Income Prediction

Company: Verivox
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AGENDA

- Introduction
- Data Analysis and Exploration
- Model Approach
- Model Evaluation Metrics
- Model Performance
- Driving Factors Analysis
- Model Deployment
- Conclusion

INTRODUCTION

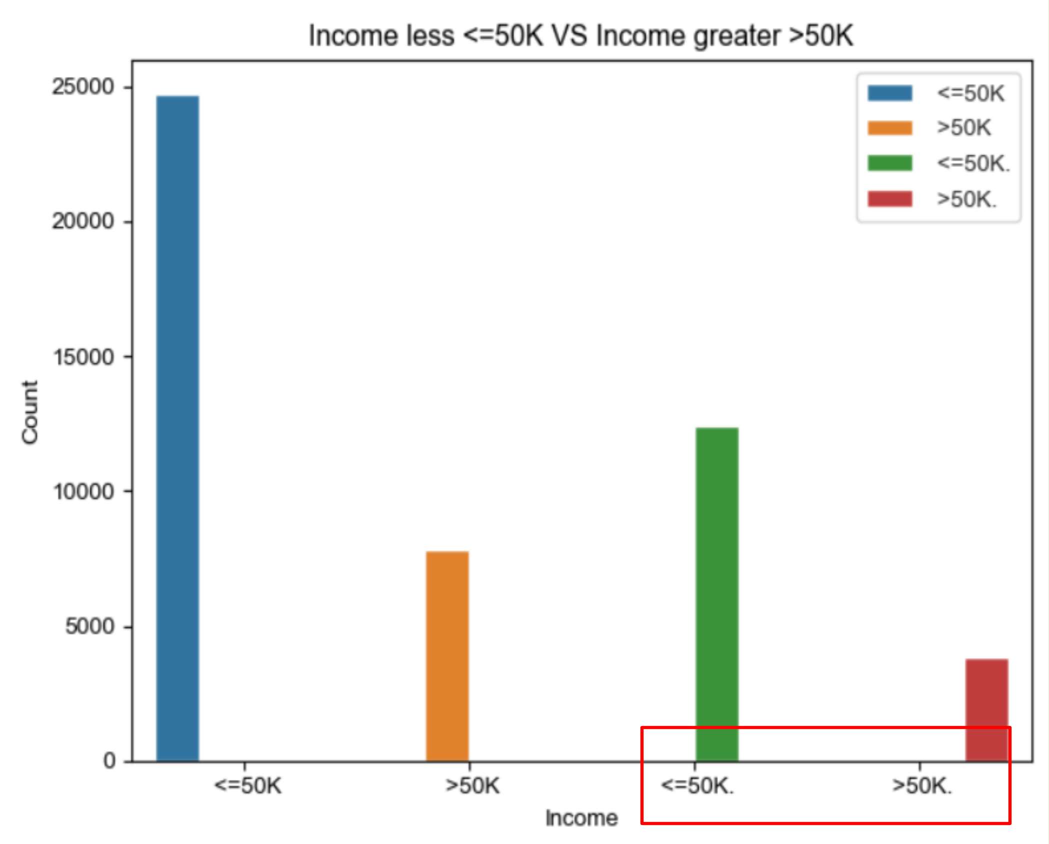
- This is a simple case study as part of an interview process for a position of Data Scientist at Verivox
- In this task I have to analyse the given “Census” dataset and build a predictive model that can predict wether a person can earn more than 50k or not. Moreover, highlight some of the techniques for model deployment.
- Also, point out some of the techniques for model deployment.

DATA ANALYSIS AND EXPLORATION

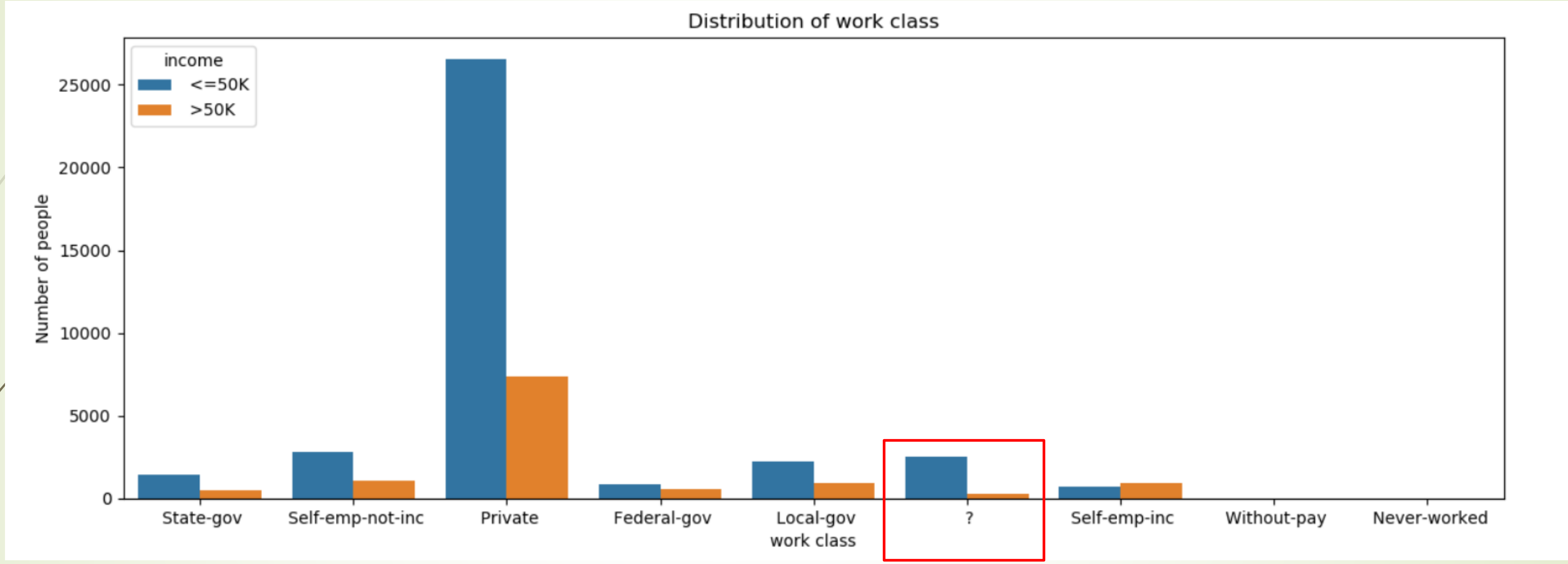
- Data exploration and analysis is mostly used in order to understand the distrubution of the data.

- Moreover, to detect the outliers in the dataset.

- We came to know that our target variable is inconsistent.



DATA ANALYSIS AND EXPLORATION

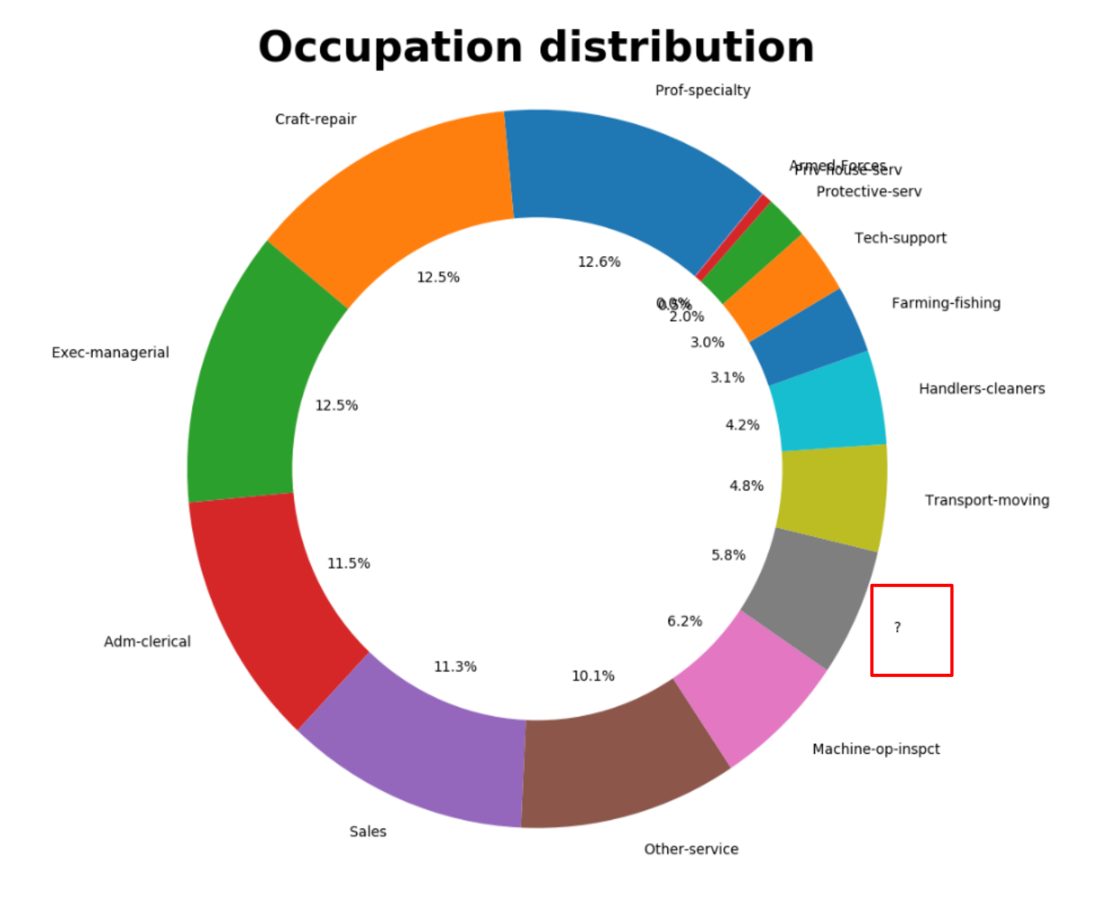


- Most of the population in our dataset is for private individuals.
- We can also spot an outlier in this columns that need to be pre-processed.

DATA ANALYSIS AND EXPLORATION

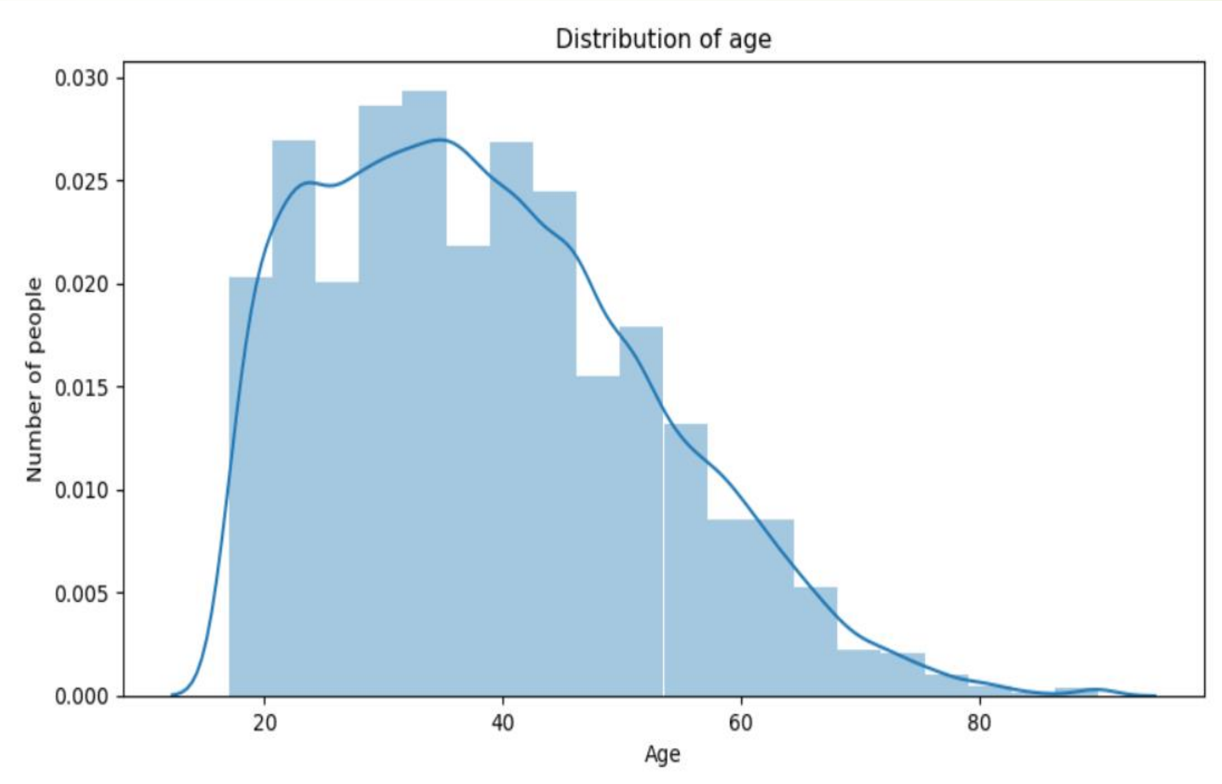
- Around 60% of the occupation is made of Prof-Specially, Craft-repair and sales etc.

- We can also spot an outlier in this columns that need to be pre-processed.



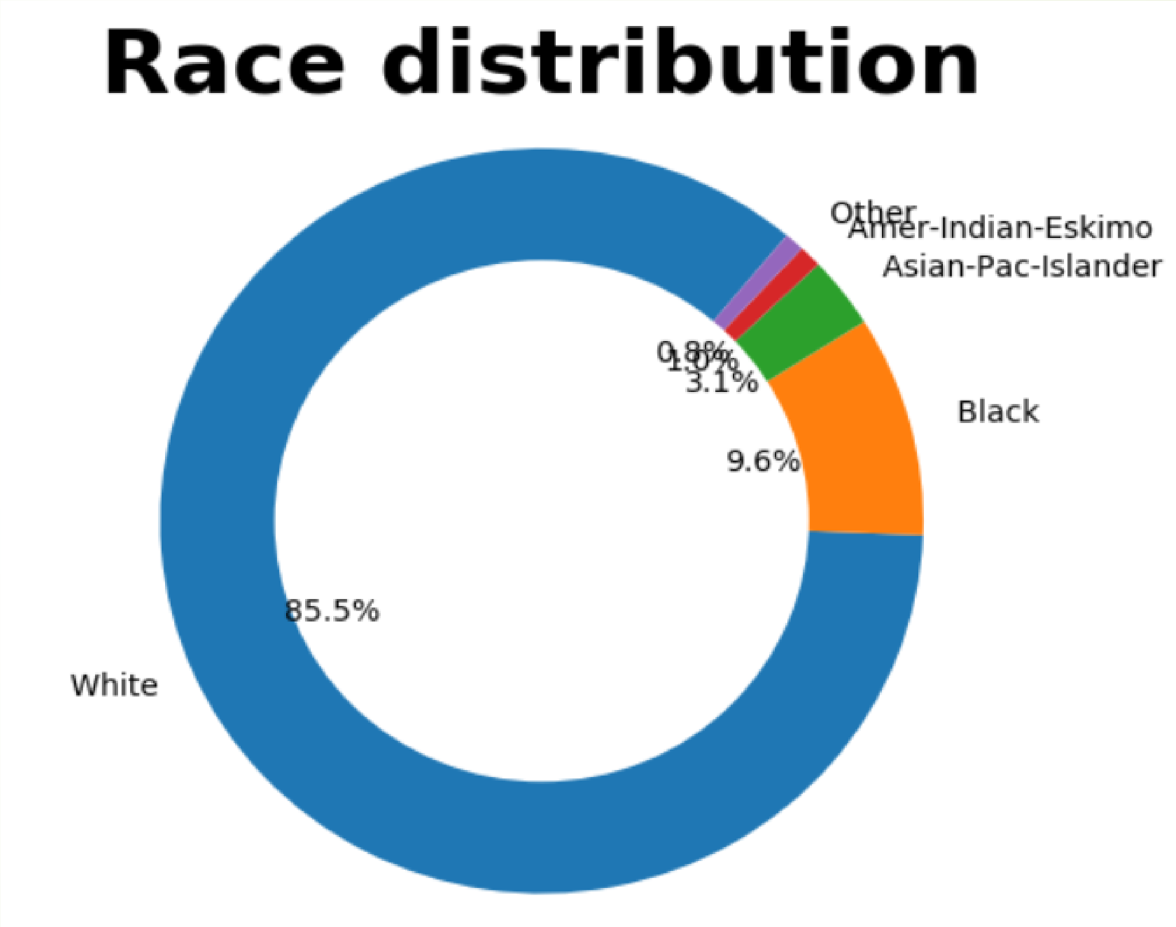
DATA ANALYSIS AND EXPLORATION

- Most of the distribution of age lies in our dataset is between 25 to 45 years



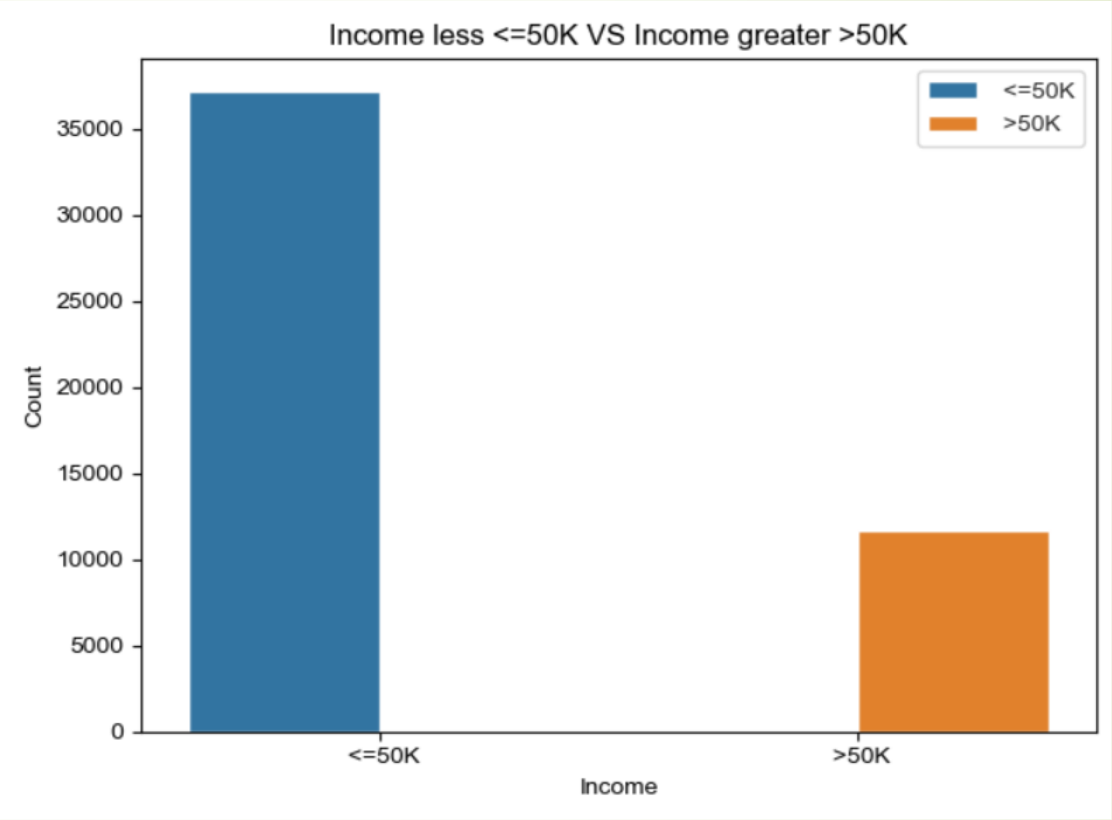
DATA ANALYSIS AND EXPLORATION

- Around 35% of the race distibution is made of White's



DATA ANALYSIS AND EXPLORATION

- We have less number of Income greater than 50k that is obvious.
- As, number of Income greater than 50k is less, that leads us to a common Machine Learning problem of data imbalance.
- E.g. fraud detection



MODEL APPROACH

- LogisticRegression is used as a baseline model. The performance is improved by using tree based models i.e. Random Forest and XGBoost.
- Random Forest and XGBoost are highly interpretable and easy to understand as compared to regression based models.
- If you want to explain the model performance and working to the business people, then these tree based models are the best option to work with. This is the reason I am working with these models.
- I achieved best performance and AUC with XGBoost while LogisticRegression performs quite low.
- To deal with the data imbalance problem I used a weighted loss technique which is considered to be the most effective Machine Learning technique as compared to down sampling and over sampling.
- For features selection, I extensively used feature importance, panda profile report and L1 regularization (Lasso Technique).

MODEL EVALUATION METRICS

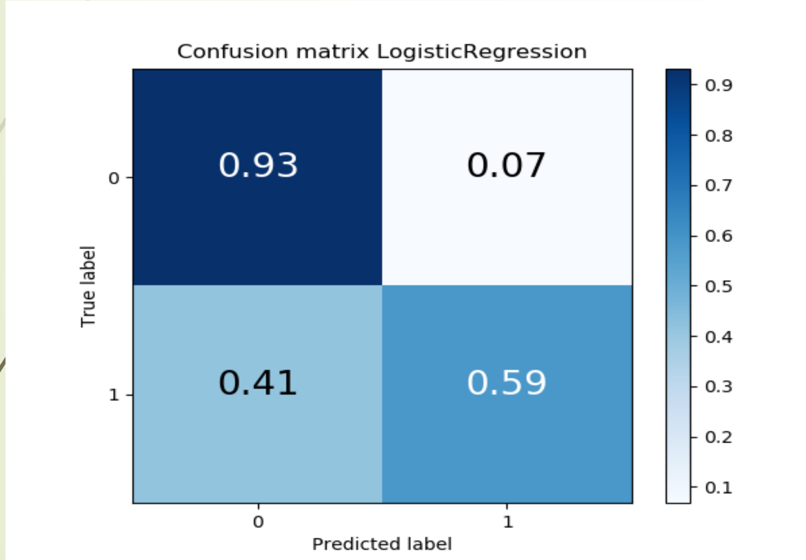
- As, we are dealing with the supervised classification problem, for this type of problems "Accuracy" is the most suitable evaluation metrics.
- However, we have a data imbalance problem, in our case "Accuracy" metrics will not work.
- We will get 90% accuracy as our model is predicting negative class every time and unable to classify the Positive class at all. Then this 90% accuracy is actually wrong.
- For our special case, I used "Area under the curve" metrics which is the suitable metrics for imbalance datasets.
- Our main goal is to Improve the "Precision" of the negative class (Income <=50k) as well as "Recall" of the positive class (Income >50K).
- For analysing the driving factors I am using "SHAP Package" from python.

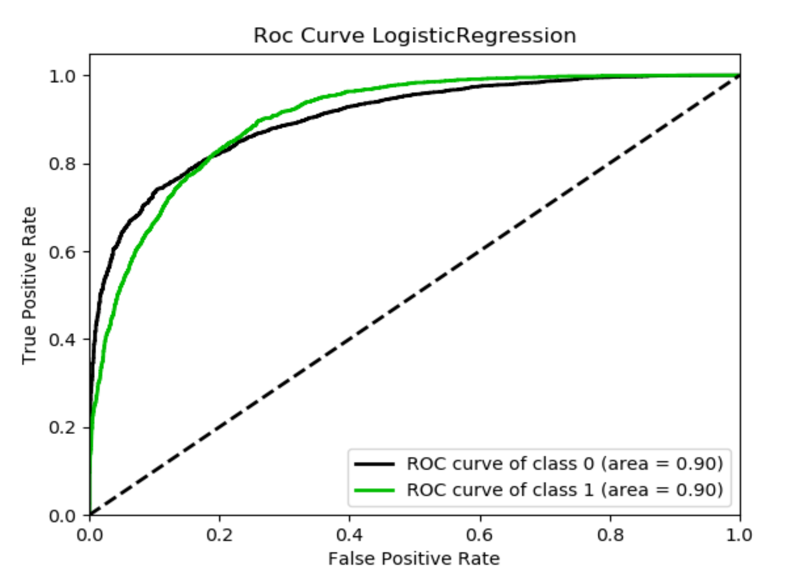
MODEL PERFORMANCE AND RESULTS

- XGBoost is trained on 80% of the final dataset and 20% of the dataset was used to validate/test the performance of the model.
- Trained LogisticRegression, Random Forest and XGBoost. However, final submission contains the best performed model i.e. XGBoost.
- All the model hyper parameters are also tuned and final model is trained on the best parameters.
- Final result contains ROC curve, Confusion Matrix, SHAP analysis and model deployment.

MODEL PERFORMANCE

LogisticRegression with weighted loss technique:

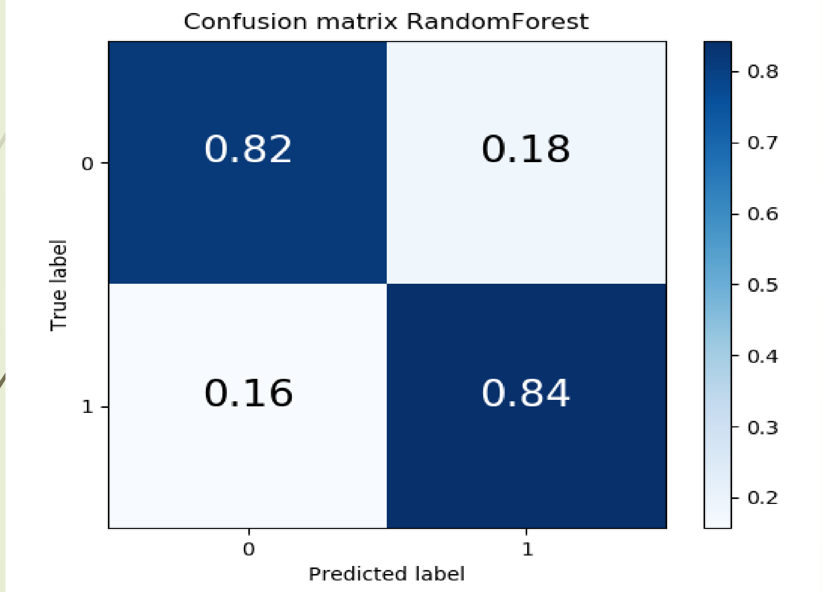


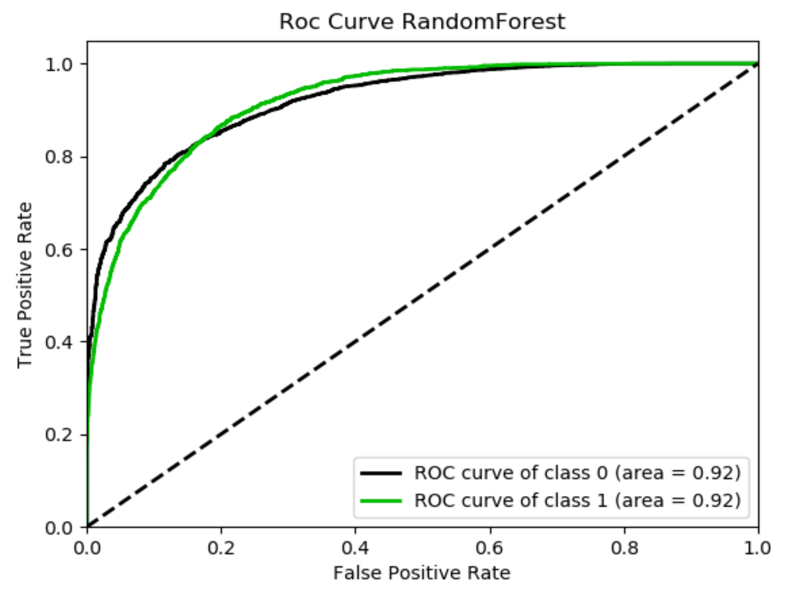


- LogisticRegression is covering 90% of the area under the curve (AUC) and also predicting both classes perfectly. However, some of the negative labels are wrongly classified which needs to be improve.

MODEL PERFORMANCE

Random Forest with weighted loss technique:

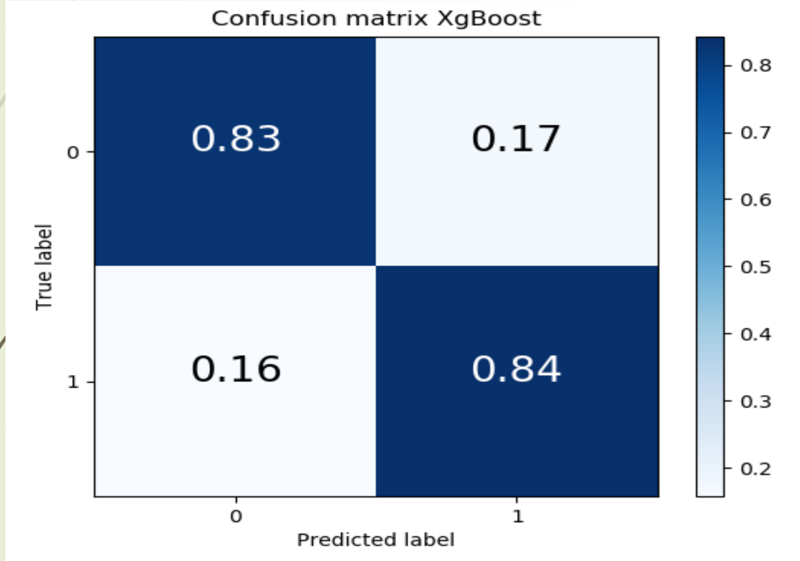


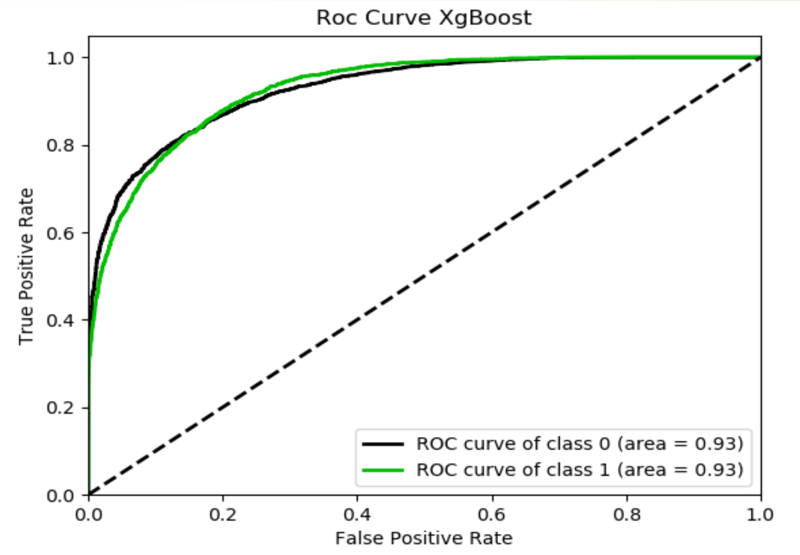


- Random forest is covering 92% of the area under the curve (AUC) and also predicting both classes perfectly. However, we can try further to improve the AUC.

MODEL PERFORMANCE

XGBoost with weighted loss technique :

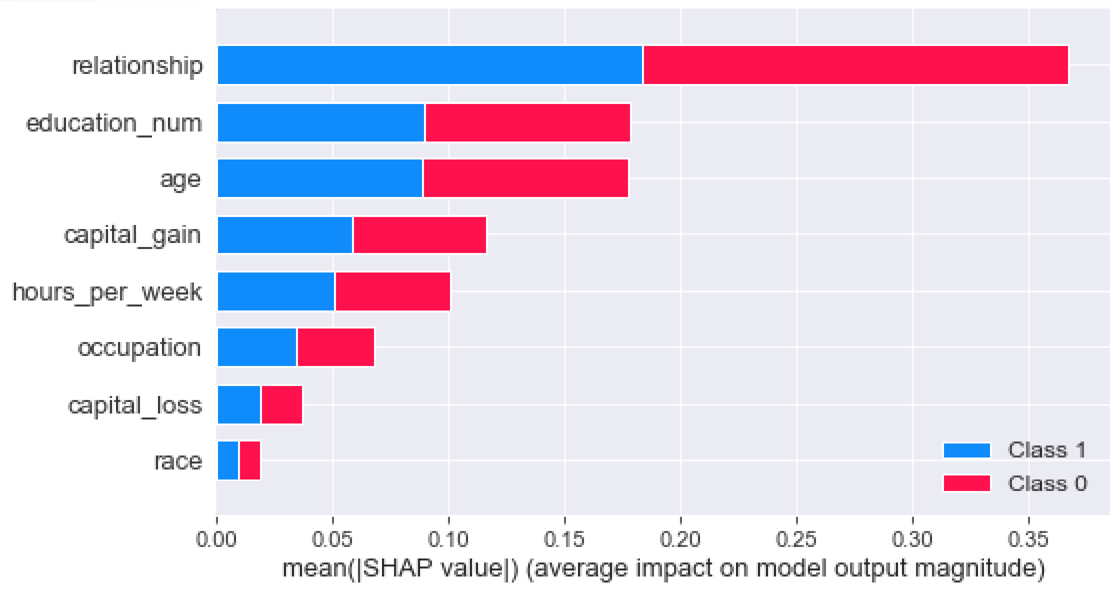




- XGBoost is performing the best so far on the dataset by covering 93% of the area under the curve. Moreover, model is predicting both classes perfectly.

DRIVING FACTORS ANALYSIS

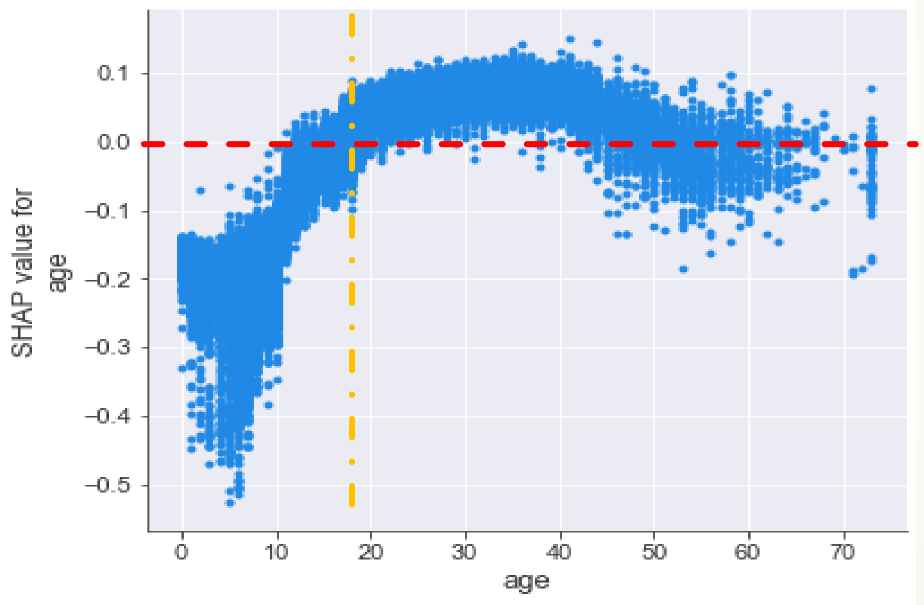
Shap features importance:



- Relationship, number of education years and age are the top three influencing factors for the model prediction. We can further analyse these factors by their shap explaination.

DRIVING FACTORS ANALYSIS

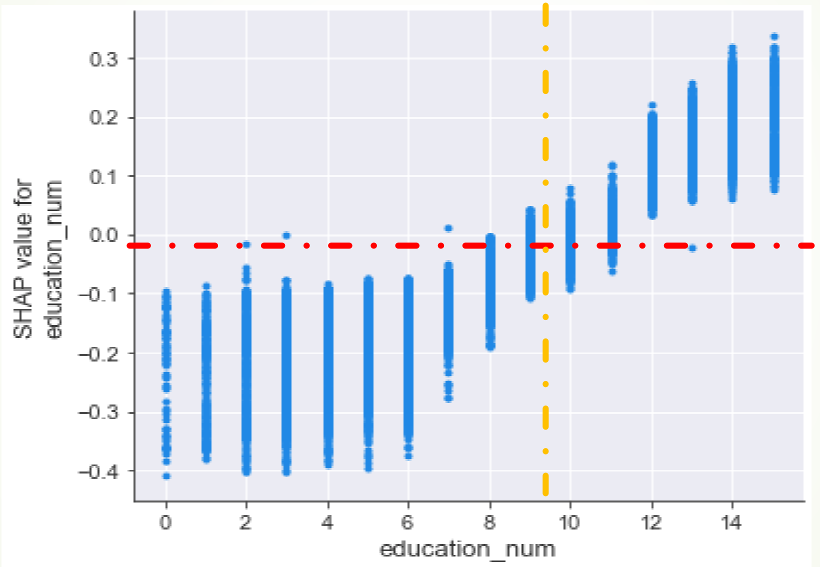
Age dependency plot:



- From 18 to 40 years of age, It has a positive effect on the prediction.

DRIVING FACTORS ANALYSIS

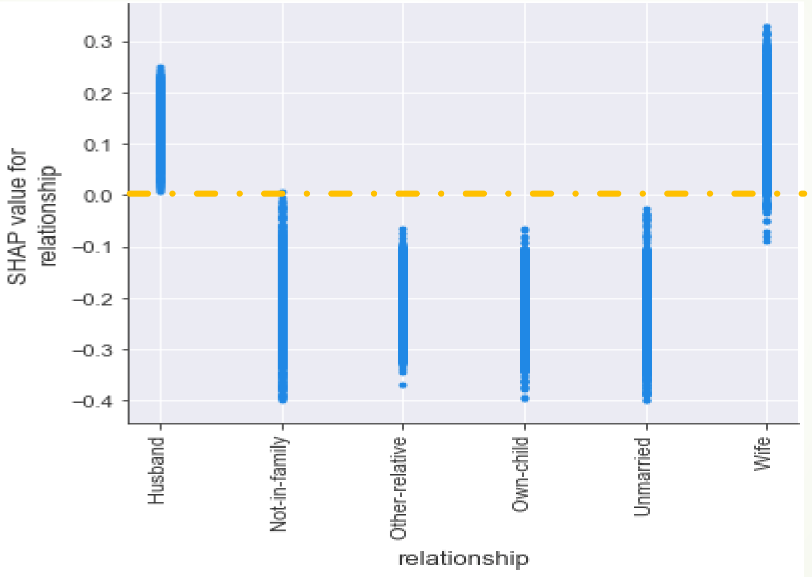
Education years dependency plot:



- We can clearly see a significant lift after 10 years of education that has a postive influence on the prediction.

DRIVING FACTORS ANALYSIS

Relationship dependency plot:



- We can clearly from the graph that relation of husband and wife have a positive impact on the prediction as compare to the other relationships.

MODEL DEPLOYMENT

- There are many ways to serve the model in production.
- Model deployment always depands upon stakeholders.
- Some of the techniques listed down:
  - Flask deployment with web interface. (Included in the Implementation)
  - API endpoint.
  - Cloud deployment. E,g. EC2 instance.
  - Cloud Infrastructure E.g, Kibana deployment (Model monitoring)

CONCLUSION

- Mode performance is in green area as we are acheiving 93% of AUC,
- Model performance could be improved but it will be very hard to improve that and also rate to improve will be also low.
- We see from the SHAP analysis that Relationship, age and number of education years are the top influenceing factors for the model.
- We further analyze these driving factors by SHAP explainer.
- I choose XGBoost my preferred approach as we are getting high AUC with it.
- XGBoost is not only simple but also easy to interpert by the stakeholders with the help of features importance and SHAP values.
- It also reduce the chance of overfitting.

Thank You…. !!!!