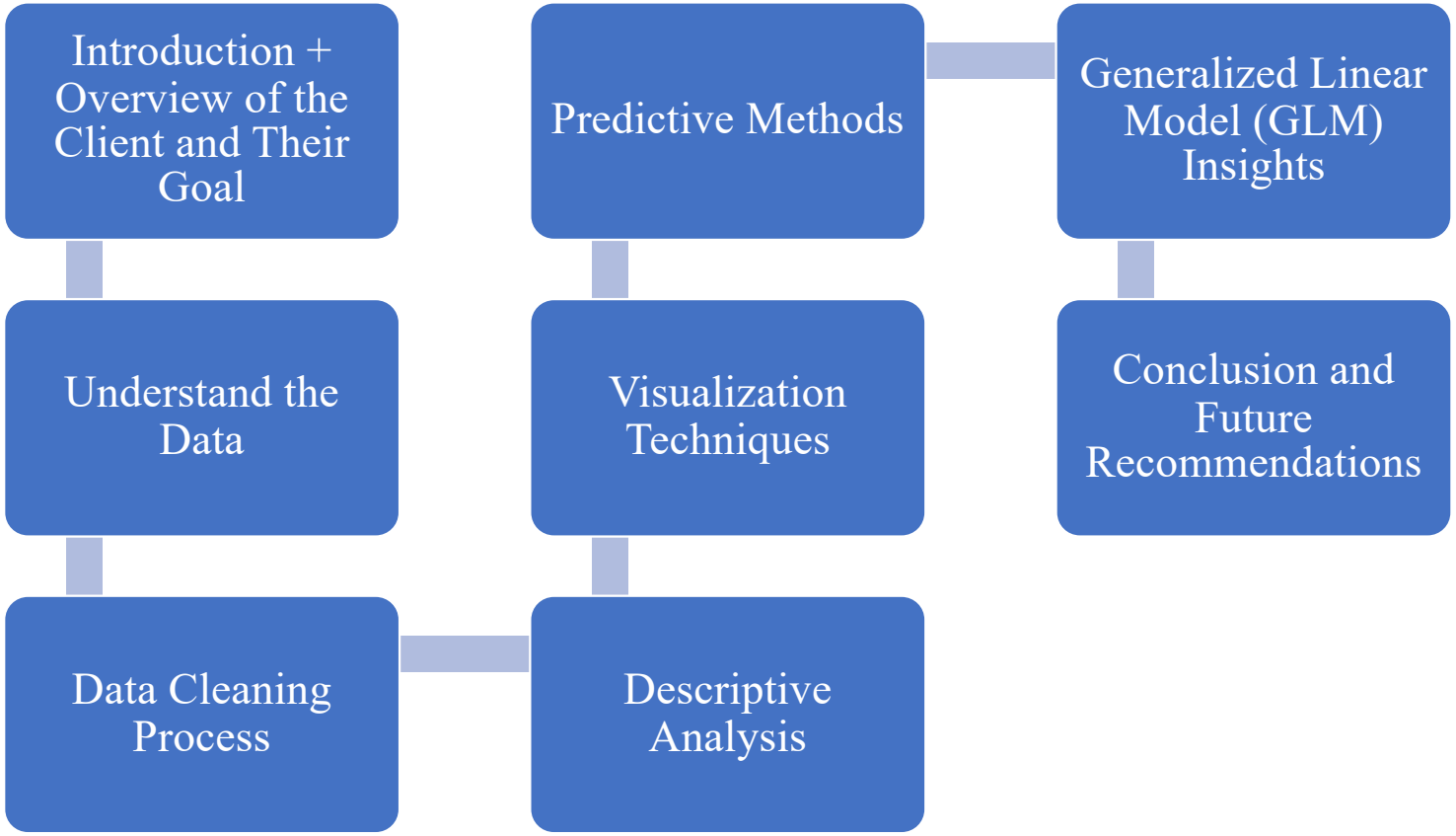

Enhancing Skincare Recommendations for The Glow Company
By Chi Dang

Agenda:


Introduction + Overview of the Client and Their Goal
Understand the Data
Data Cleaning Process
Descriptive Analysis
Visualization Techniques
Predictive Methods
Generalized Linear Model (GLM) Insights
Conclusion and Future Recommendations

Data Introduction + Client's Overview & Goals

- Client: The Glow Company
- Question: What demographic and employment factors have the strongest correlation with high income status (over $50K/year)? Identifying key predictors.
- Focus/ Goals: What influencing factors that The Glow Company's consumers have income above $50K
- Collaboration Objective: Refining skincare recommendations for a more effective and personalized routine

Understand the Data

- Dataset: Adult Income Census from Kaggle
- Origin: Extracted from 1994 Census Bureau by Ronny Kohavi and Barry Becker.
- Number of Rows: 32,561
- Number of Columns: 15
- Y variable: Binary outcome indicating income >$50K
- X variables: Age, Marital_Status, Race, Sex, Hrs_per_Week, Income, Net_Capital, EducationLevel_clean, Occupation_clean, & WorkingClass_clean.
- Tools using in this project: R Studio & SAS

Data Cleaning Process

- Handling Special Characters, like '?' in the dataset
- Rename columns for a purpose of using it easily in both R & SAS
- Adding a new column Net_Capital by subtracting Net_Gain to Net_Loss
- Transform the irrelevant variables into one group
- Using R Studio to finish the cleaning process and extracting file to computer to upload on SAS
- Transform Y variables into binary variable, 0 as <=50K & 1 as >50K

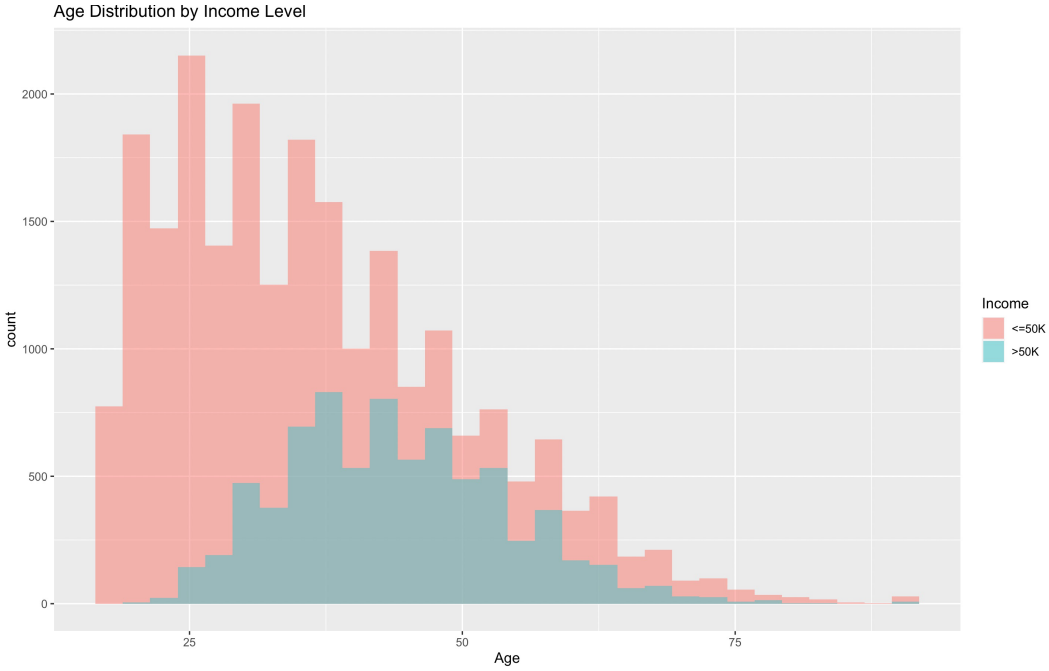
Before Cleaning:

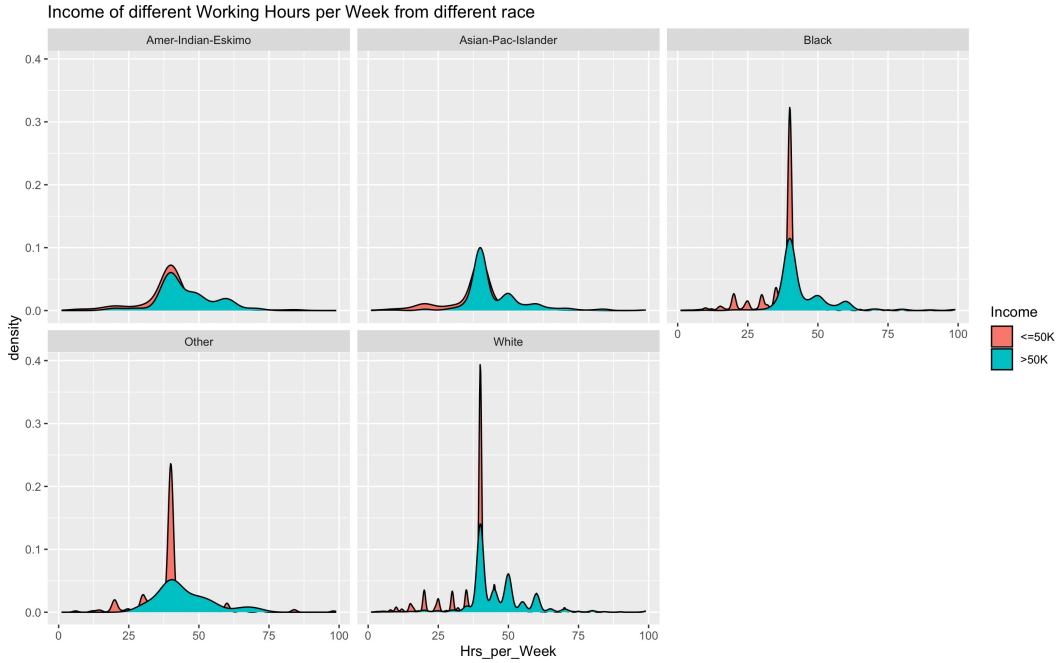
```
> str(adult)        # look at the structure of the data
'data.frame':   32561 obs. of  15 variables:
 $ age           : int  90 82 66 54 41 34 38 74 68 41 ...
 $ workclass     : Factor w/ 9 levels "?","Federal-gov",..: 1 5 1 5 5 5 5 8 2 5 ...
 $ fnlwgt        : int  77053 132870 186061 140359 264663 216864 150601 88638 422013 70037 ...
 $ education     : Factor w/ 16 levels "10th","11th",..: 12 12 16 6 16 12 1 11 12 16 ...
 $ education.num : int  9 9 10 4 10 9 6 16 9 10 ...
 $ marital.status: Factor w/ 7 levels "Divorced","Married-AF-spouse",..: 7 7 7 1 6 1 6 5 1 5 ...
 $ occupation    : Factor w/ 15 levels "?","Adm-clerical",..: 1 5 1 8 11 9 2 11 11 4 ...
 $ relationship  : Factor w/ 6 levels "Husband","Not-in-family",..: 2 2 5 5 4 5 5 3 2 5 ...
 $ race          : Factor w/ 5 levels "Amer-Indian-Eskimo",..: 5 5 3 5 5 5 5 5 5 5 ...
 $ sex           : Factor w/ 2 levels "Female","Male": 1 1 1 1 1 1 2 1 1 2 ...
 $ capital.gain  : int  0 0 0 0 0 0 0 0 0 0 ...
 $ capital.loss  : int  4356 4356 4356 3900 3900 3770 3770 3683 3683 3004 ...
 $ hours.per.week: int  40 18 40 40 40 45 40 20 40 60 ...
 $ native.country: Factor w/ 42 levels "?","Cambodia",..: 40 40 40 40 40 40 40 40 40 1 ...
 $ income        : Factor w/ 2 levels "<=50K",">50K": 1 1 1 1 1 1 1 2 1 2 ...
```

After Cleaning:

```
> str(adult2)
'data.frame':   30162 obs. of  10 variables:
 $ Age                 : int  82 54 41 34 38 74 68 45 38 52 ...
 $ Marital_Status      : Factor w/ 7 levels "Divorced","Married-AF-spouse",..: 7 1 6 1 6 5 1 1 5 7 ...
 $ Race                : Factor w/ 5 levels "Amer-Indian-Eskimo",..: 5 5 5 5 5 5 5 3 5 5 ...
 $ Sex                 : Factor w/ 2 levels "Female","Male": 1 1 1 1 2 1 1 1 2 1 ...
 $ Hrs_per_Week        : int  18 40 40 45 40 20 40 35 45 20 ...
 $ Income              : Factor w/ 2 levels "<=50K",">50K": 1 1 1 1 1 2 1 2 2 2 ...
 $ Net_Capital         : int  -4356 -3900 -3900 -3770 -3770 -3683 -3683 -3004 -2824 -2824 ...
 $ EducationLevel_clean: chr  "HighSchool" "MiddleSchool" "Post-High_School" "HighSchool" ...
 $ Occupation_clean    : chr  "Professional" "SkilledLabor" "Professional" "Services" ...
 $ WorkingClass_clean  : chr  "Private" "Private" "Private" "Private" ...
```

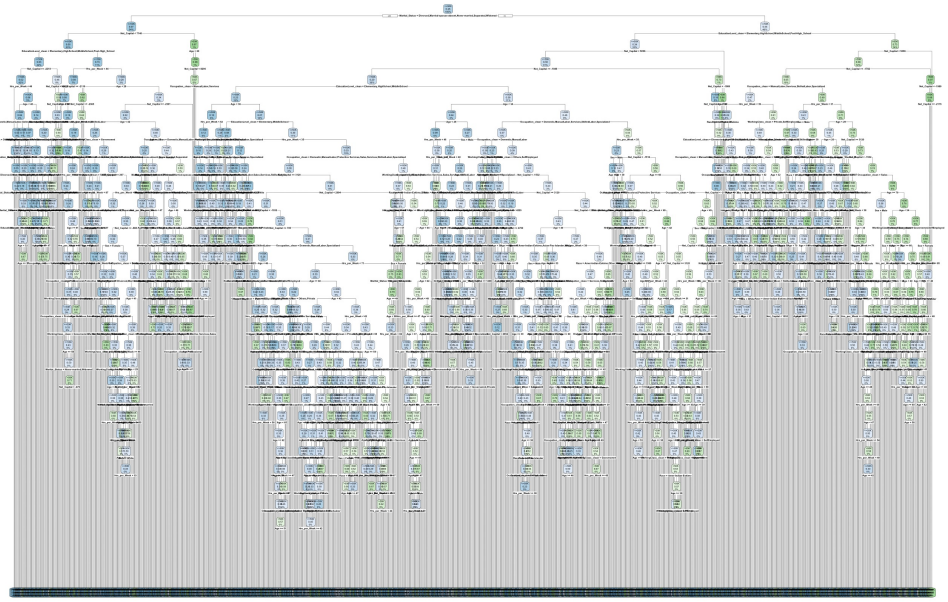
Visualization

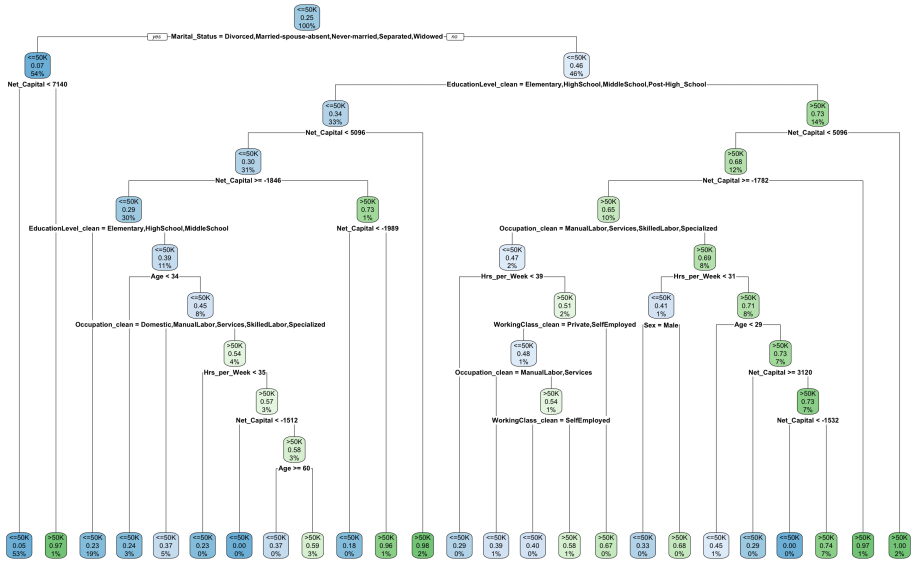




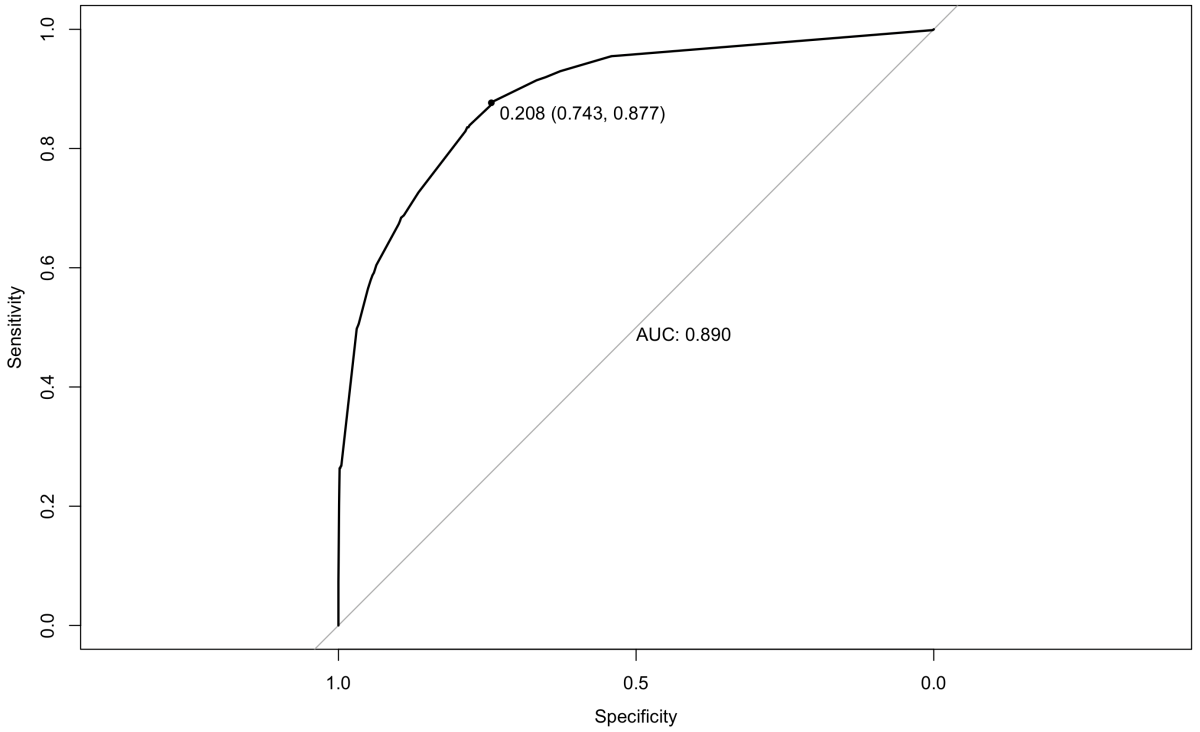
Predictive Methods Pt.1 (Decision Tree Pt.1)

Before and After Tunning the tree

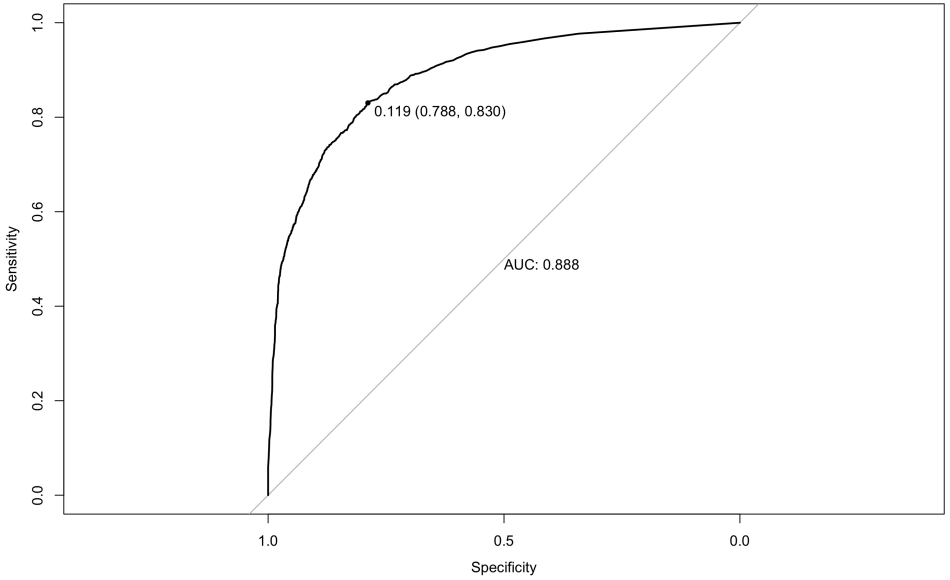


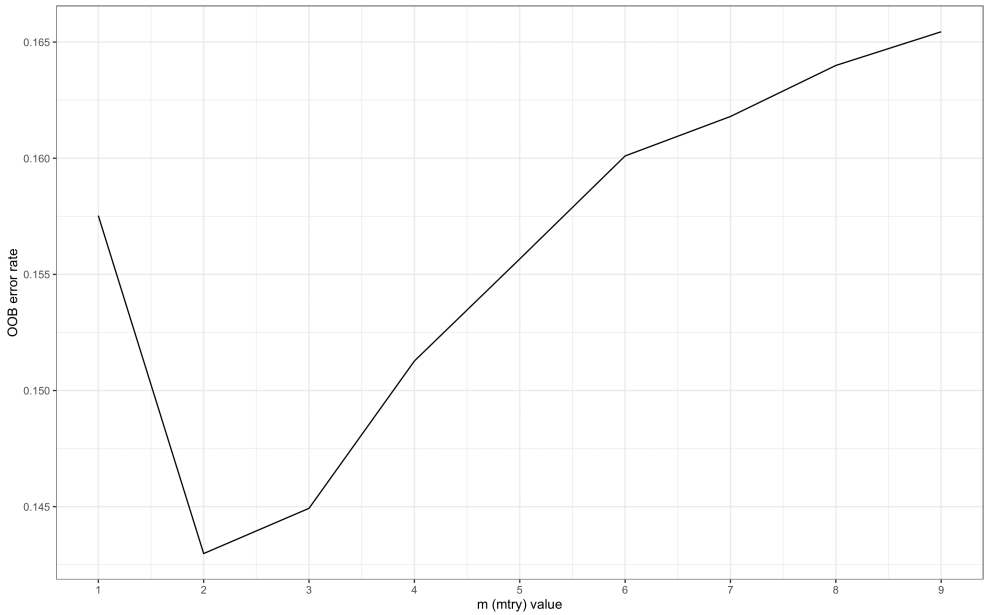


Predictive Methods Pt.2 (Decision Tree Pt.2)



- We will predict 74.3% of the time when an individual's earning is less than $50K and 87.7% of the time when an individual's earning is more than $50K.
- Area Under the Curve is 0.890



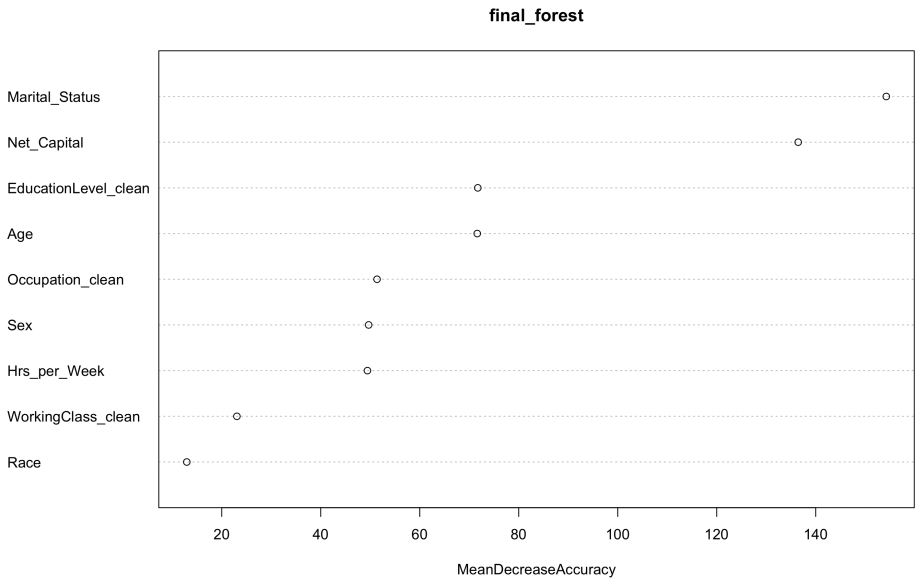


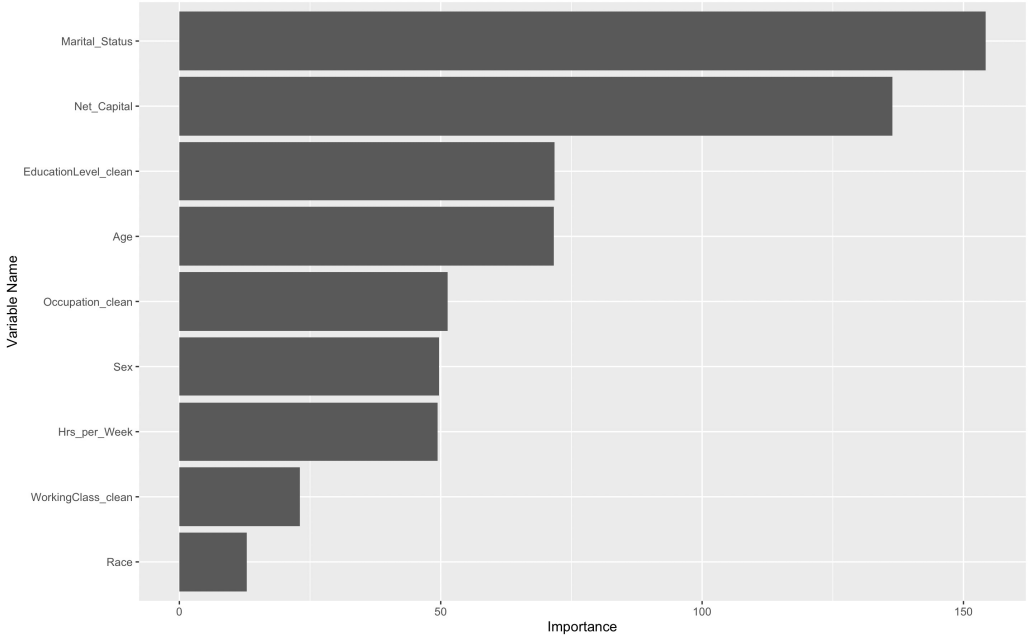
Predictive Method Pt.3 (Random Forest)

- We will predict 78.8% of the time when an individual's earning is less than $50K and 83% of the time when an individual's earning is more than $50K.
- Area Under the Curve is 0.888

Useful plots for creating GLM

- The graph shows us that Martial_Status is the most important variable that affects an individual's income to be more than >$50K.
- However, I took a further step to understand the relationship between income and other variables can affect a person's earning.
- And, all of variables affects a person's incoming by fitting the model and comparing their AIC/BIC, which the m8 includes all of variables in has the smallest AIC.





GLM Descriptive Methods (Bernoulli)

- Y ~ Bernoulli (π_i)
  - g (π_i) = $\eta_i = \log(\frac{\pi_i}{1-\pi_i})$

η_i = -5.4880 + 0.0279*(Age) + 0.3179*(WorkingClass_Clean_Government) - 1.9377*(WorkingClass_clean_Others) + 0.3281*(WorkingClass_clean_Private) + 0.000245*(Net_Capital) - 0.679*(Race_Amer-In) - 0.1146*(Race_ Amer-P) - 0.154*(Race_Black) – 0.7889*(Race_Other) +) - 2.1163*(EducationLevel_clean_Elementary) – 0.5298*(EducationLevel_clean_HighSchool) + 0.8685*(EducationLevel_clean_HigherEducation) - 1.8588*(EducationLevel_clean_MiddleSchool) - 0.1691*(Sex_Female) + 0.0298*(Hrs_per_Week) + 0.00982 *(Marital_Status_Divorced) + 2.9706*(Marital_Status_Married-AF-spouse) + 2.1275*(Marital_Status_Married-civ-spouse) – 0.0792*(Marital_Status_Married-spouse-absen) – 0.5231*(Marital_Status_Never-married) - 0.0887*(Marital_Status_Separated) - 3.4447*(Occupation_clean_Domestic) - 0.1809*(Occupation_clean_ManualLabor) + 0.8786*(Occupation_clean_Professional) + 0.5492*(Occupation_clean_Protective Ser) + 0.4277*(Occupation_clean_Sales) - 0.1114*(Occupation_clean_Services) + 0.0739*(Occupation_clean_SkilledLabor)

Analysis of Penalized Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept		1	-5.4880	0.2084	693.6576	<.0001
Age		1	0.0279	0.00160	304.3733	<.0001
WorkingClass_clean	Governemnt	1	0.3179	0.0661	23.1022	<.0001
WorkingClass_clean	Others	1	-1.9377	1.5799	1.5042	0.2200
WorkingClass_clean	Private	1	0.3281	0.0515	40.6720	<.0001
Net_Capital		1	0.000245	8.638E-6	803.1012	<.0001
Race	Amer-In	1	-0.6790	0.2193	9.5863	0.0020
Race	Asian-P	1	-0.1146	0.1006	1.2961	0.2549
Race	Black	1	-0.1540	0.0729	4.4594	0.0347
Race	Other	1	-0.7899	0.2809	7.9105	0.0049
EducationLevel_clean	Elementary	1	-2.1163	0.2564	68.1085	<.0001
EducationLevel_clean	HighSchool	1	-0.5298	0.0442	143.6988	<.0001
EducationLevel_clean	HigherEducation	1	0.8685	0.0471	339.5380	<.0001
EducationLevel_clean	MiddleSchool	1	-1.8588	0.1462	161.7114	<.0001
Sex	Female	1	-0.1691	0.0517	10.7148	0.0011
Hrs_per_Week		1	0.0298	0.00158	352.6052	<.0001
Marital_Status	Divorced	1	0.00982	0.1485	0.0044	0.9473
Marital_Status	Married-AF-spouse	1	2.9743	0.5130	33.6142	<.0001
Marital_Status	Married-civ-spouse	1	2.1275	0.1428	221.8993	<.0001
Marital_Status	Married-spouse-absen	1	-0.0792	0.2580	0.0943	0.7588
Marital_Status	Never-married	1	-0.5231	0.1515	11.9142	0.0006
Marital_Status	Separated	1	-0.0887	0.2004	0.1961	0.6579
Occupation_clean	Domestic	1	-3.4447	1.2394	7.7244	0.0054
Occupation_clean	ManualLabor	1	-0.1809	0.0932	3.7640	0.0524
Occupation_clean	Professional	1	0.8786	0.0762	133.0843	<.0001
Occupation_clean	Protective Ser	1	0.5492	0.1260	18.9848	<.0001
Occupation_clean	Sales	1	0.4277	0.0837	26.1002	<.0001
Occupation_clean	Services	1	-0.1114	0.0861	1.6754	0.1955
Occupation_clean	SkilledLabor	1	0.0739	0.0790	0.8769	0.3490

Coefficient Interpretations

95% confident interval for the odds ratio corresponding to a female is (e^[(- 0.2705)], e^[(-0.0679)]) = (0.7629, 0.9343). It means that we are 95% confident that the odds of a female's income is more than $50k is increasing from 6.6% to 23.7%.

95% confident interval for the odds ratio corresponding to a 20-year-old is (e^[3*(0.0247)], e^[3*(0.0310)]) = (1.0769, 1.097). It means that we are 95% confident that the odds of a 20-year-old's income is more than $50k is increasing from 7.7% to 9.7%.

For a year increase in age, an individual's odds of having income more than $50K change by a factor of e^(0.279) = 1.0289, hold other factors constant.

Conclusion:

The project's consideration of a wide range of demographic variables as potential predictors, from marital status to race demonstrates a comprehensive approach to understanding income determinants.

Aiming to refine analysis and align with The Glow Company's mission for a more effective and personalized skincare routine.

Strengthened Predictive Models by using both decision tree and random forest, to see which model predicts the data better and decision tree has a larger AUC which I will choose it over random forest

If you have any questions, please don’t hesitate to reach out to me via chi.dang@drake.edu