

## **Approach Zindi UmojaHack India Income Prediction Challenge**

Create a machine learning model to predict whether an individual earns above 50,000 in a specific currency or not.

- Basic exploratory data analysis using pandas, matplotlib, seaborn packages.
- Data pre-processing
  - Replace the numerical column's unknown values.
  - Clean the categorical column's unknown values.
  - Missing value mode imputation for the categorical columns,
    - class
    - occupation\_code\_main
    - is\_hispanic
    - country\_of\_birth\_own
    - country\_of\_birth\_father
    - country\_of\_birth\_mother
    - migration\_code\_change\_in\_msa
    - migration\_prev\_sunbelt
    - migration\_code\_move\_within\_reg
    - migration\_code\_change\_in\_reg

- Missing value mean imputation for the numerical columns,
  - age
  - wage\_per\_hour
  - gains
  - losses
  - stocks\_status
  - importance\_of\_record
- Feature Engineering
  - Age check
  - Group by numerical summary
- Missing value indicator
- The final features for the model
  - 1\_age
  - 2\_gender
  - 3\_education
  - 4\_class
  - 5\_marital\_status
  - 6\_race
  - 7\_is\_hispanic
  - 8\_employment\_commitment
  - 9\_employment\_stat
  - 10\_wage\_per\_hour
  - 11\_working\_week\_per\_year

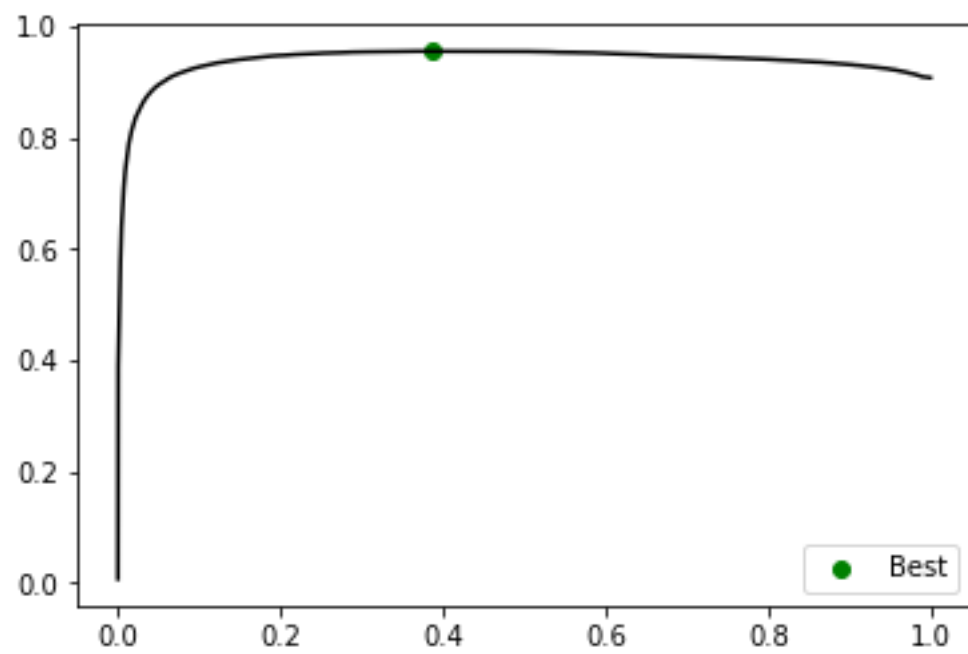
- 12\_industry\_code
- 13\_industry\_code\_main
- 14\_occupation\_code
- 15\_occupation\_code\_main
- 16\_total\_employed
- 17\_household\_stat
- 18\_household\_summary
- 19\_vet\_benefit
- 20\_tax\_status
- 21\_gains
- 22\_losses
- 23\_stocks\_status
- 24\_citizenship
- 25\_mig\_year
- 26\_country\_of\_birth\_own
- 27\_country\_of\_birth\_father
- 28\_country\_of\_birth\_mother
- 29\_migration\_code\_change\_in\_msa
- 30\_migration\_prev\_sunbelt
- 31\_migration\_code\_move\_within\_reg
- 32\_migration\_code\_change\_in\_reg
- 33\_residence\_1\_year\_ago
- 34\_importance\_of\_record
- 35\_income\_above\_limit
- 36\_data

- 37\_age\_less\_18
- 38\_age\_isnull
- 39\_class\_isnull
- 40\_wage\_per\_hour\_isnull
- 41\_occupation\_code\_main\_isnull
- 42\_gains\_isnull
- 43\_losses\_isnull
- 44\_stocks\_status\_isnull
- 45\_migration\_code\_change\_in\_msa\_isnull
- 46\_migration\_prev\_sunbelt\_isnull
- 47\_migration\_code\_move\_within\_reg\_isnull
- 48\_migration\_code\_change\_in\_reg\_isnull
- 49\_residence\_1\_year\_ago\_isnull
- 50\_income\_above\_limit\_isnull
- 51\_gender\_count
- 52\_education\_count
- 53\_class\_count
- 54\_marital\_status\_count
- 55\_race\_count
- 56\_is\_hispanic\_count
- 57\_employment\_commitment\_count
- 58\_industry\_code\_main\_count
- 59\_occupation\_code\_main\_count
- 60\_household\_stat\_count
- 61\_household\_summary\_count

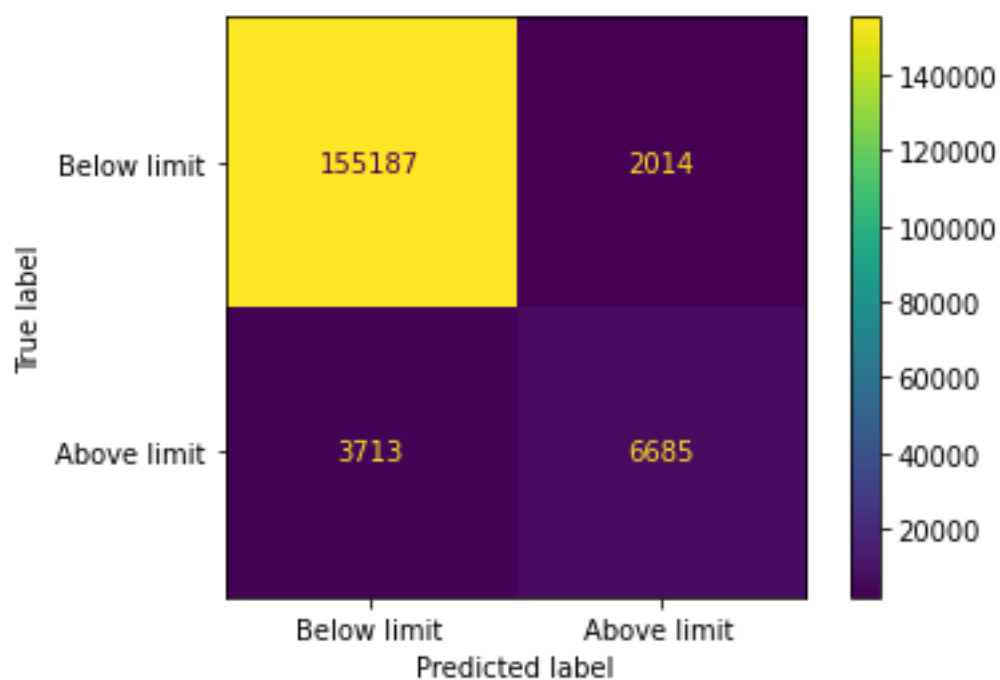
- 62\_tax\_status\_count
- 63\_citizenship\_count
- 64\_country\_of\_birth\_own\_count
- 65\_country\_of\_birth\_father\_count
- 66\_country\_of\_birth\_mother\_count
- 67\_migration\_code\_change\_in\_msa\_count
- 68\_migration\_prev\_sunbelt\_count
- 69\_migration\_code\_move\_within\_reg\_count
- 70\_migration\_code\_change\_in\_reg\_count
- 71\_residence\_1\_year\_ago\_count
- 72\_employment\_stat\_count
- 73\_working\_week\_per\_year\_count
- 74\_industry\_code\_count
- 75\_occupation\_code\_count
- 76\_total\_employed\_count
- 77\_vet\_benefit\_count
- 78\_mig\_year\_count
- 79\_income\_cat\_count
- 80\_age\_mean
- 81\_age\_median
- 82\_age\_min
- 83\_age\_max
- 84\_wage\_per\_hour\_mean
- 85\_wage\_per\_hour\_median
- 86\_wage\_per\_hour\_min

- 87\_wage\_per\_hour\_max
  - 88\_gains\_mean
  - 89\_gains\_median
  - 90\_gains\_min
  - 91\_gains\_max
  - 92\_losses\_mean
  - 93\_losses\_median
  - 94\_losses\_min
  - 95\_losses\_max
  - 96\_stocks\_status\_mean
  - 97\_stocks\_status\_median
  - 98\_stocks\_status\_min
  - 99\_stocks\_status\_max
  - 100\_importance\_of\_record\_mean
  - 101\_importance\_of\_record\_median
  - 102\_importance\_of\_record\_min
  - 103\_importance\_of\_record\_max
- 
- Train the catboost classifier model and evaluated with f1 metric.
  - Tune the probability threshold based on the validation data.

- The optimal threshold is : 0.3862



- Confusion matrix for train data

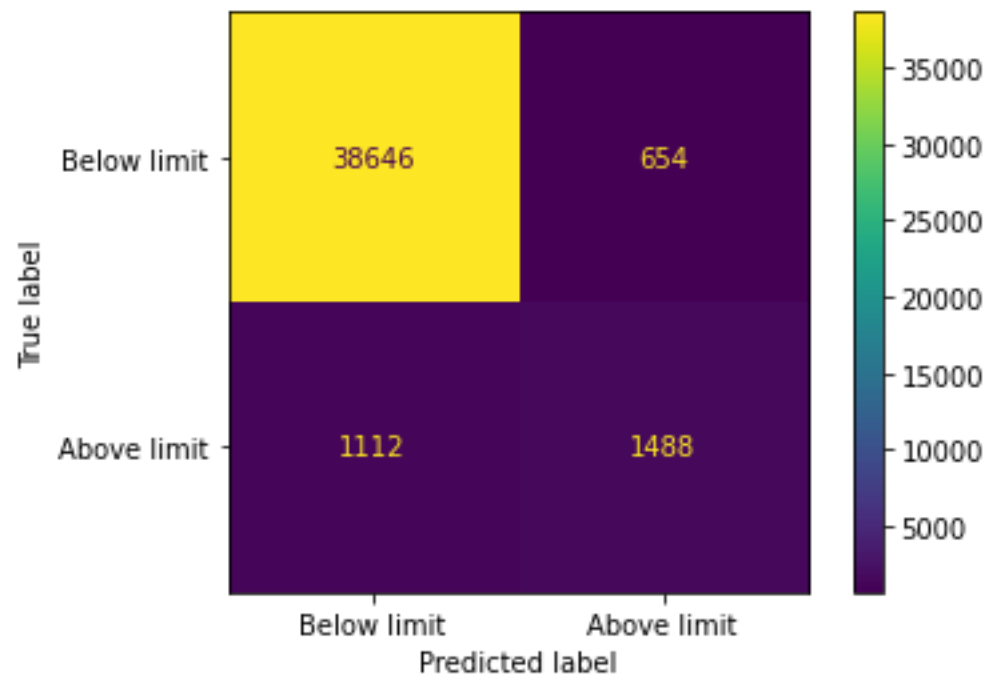


- Classification report for train data

	precision	recall	f1-score	support
Below limit	0.98	0.99	0.98	157201
Above limit	0.77	0.64	0.70	10398
accuracy			0.97	167599
macro avg	0.87	0.82	0.84	167599
weighted avg	0.96	0.97	0.96	167599



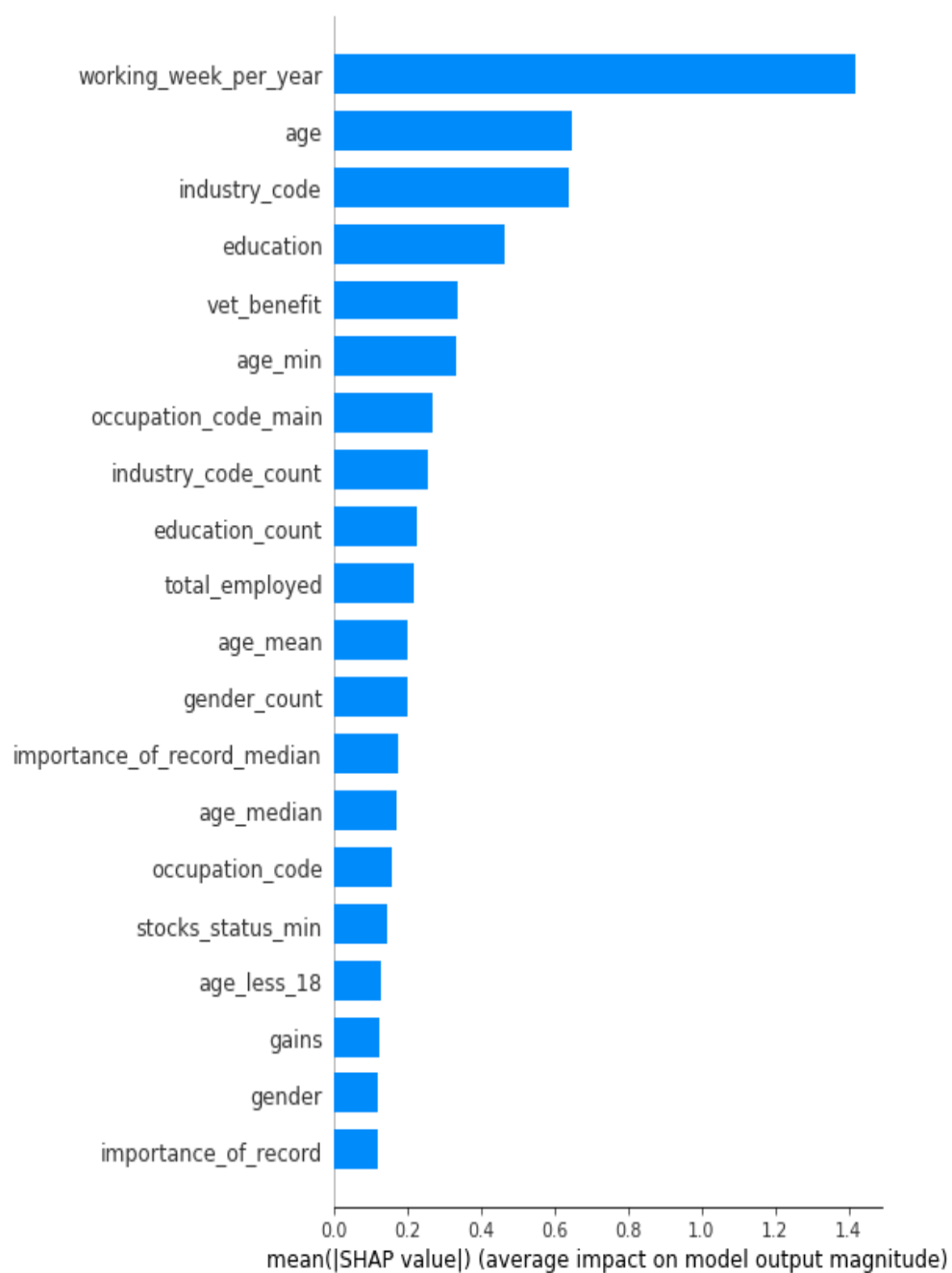
- Confusion matrix for validation data



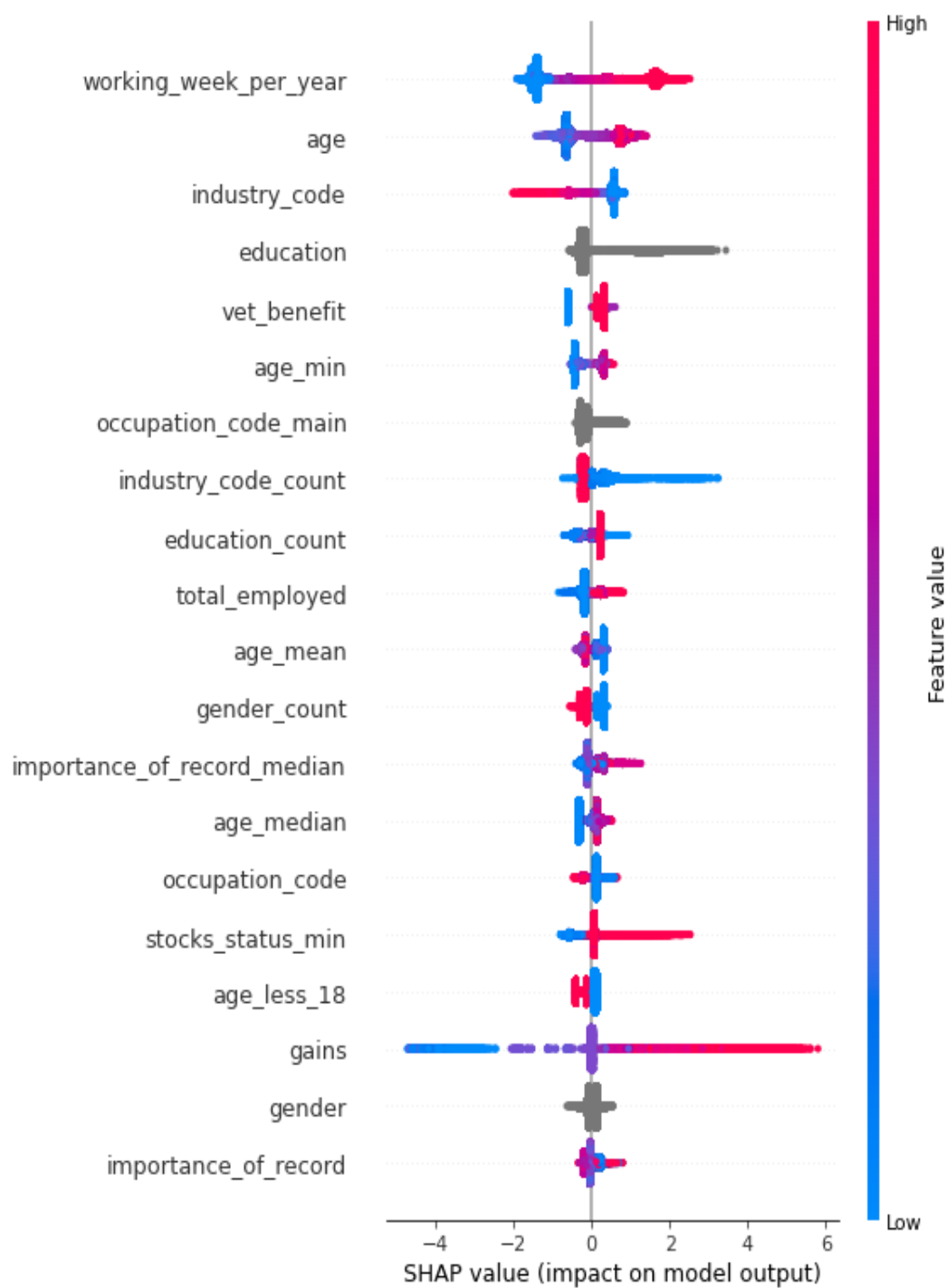
- Classification report for validation data

	precision	recall	f1-score	support
Below limit	0.97	0.98	0.98	39300
Above limit	0.69	0.57	0.63	2600
accuracy			0.96	41900
macro avg	0.83	0.78	0.80	41900
weighted avg	0.95	0.96	0.96	41900

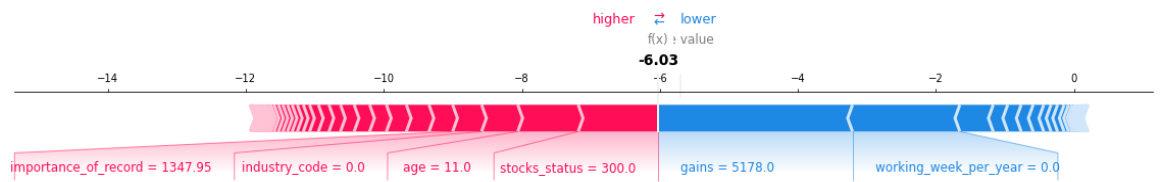
- Catboost model interpretation with SHAP
- Catboost – SHAP feature importances



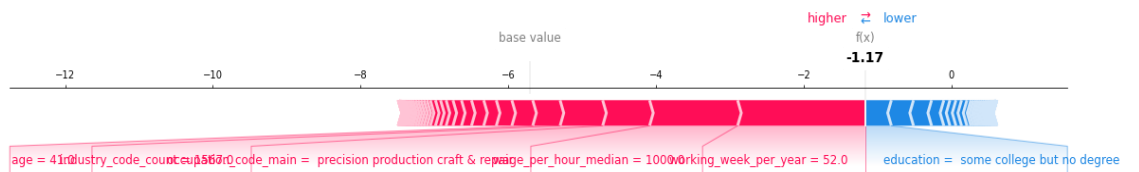
- Catboost – SHAP top feature impact



- SHAP Feature impact for single observation(class 0)



- SHAP Feature impact for single observation(class 1)



- Final score is 0.613205338