

# **INCOME PREDICTIONS**

Presented By: Maybelline Monge

### **AGENDA**

- Data Description
- Project Objective
- Exploratory Data Analysis
- Machine Learning Model
- Recommendation

### DATA DESCRIPTION

Classification Dataset

• The target is adult income levels based on various demographic attributes

• Each row in the dataset provides statistical record pertaining to income level

• Each column represents a demographic feature of an individual

### PROJECT OBJECTIVE

EXPLORE DATA

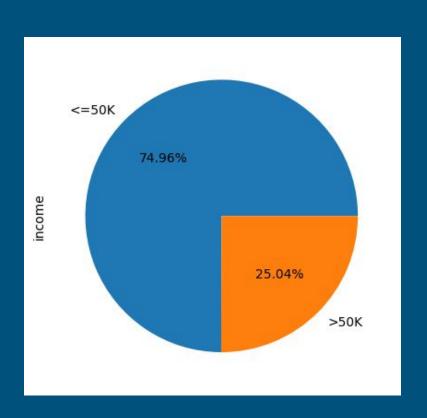
• CREATE & RECOMMEND A MACHINE LEARNING MODEL THAT PREDICTS WHETHER AN ADULTS SALARY CROSSES A THRESHOLD OF \$50K OR HIGHER

CLASSIFYING YES OR NO FOR OUR TARGET "ADULT INCOME"

## **EXPLORATORY DATA ANALYSIS**

age	workclass	fnlwgt	education	educational-num	marital-status	occupation	relationship	race	gender	capital-gain	capital-loss	hours-per-week	native-country	income
25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0	0	40	United-States	<=50K
38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	0	50	United-States	<=50K
28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0	0	40	United-States	>50K
44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688	0	40	United-States	>50K
18	?	103497	Some-college	10	Never-married	?	Own-child	White	Female	0	0	30	United-States	<=50K
34	Private	198693	10th	6	Never-married	Other-service	Not-in-family	White	Male	0	0	30	United-States	<=50K
29	?	227026	HS-grad	9	Never-married	?	Unmarried	Black	Male	0	0	40	United-States	<=50K
63	Self-emp-not-inc	104626	Prof-school	15	Married-civ-spouse	Prof-specialty	Husband	White	Male	3103	0	32	United-States	>50K

age	workclass	education	marital_status	occupation	race	gender	hours-per-week	continent	income
25	Private	<b>11</b> th	Never-married	Machine-op-inspct	Black	Male	40	N_America	<=50K
38	Private	HS-grad	Married-civ-spouse	Farming-fishing	White	Male	50	N_America	<=50K
28	Government	Assoc-acdm	Married-civ-spouse	Protective-serv	White	Male	40	N_America	>50K
44	Private	Some-college	Married-civ-spouse	Machine-op-inspct	Black	Male	40	N_America	>50K
34	Private	10th	Never-married	Other-service	White	Male	30	N_America	<=50K

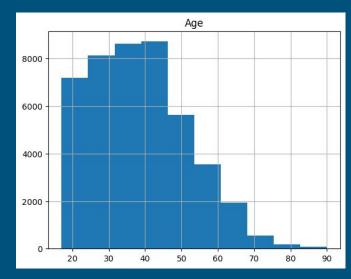


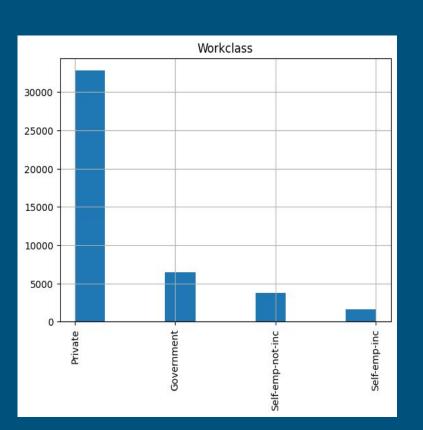
- ABOUT 75% OF ADULTS IN THE DATASET MAKE A SALARY EQUAL OR LESS THAN \$50K
- REMAINING 25% MAKE A SALARY GREATER THAN \$50K

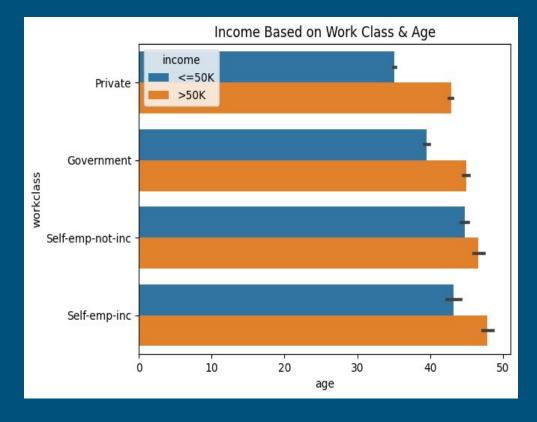
HIGHLY IMBALANCED

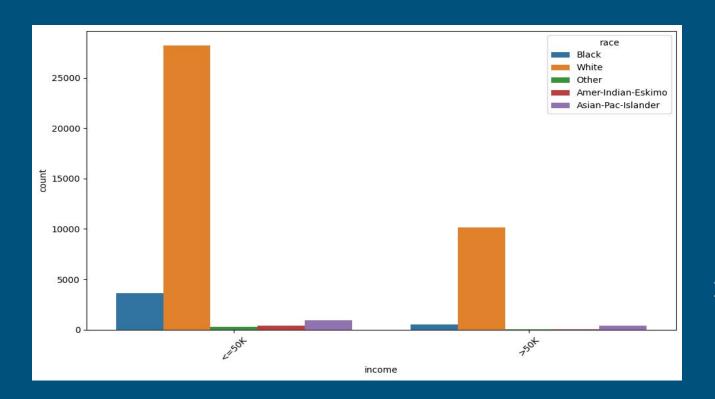


- THE "AGE" FEATURE
  APPEARS TO HAVE
  OUTLIERS FROM 47 YEARS
  OF AGE AND BEYOND 75.
- AGE 37 IS THE MEDIAN IN THE WHOLE DATASET







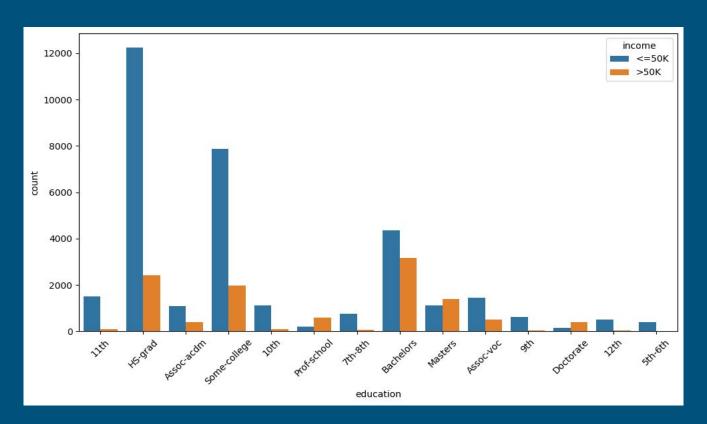


GREAT DISPARITY
BETWEEN INCOME
& RACE
DISTINCTION

NOTABLE INFORMATION

#### CORRELATION OF INCOME RELATIVE TO EDUCATION

#### **YIELDS SOME INTERESTING TRENDS**



# MACHINE LEARNING MODELS

1.5	Train Accuracy	Train Recall	Train Precision	Train F1-Score T	est Accuracy	Test Recall	Test Precision	Test F1-Score
KNN Tuned Model	0.850558	0.661957	0.721496	0.690445	0.818223	0.611354	0.636605	0.623724
	Train Ac	curacy Train R	ecall Train Precisi	ion Train F1-Score	Test Accuracy	Test Recall	Test Precision	Test F1-Score
Random Forest Tuned	Model (	).83277	0.5 0.7527	771 0.600885	0.827459	0.495997	0.716614	0.586237
Trai	n Accuracy Tr	ain Recall Tr	ain Precision Tra	ain F1-Score Tes	t Accuracy Te	est Recall Te	est Precision	Test F1-Score
RF PCA Model	0.959403	0.906792	0.930207	0.91835	0.805668	0.555677	0.617469	0.584945
т	rain Accuracy	Train Recall	Train Precision	Train F1-Score To	est Accuracy	Test Recall	Test Precision	Test F1-Score
LREG PCA Model	0.822606	0.539064	0.688714	0.604769	0.823693	0.549491	0.67471	0.605696
	Train Accurac	y Train Recal	l Train Precision	Train F1-Score	Test Accuracy	Test Recall	Test Precision	Test F1-Score
LREG Tuned Model	0.82670	2 0.55200	7 0.696688	0.615966	0.831316	0.568049	0.692239	0.624026

#### RECOMMENDATION

• The Tuned Logistic Regression Model is the best production model for the business problem at hand.

 The model accuracy score being the highest at 83% implies it's the highest predictive model with the most number of samples that display out to be in the positive class.

• As this is a classification task of whether the income in the sample crosses a threshold of \$50k or higher, yes or no, this metric yields the most value with fewer false positives.