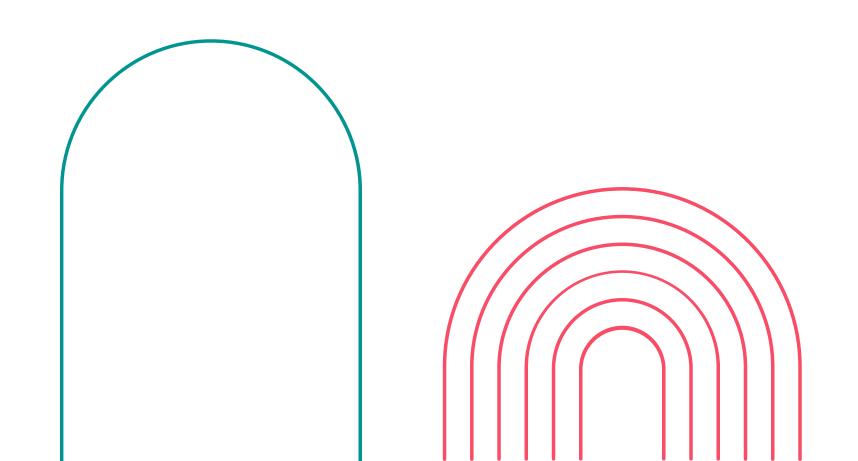




## INCOME CLASSIFICATION

DATA SCIENTIST INTERVIEW PRESENTATION

Joseph Ekpenyong 05 June 2023





O2. Data and EDA

PREPROCESSING AND MODELING 03.

Data modeling lifecycle

CONCLUSION Results and insights



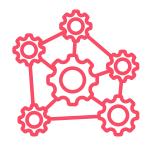
**AGENDA** 

## **EXECUTIVE SUMMARY**



#### **INCOME INEQUALITY**

Plays a significant role in determining individuals' opportunities and quality of life



#### **COMPLEX FACTORS**

Understanding factors that contribute to different income levels can be complex and challenging



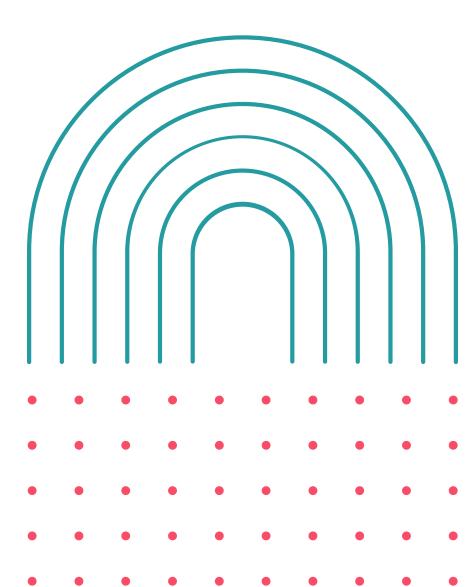
#### **MACHINE LEARNING**

We leverage machine learning to uncover underlying patterns that impact income levels

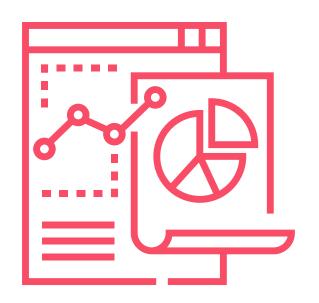


#### **FINDINGS**

We learn that investment income, sex, age, education, and occupational roles are associated with income class



## CONTEXT



#### **DATA**

US Census Bureau



#### **ACCESS**

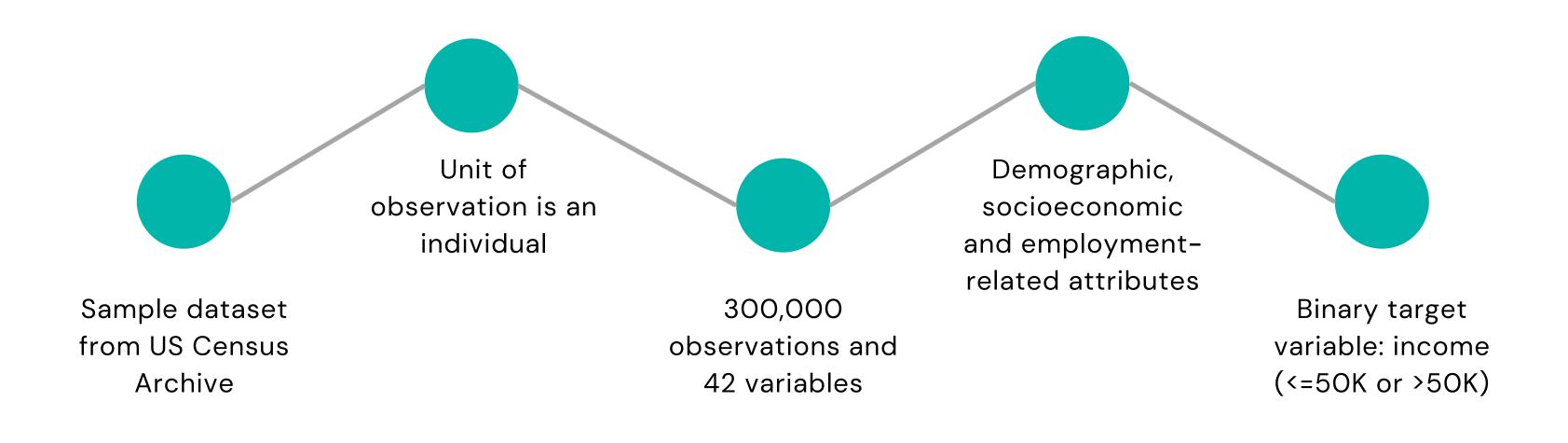
Information is publicly available



## QUESTION

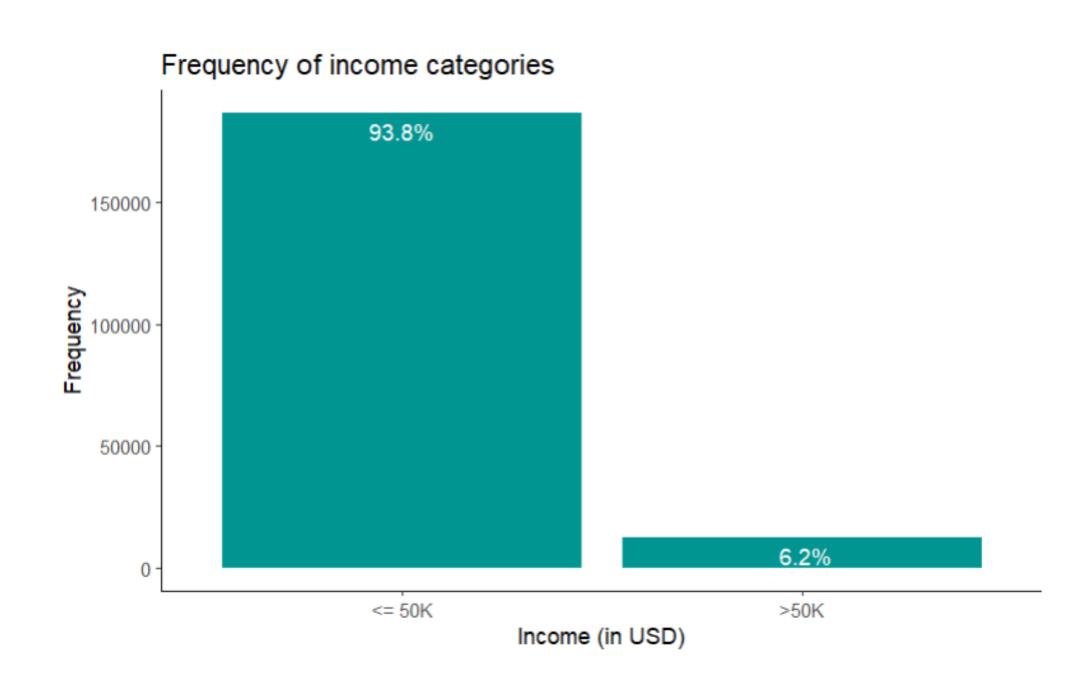
What characteristics are associated with a person making more or less than \$50,000 per year.

## DATA SUMMARY

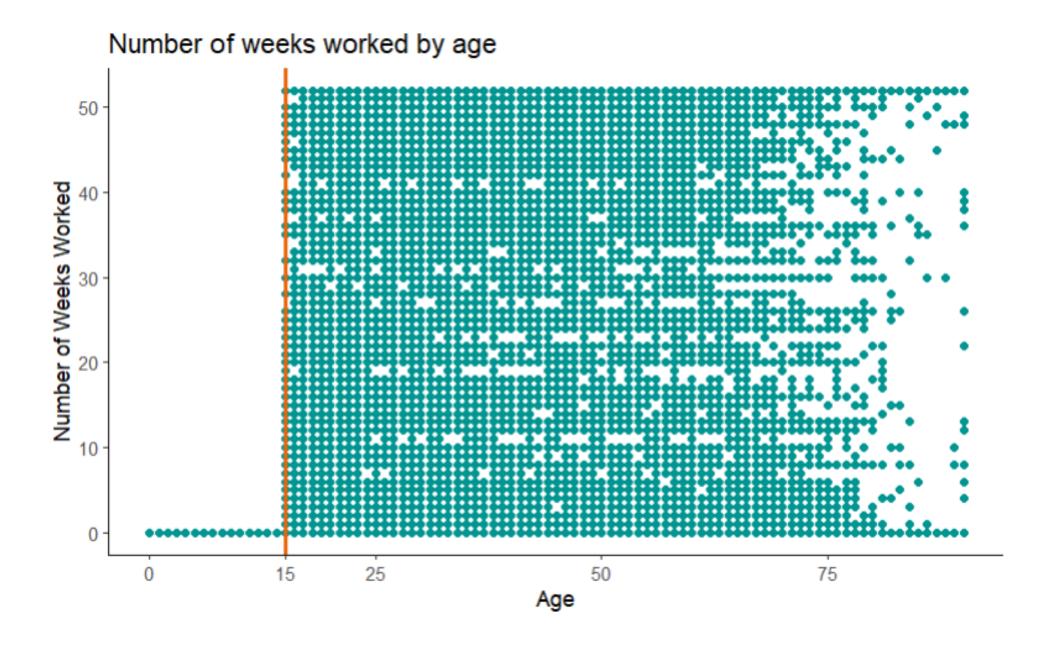


The target variable is highly imbalanced

**OBSERVATION** 



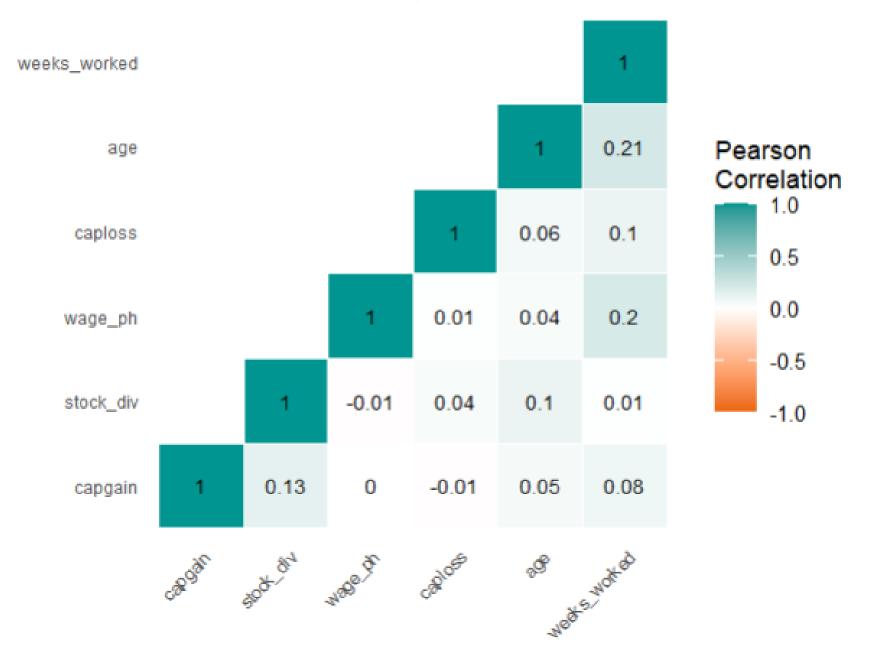
Children
(persons under 15) do not work



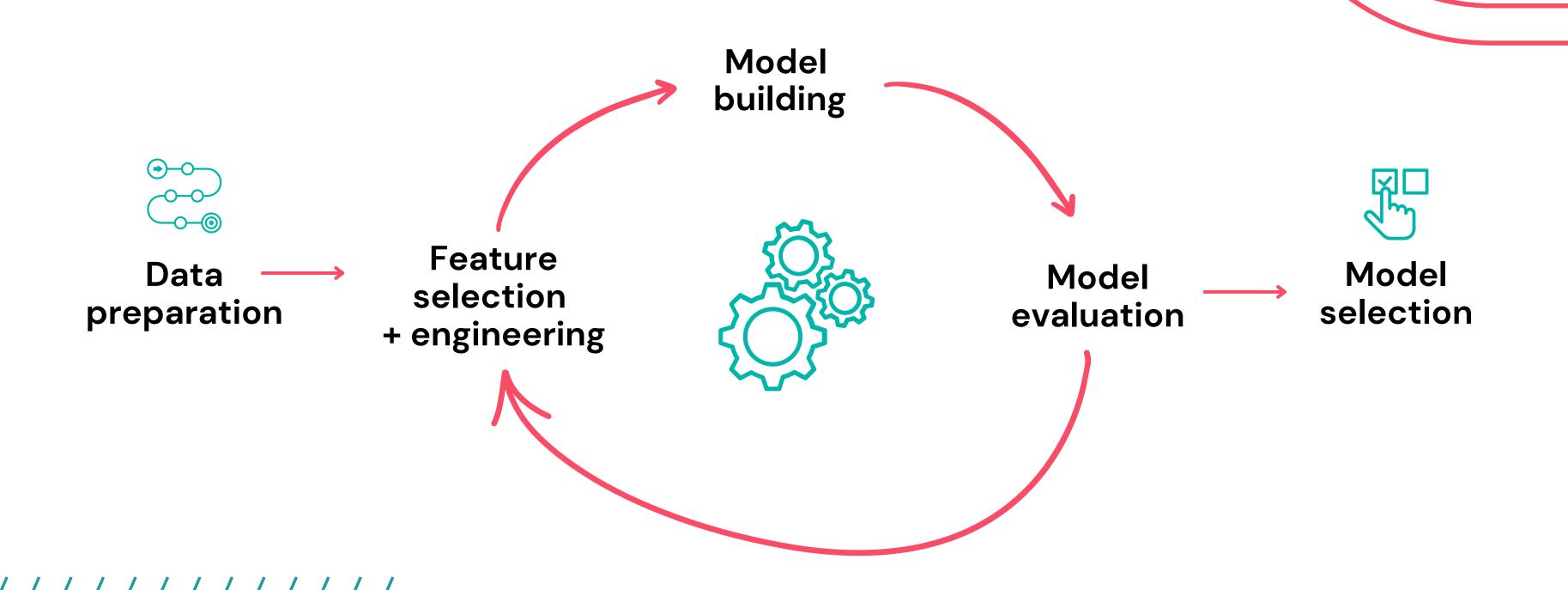
#### **OBSERVATION**

There is weak-to-no correlation among numeric variables

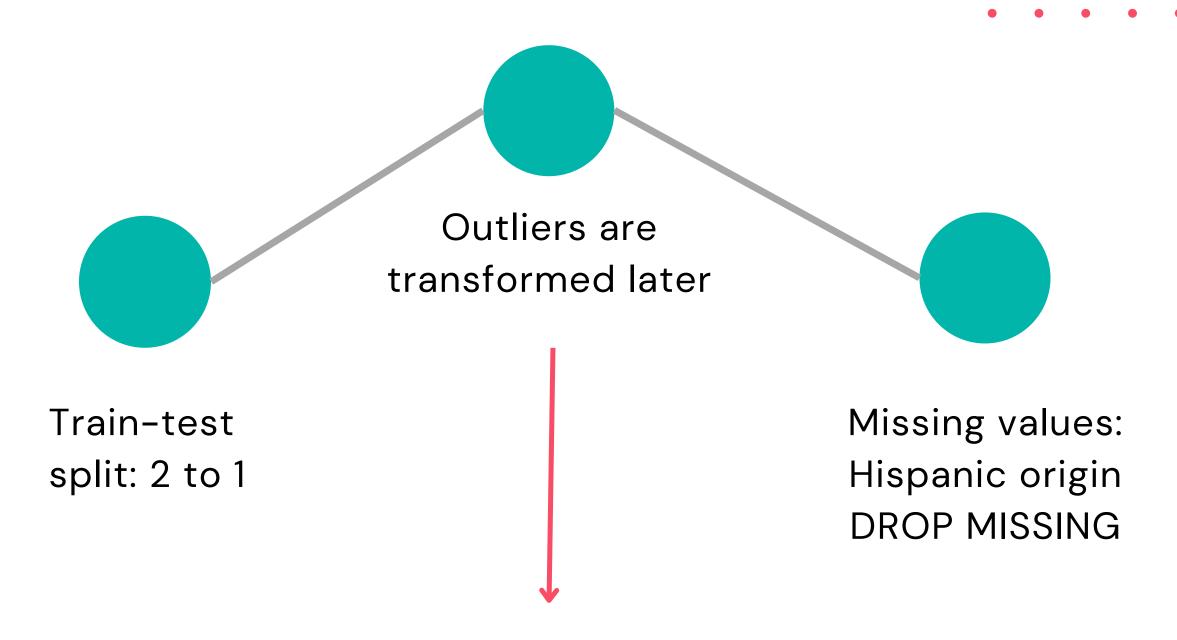
#### Correlation heatmap for numeric variables



## OVERVIEW OF MODELING STEPS



### DATA PREPARATION

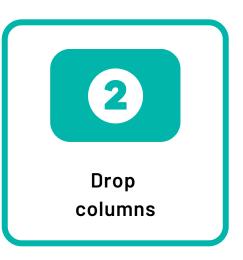


Outliers: capital gain, stock dividends, wage per hour TRANSFORM LATER

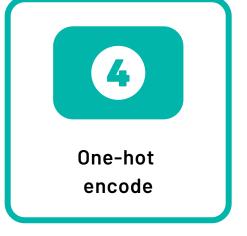
## FEATURE SELECTION + ENGINEERING

Apply to train and test sets







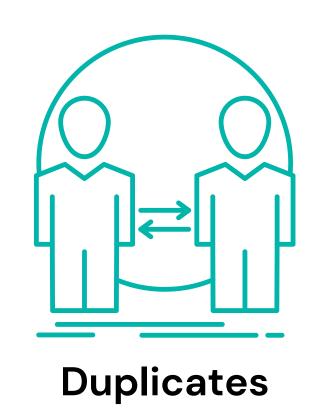




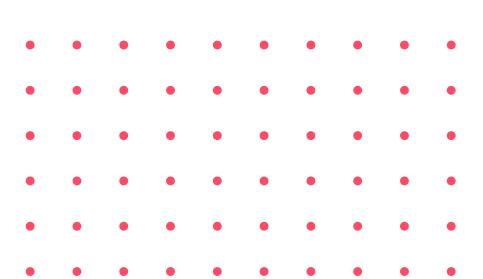
## TARGET CLASS IMBALANCE



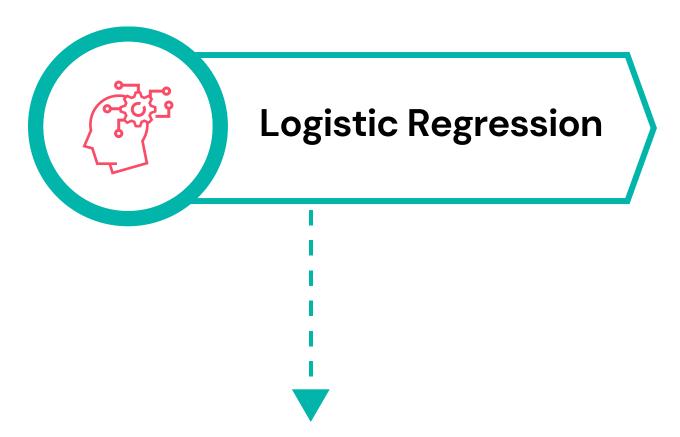
Undersampling to address class imbalance







## THIS IS A CLASSIFICATION PROBLEM



- Linear classifier
- Predicts probabilities
- Interpretatable



- Ensemble learning method
- Handles complexity better
- Resistant to overfitting

# MODEL EVALUATION (with undersampling)



Confusion matrix:

[[90930 2646]

[ 3692 2494]]

Classification Report:

	precision	recall	f1-score	support
- 50000. 50000+.	0.96 0.49	0.97 0.40	0.97 0.44	93576 6186
300001.	0.43	0.40	0.44	0100
accuracy			0.94	99762
macro avg	0.72	0.69	0.70	99762
weighted avg	0.93	0.94	0.93	99762

#### Random Forest

Confusion matrix:

[[89745 3831]

[ 3718 2468]]

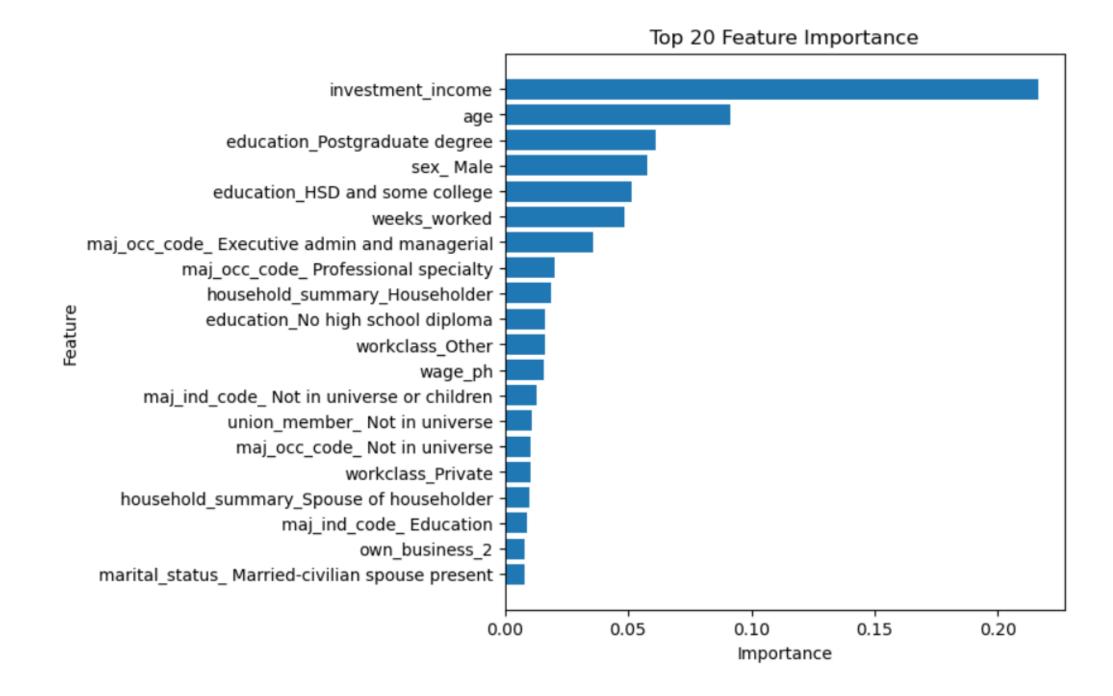
Classification Report:

	precision	recall	f1-score	support
- 50000.	0.96	0.96	0.96	93576
50000+.	0.39	0.40	0.40	6186
accuracy macro avg weighted avg	0.68 0.92	0.68 0.92	0.92 0.68 0.92	99762 99762 99762

## FINAL MODEL: Random Forest

#### **OBSERVATION**

Investment income, age, education, and being an executive are all important characteristics associated with income class.



## **FUTURE WORK**



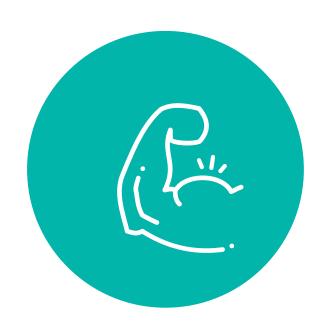
Feature Engineering

Spend more time exploring relationships between variables



**Best Parameters** 

Use grid search to select the best parameters for a model



**Robust Metrics** 

Build more robust model evaluation metrics

What would we do if we had more time and computing power?

## CONCLUSION RESULTS AND FINDINGS

What characteristics are associated with a person making more or less than \$50,000?

- Investment Income
   provides insights into an individual's financial portfolio and wealth accumulation.
- Sex or gender disparities exist in income levels and should be approached with caution.
- Occupational roles can be associated with higher incomes.

 Age correlates with work experience and seniority level in a job.

 Education can provide individuals with the knowledge and skills required for higher-paying professions.