Group 2

US Census 1994 Income Data

Exploration Data, Machine Learning Model, Optimization, Visualization

AI Bootcamp Class with Suzanna Ayash

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Contributors

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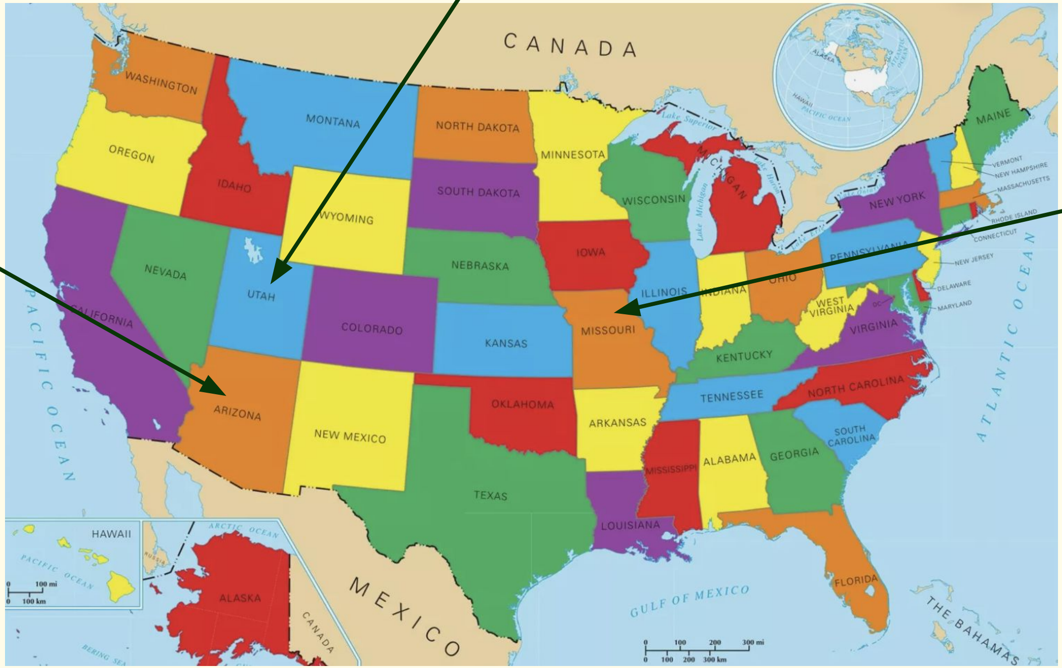


Income Census Data is important! Why?

- Economic planning and resource allocation
- Identify Socio/Economic inequalities
- Helps business sell by income segments
- Helps government create laws and policies

AI Can Help Us with Analyzing Income Census Data. How?

AI Tools

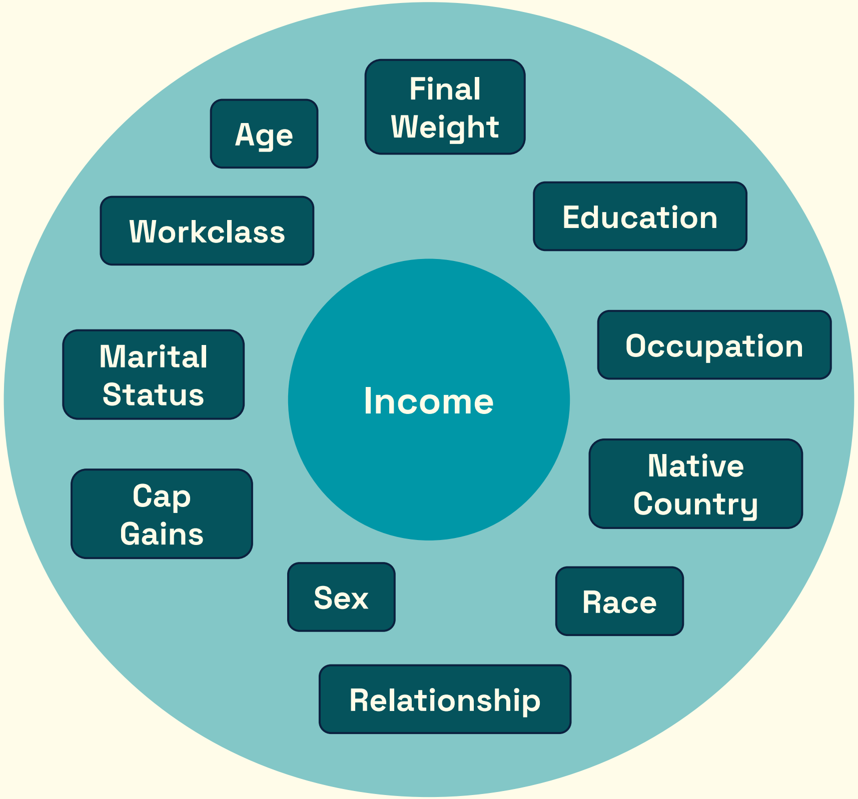
SciKit-Learn
Imbalanced-Learn
Pandas
Random Forest
MatPlotLib
& More

- Reduce Data Collection & Processing Time
- Data Quality and Validation Improvement
- Identifying Patterns
- Demographic Insights
- Real-time populating tracking
- Automate Predictive Analytics

Overview of the 1994 Income Census Data

- 14 Total features
- 48K rows with over 1K unique values
- Target is Income
- Greater or less than $50K

Too much 'chaos' in this data…let's talk 'Data Prep!'



Data Preparation - Overview

Visualization

Discover meaningful relationships between each feature and income, possible imbalances

Clean

Remove duplicates, redundant columns (ie: relationship, education-num, native-country)

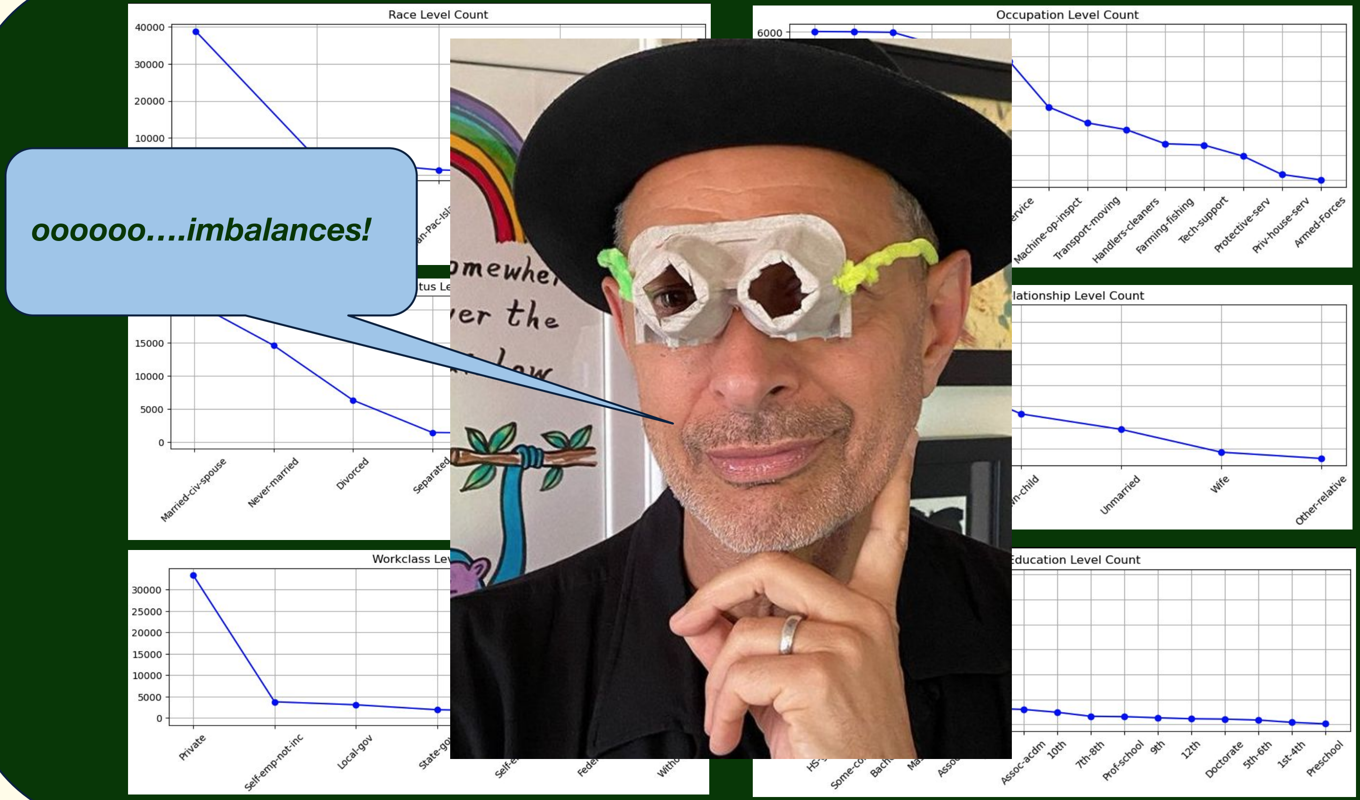
Feature Engineering

Create new ‘assets’ by taking ‘Capital Gain’ minus ‘Capital Loss.’

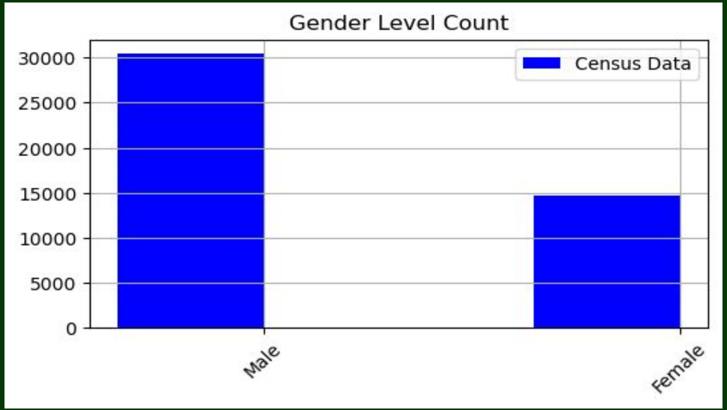
Encoding & Scaling

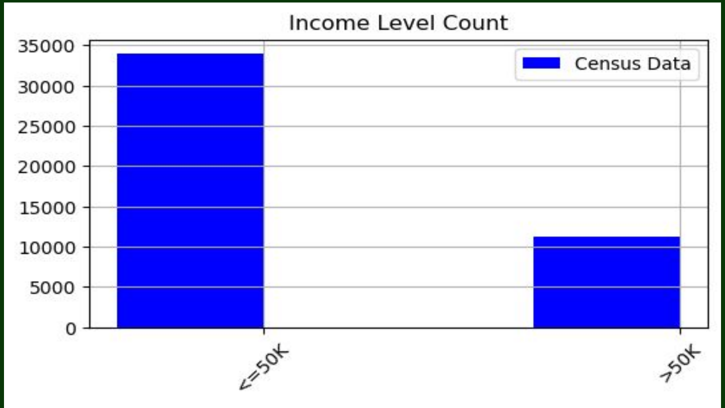
Binary assignment, numerical categorization, and post-split scaling new ‘assets’ column.

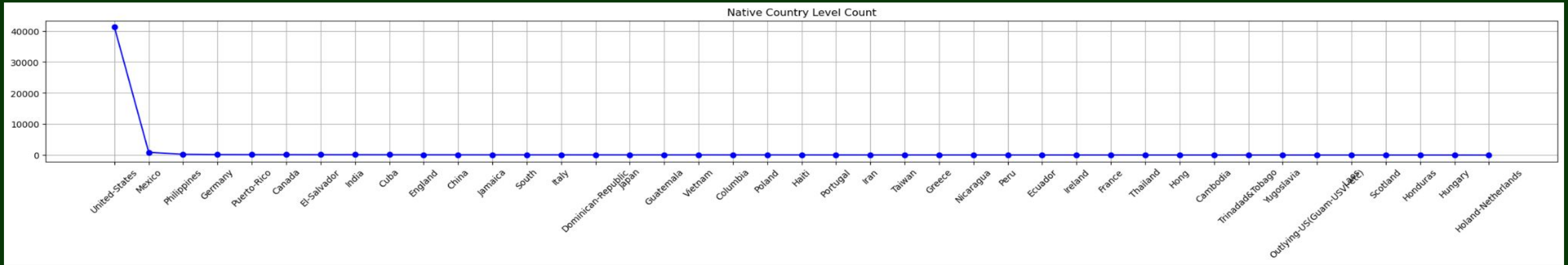
Data Preparation - Visualization



Data Preparation - Visualization (cont'd)







Categorical Encoding

LEGEND	Age	Workclass	Education	Marital Status	Occupation	Race	Sex	Hours per week	Income
0	Less than 30 years	Private sector	Preschool - 6th grade	Single, Divorced, Never Married, Widowed	Blue-collar	White	Male	Part time for less than 30 hours/week	<= 50K
1	30 to 50 years	Self Employment	7th - High School grad	Married	White-collar	Black	Female	Full time for 30-40 hours/week	> 50K
2	Above 50 years	Government Worker	Some College, Assoc, Bachelors Degree	N/A		Asian and Pacific Islander	N/A	Over time for above 40 hours/week	N/A
3	N/A		Masters, Doctorate, Prof School	N/A		American Indian, Eskimo	N/A	N/A	N/A
4	N/A			N/A		Other	N/A	N/A	N/A

	age	workclass	fnlwgt	education	marital-status	occupation	race	sex	hours-per-week	income	assets
count	41254	41254	41254	41254	41254	41254	41254	41254	41254	41254	41254
mean	0.88	0.418	187263.564	1.635	0.504	0.549	0.162	0.326	1.166	0.253	1037.596
std	0.702	0.734	105039.504	0.64	0.5	0.498	0.514	0.469	0.656	0.435	7629.923
min	0	0	13492	0	0	0	0	0	0	0	-4356
25%	0	0	115803	1	0	0	0	0	1	0	0
50%	1	0	176728	2	1	1	0	0	1	0	0
75%	1	1	234640.75	2	1	1	0	1	2	1	0
max	2	2	1490400	3	1	1	4	1	2	1	99999

Now we work with 41,254 records out of 48,840 original records

Variance Inflation Factor (VIF)

- All features VIF values ranged from 1.018 to 1.334 which means NO collinearity detected!
- Importantly, all of these features also had low VIF scores, meaning they weren’t collinear with each other

	feature	VIF
3	marital-status	1.337080
6	sex	1.314780
4	occupation	1.304685
2	education	1.271688
0	age	1.143666
7	hours-per-week	1.126601
1	workclass	1.060613
8	assets	1.024331
5	race	1.017819

Coefficients for Feature Importances

We found that Marital Status was the strongest predictor, followed by Education, Age, and Occupation.

So, we can trust that their influence is statistically sound and not inflated due to overlap with other variables.

```
[(0.34918395491982024, 'marital-status'),
 (0.17711134368003462, 'education'),
 (0.12974789081621338, 'age'),
 (0.11501608825273132, 'occupation'),
 (0.09513362543523164, 'hours-per-week'),
 (0.06546328706006603, 'sex'),
 (0.03469961356030286, 'workclass'),
 (0.03364419627559988, 'race')]
```

So 11 features and a target binary classification….what model to organize this 'chaos?'

Let's run an accuracy test on all!

Accuracy Score and Model Coefficients

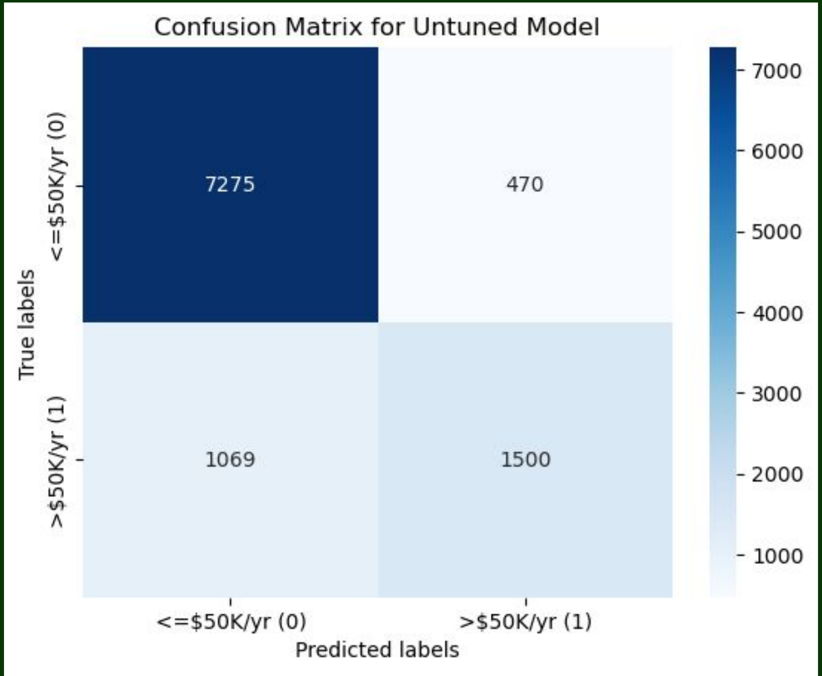
```
XGBClassifier: Train Accuracy = 0.8622, Test Accuracy = 0.8555, Balanced Accuracy = 0.7736, F1 Score = 0.6779
GradientBoostingClassifier: Train Accuracy = 0.8546, Test Accuracy = 0.8508, Balanced Accuracy = 0.7616, F1 Score = 0.6609
ExtraTreesClassifier: Train Accuracy = 0.8667, Test Accuracy = 0.8424, Balanced Accuracy = 0.7561, F1 Score = 0.6487
RandomForestClassifier: Train Accuracy = 0.8667, Test Accuracy = 0.8481, Balanced Accuracy = 0.7653, F1 Score = 0.6631
DecisionTreeClassifier: Train Accuracy = 0.8667, Test Accuracy = 0.8492, Balanced Accuracy = 0.7668, F1 Score = 0.6657
KNeighborsClassifier: Train Accuracy = 0.8118, Test Accuracy = 0.7900, Balanced Accuracy = 0.7092, F1 Score = 0.5652
AdaBoostClassifier: Train Accuracy = 0.8392, Test Accuracy = 0.8351, Balanced Accuracy = 0.7535, F1 Score = 0.6409
LogisticRegression: Train Accuracy = 0.8293, Test Accuracy = 0.8271, Balanced Accuracy = 0.7348, F1 Score = 0.6135
```

XGBClassifier and GradientBoostingClassifier gave the top 2 best model scores

Ingrid

Confusion Matrix For Gradient Boosting Classifier

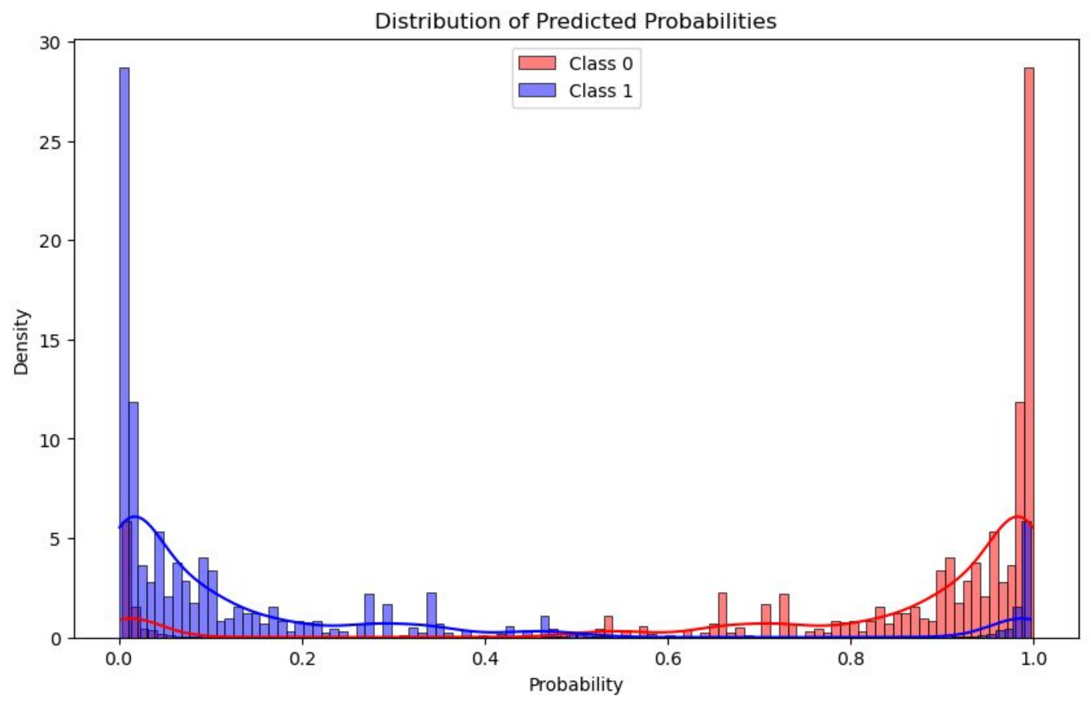
(Train Acc=0.8546, Test Acc=0.8508, Balanced Acc Score=0.7616, F1 Score=0.6609, ROC AUC=0.87)

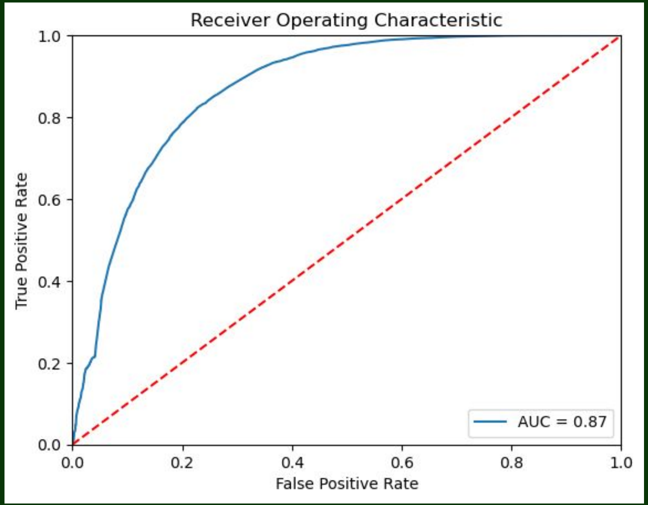


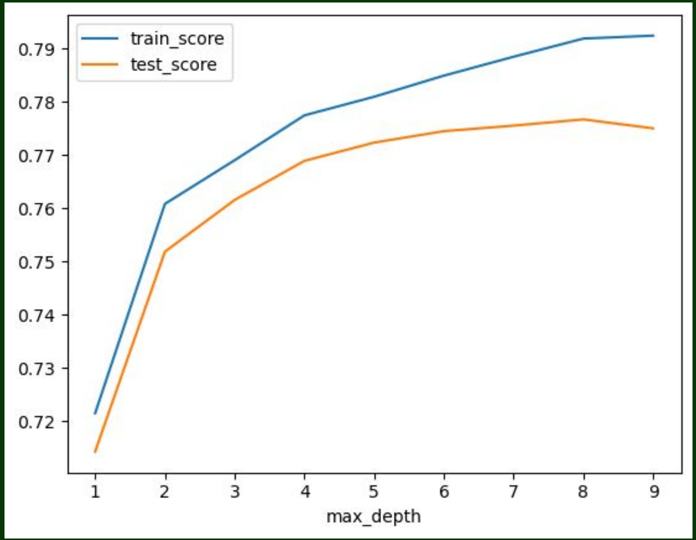
Metric	Count	Meaning
True Negatives (Top Left)	7275	Correctly predicted low income
False Positives (Top Right)	470	Mistakenly predicted high income
False Negatives (Bottom Left)	1069	Missed actual high income
True Positives (Bottom Right)	1500	Correctly predicted high income

Your 1st model is good!!

GradientBoosting Model



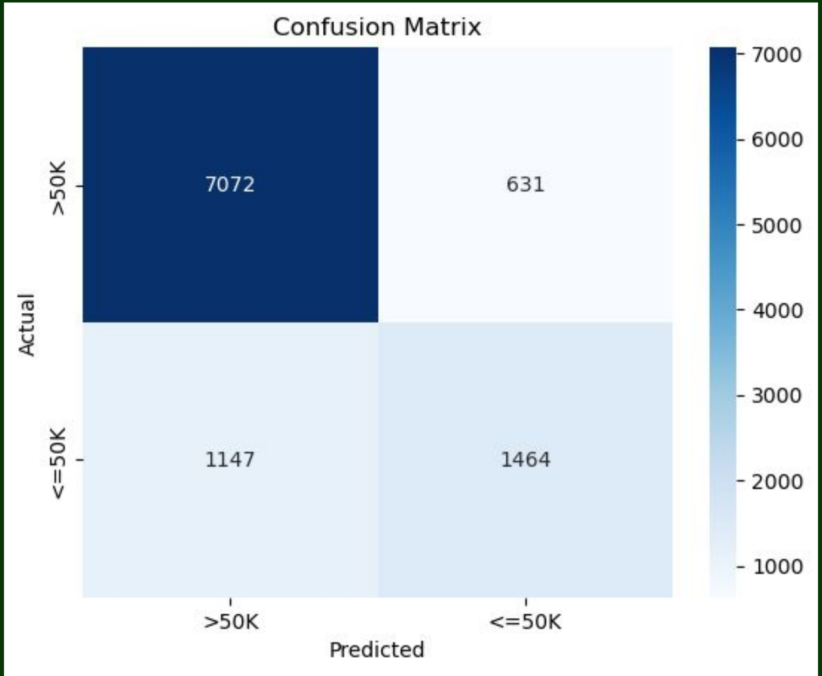




Ingrid

Confusion Matrix For XGBoost Classifier

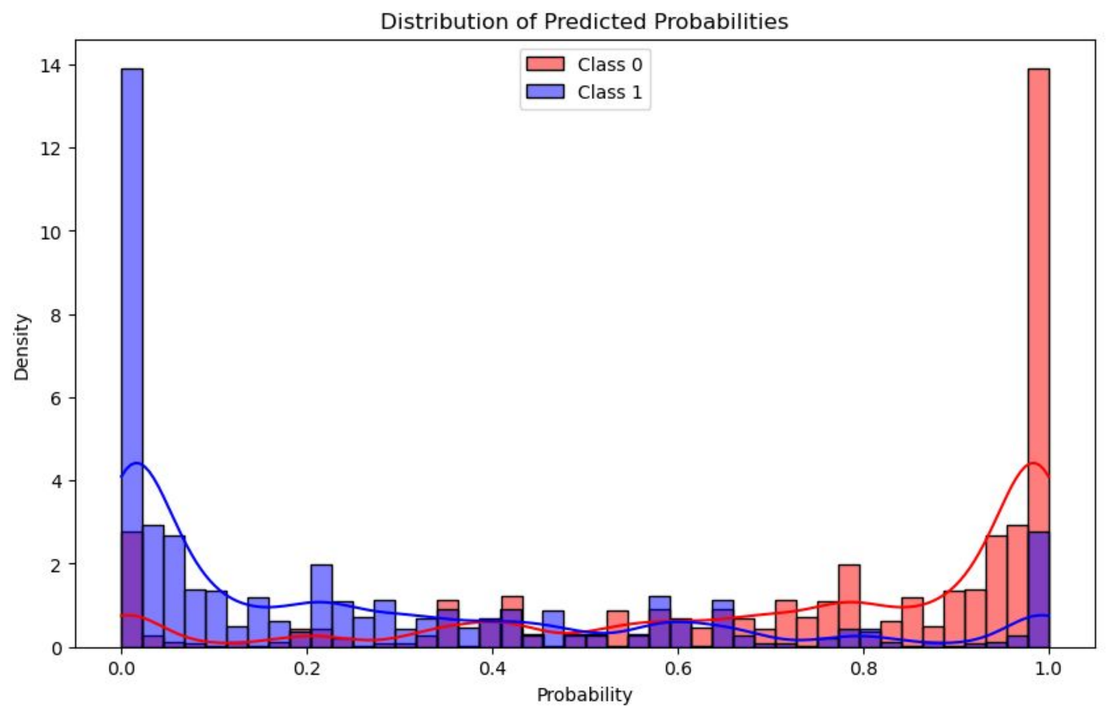
(Train Acc=0.8622, Test Acc=0.8555, Balanced Acc Score=0.7736, F1 Score=0.6779, ROC AUC=0.92)

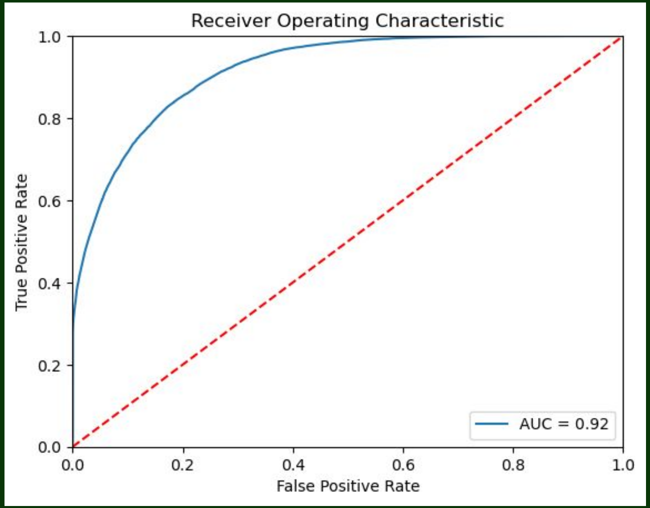


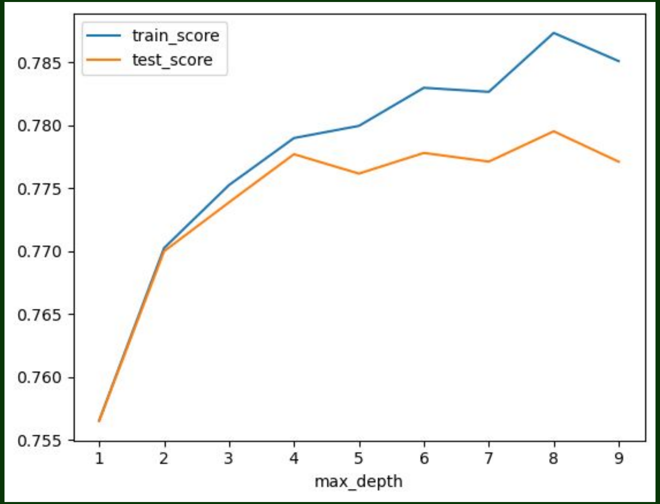
Metric	Count	Meaning
True Negatives (Top Left)	7072	Correctly predicted low income
False Positives (Top Right)	631	Mistakenly predicted high income
False Negatives (Bottom Left)	1147	Missed actual high income
True Positives (Bottom Right)	1464	Correctly predicted high income

Your 2nd model is good too, which one is better?

XGBoost Model







Which Model Wins?

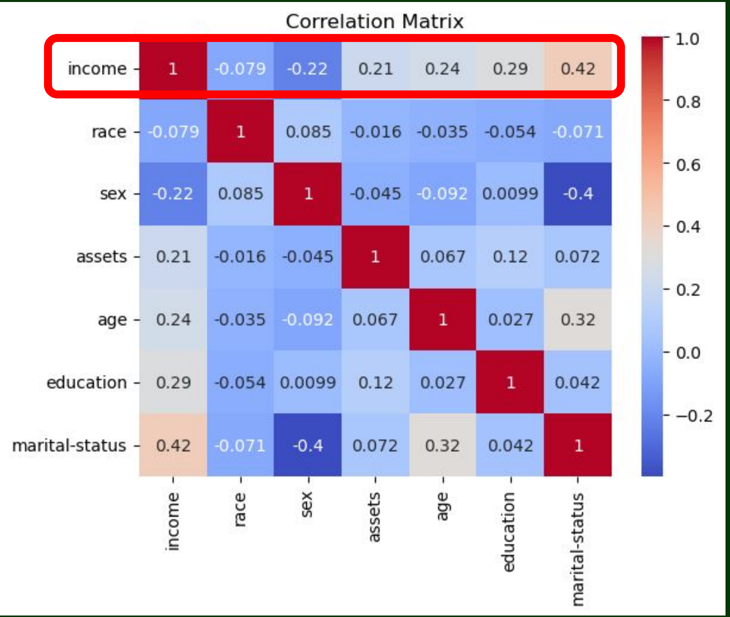
XGBoost	Vs.	Gradient Boosting
✔ (86% vs 85%)	Train and Test Accuracy	
✔ (77% vs 76%)	Balanced Accuracy	
✔ (68% vs 66%)	F1 Score	
✔ (92% vs 87%)	ROC AUC	
	Precision for >$50K	✔ (76% vs 70%)
	Overall classification accuracy correctness	✔ (85% vs 83%)
WINNER	Conclusion	RUNNER UP

Correlation Matrix - Income vs. Features

- Income level decreases
  - Race & Sex

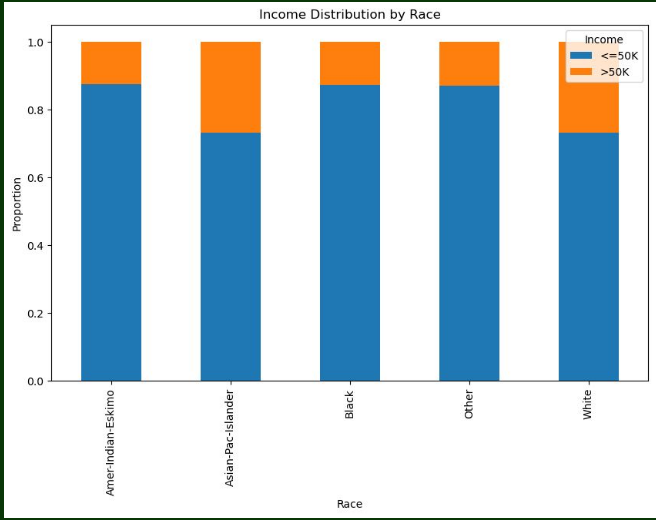
- Income level Increases
  - Assets, Age, Education and Marital Status

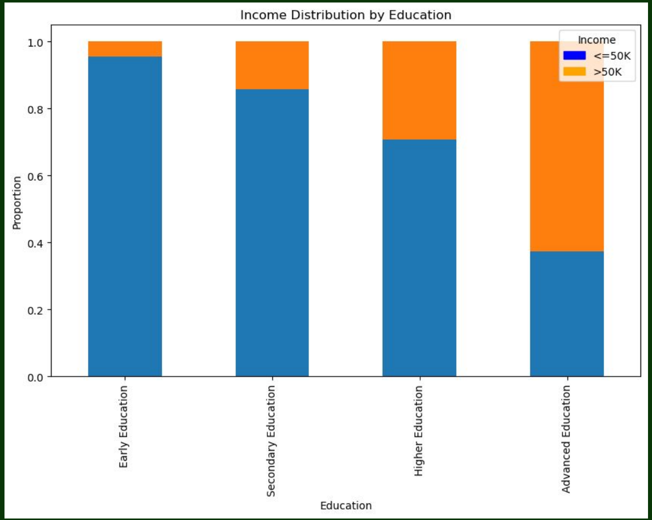
- Max correlation - Marital Status
- Min correlation - Race

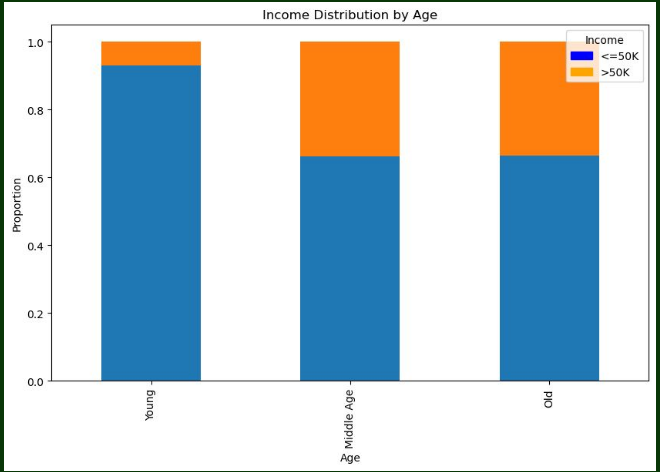


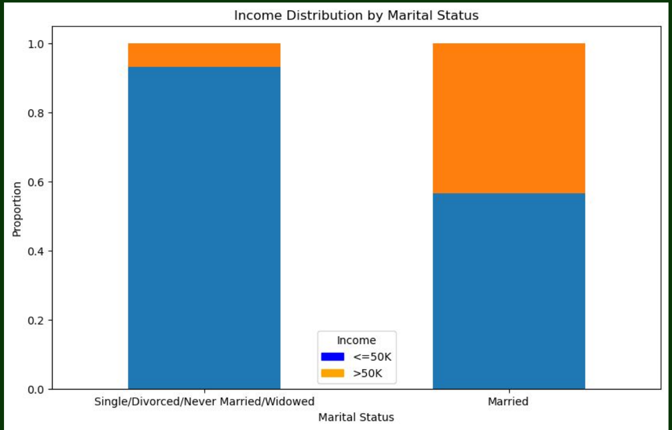
Granular look at Income Distribution by Feature

- Race
- Education
- Age
- Marital Status









Conclusion

Raw Census Data → **Cleaned the Data** → **Encoded, Feature Engineering** → **Model Evaluation** → **XGBOOST Model (83% Classification Accuracy)**

Model Prediction - factors driving people making > $50K/year based on the 1994 census data

- Race = White and Asian/Pacific Islander
- Education = College Degree or Higher
- Age = 30-50 years old
- Marital Status = Married

Future Work

Fine Tuning Model to improve F1 Score

Look at Income Balances

Explore demographic features for income < $50K

Cross granular feature analysis (i.e. - race/education vs income)

Census data is complicated!

...but it's worth analyzing to plan for a less chaotic future!

Questions?

Thank You