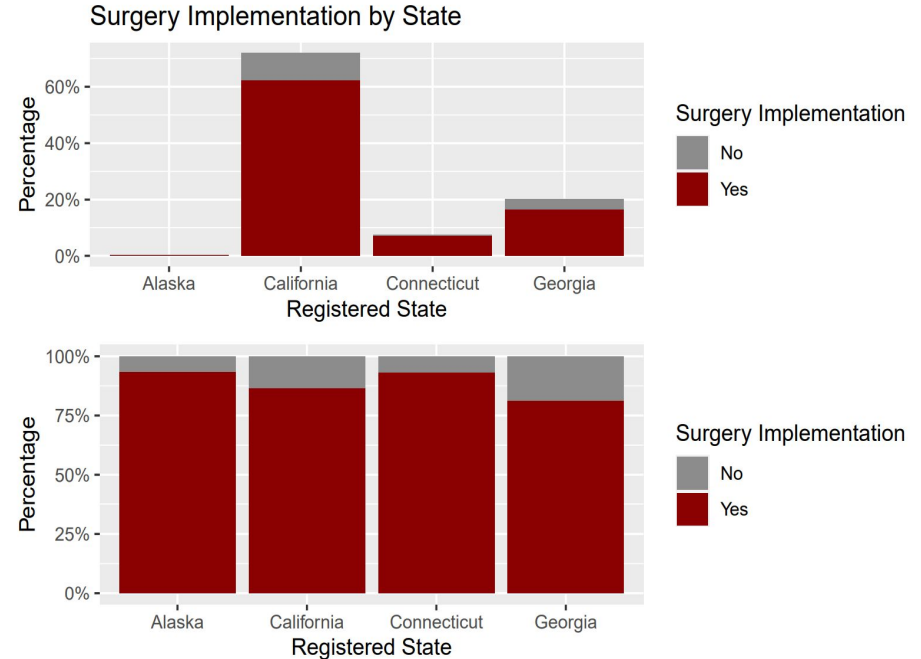
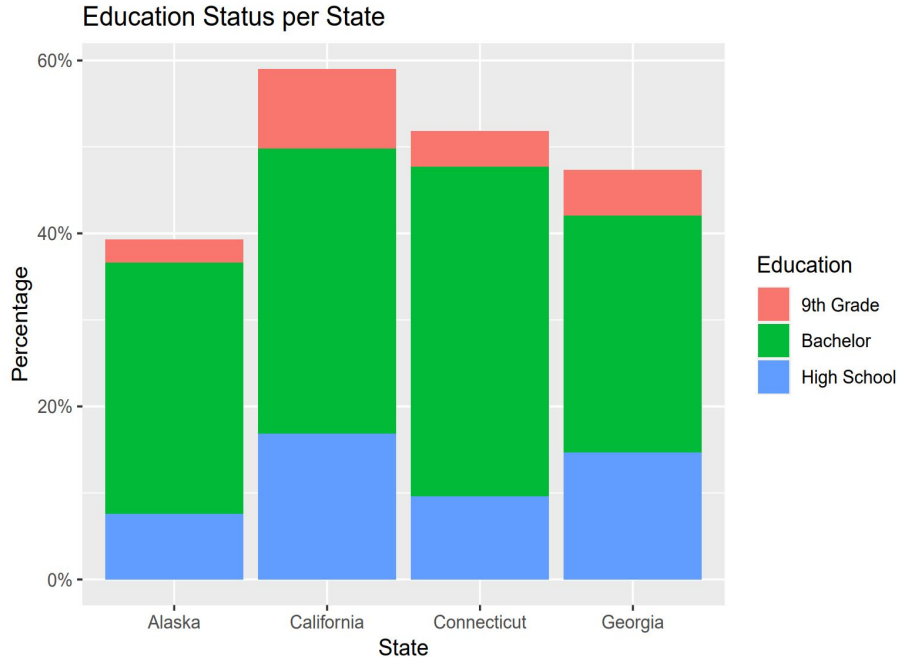
- Bias in this data existed, since we know that blacks are less likely to get correct therapy compared with other races from the result of the model.
- Patients with no insurance are less likely to take treatments.
- There are some subtle trends that patients with low educational level and patients who are unemployed are slightly tend to not follow the guideline of therapy.

# Appendix



- **Environment Attribute vs State :**  
poverty, unemployment, household income and language isolation distribution by states

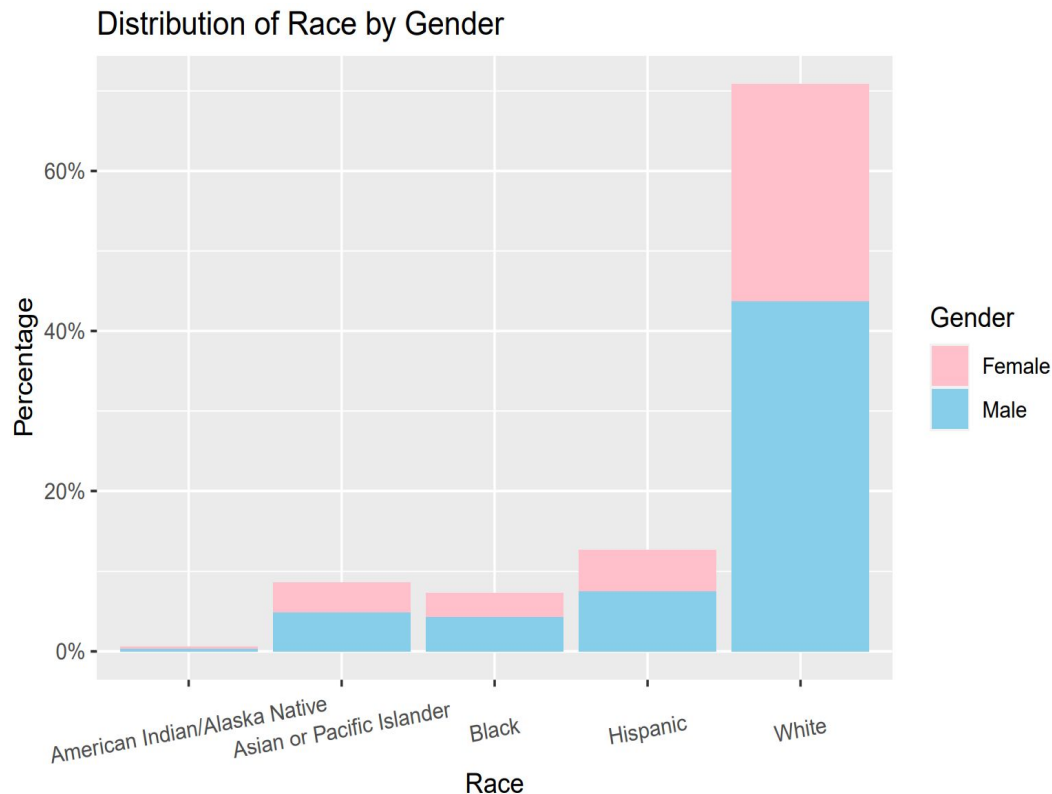
# Appendix



- **Environment Attribute vs State :**  
education status, surgery implementation distribution by state



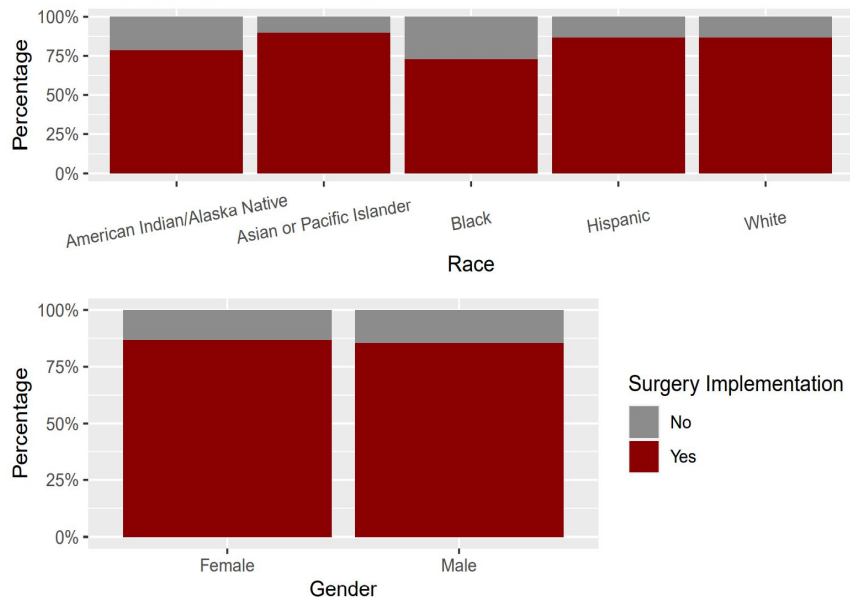
# Appendix



- more than 60% of observations are white people; more than 40% of observations are white male
- there would be an imbalance problem in the data

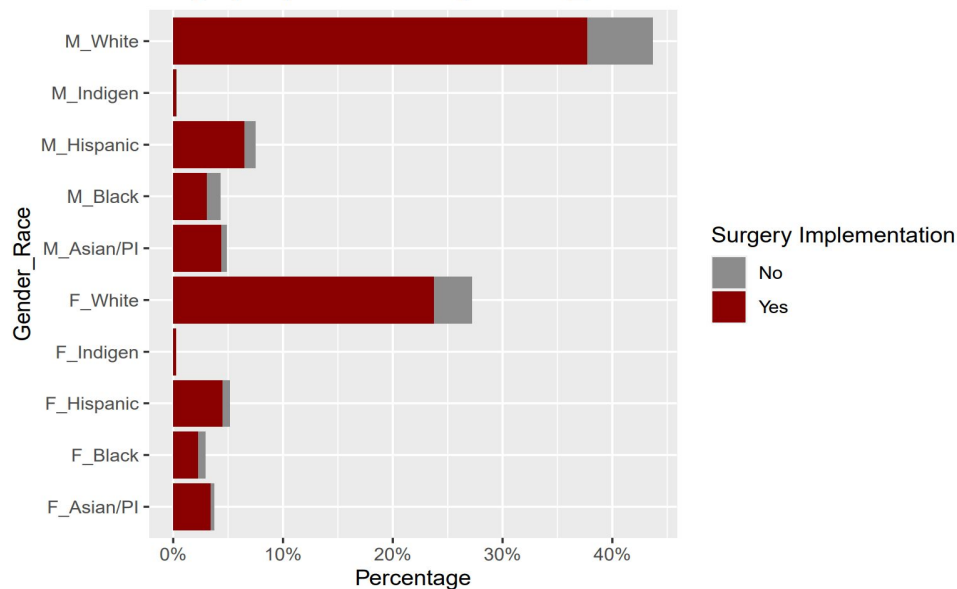
# Appendix

Surgery Implementation by Race & Gender



- surgery implementation by race
- surgery implementation by gender

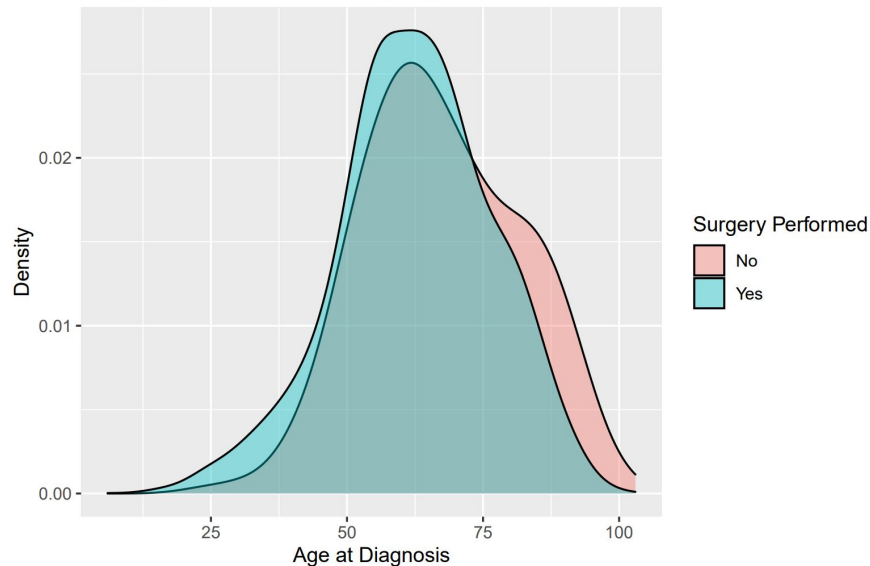
Surgery Implementation by Gender\_Race



- put these gender and race together to explore the distribution of performed surgery
- white male has the largest proportion of performing a surgery

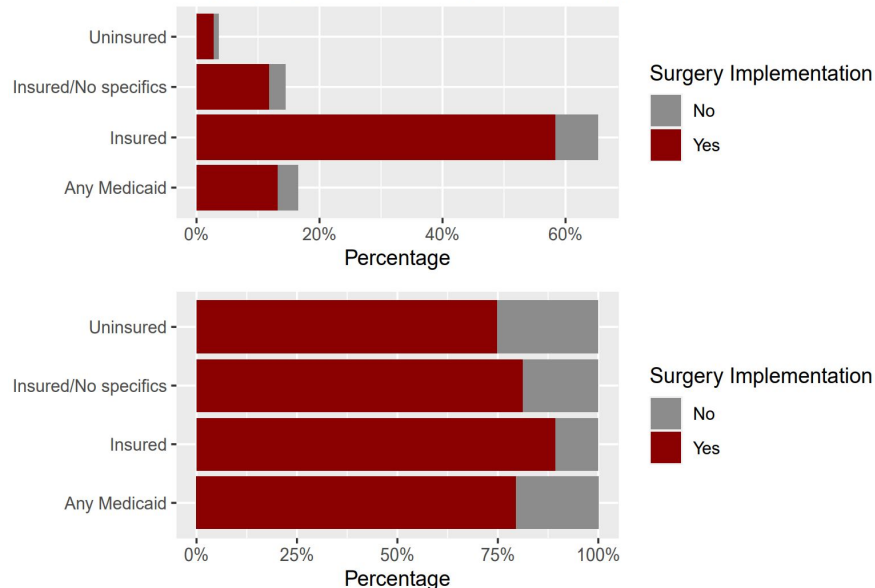
# Appendix

Surgery Performed Status by Age



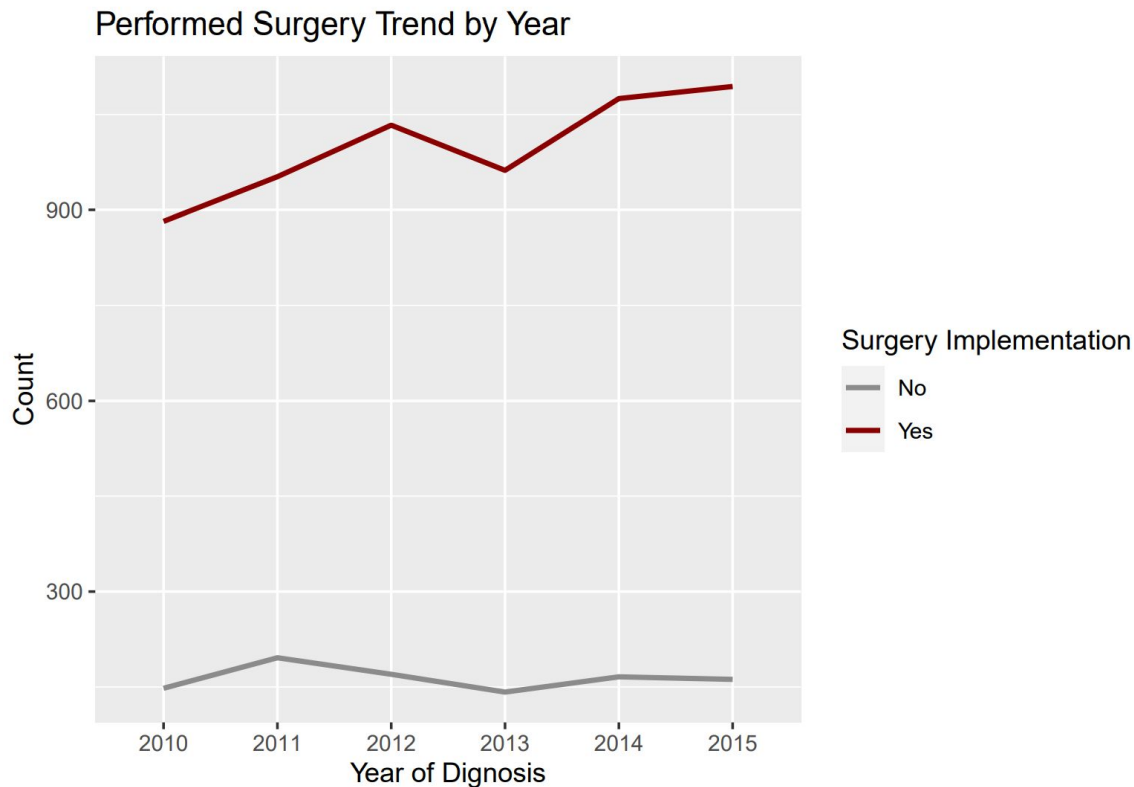
- use density plot to find the distribution of the continuous variable - age
- the distributions of performing surgery and not performing surgery on ages are mostly overlapping

Surgery Implementation by Insurance Type



- the large majority of respondents are insured
- insured people are most likely to perform the surgery

# Appendix



- The line chart shows the change of surgery implementation over time series
- As time goes by, there is an upper trend for the amount of performed surgery