





PRESENTED BY:
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#### Modeling

#### Recommendation

### 8 numerical & 9 categorical Features

### Demographical Information

- Customer Age
- Education
- Job Type
- Marital Status

## Banking Information

- Balance
- Default
- Personal Loan
- Housing Loan
- Term Deposit Subscribed (Target Variable)

### **Current and Prior Campaign Data**

- Communication Type
- Day of Month
- Month
- Last Contact Duration
- Number of contacts in campaign
- Days passed since last campaign contact
- Number of times client was approached in prior campaign
- Outcome of the previous campaign



#### **Bird Eye View**

- Positive samples:- 3394
- Negative samples:-28253
- Class Imbalance ratio- 11:89

#### **Data Preparation Steps**

Outlier Treatment using interquartile range for numeric attribute.

Imputation of missing values using mean and mode.

One hot encoding on categorical data

#### Modeling

#### Recommendation

Maximum number of customers who subscribed term deposits are from 32 to 48 years of age

Distribution of customer age is highly skewed but still very similar to normal distribution

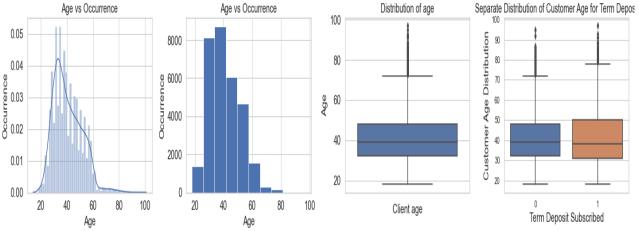
Since the dataset in imbalanced, we have used the median of age for term deposit subscribed = 1 to impute missing age with term deposit = 1

619 missing values in the customer age columns which will be imputed after treating the outliers

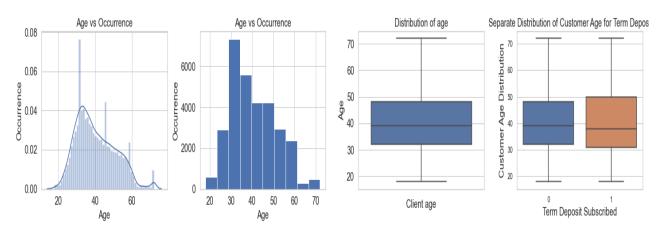
Range of customer age column is 18-97. For target class 1 and 0, outliers are behaving similarly as we can see in the box plot, so we have treated them together using the Inter-Quartile-Range and capped all all the values more than 72

Customer Age Distribution before outlier treatment and missing value imputation

Age vs Occurrence Age vs Occurrence Distribution of age Separate Distribution



Customer Age Distribution after outlier treatment and missing value imputation



#### Modeling

#### Recommendation

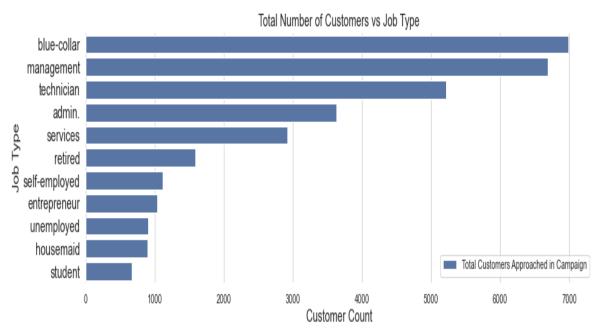


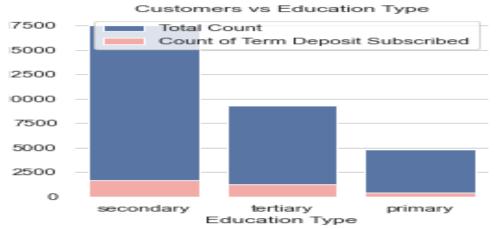
#### <u>Inferences</u>

- Term Deposits subscribed heavily by management background clients, then technician and then blue-collar workers
- Blue collar workers were approached more than management background customers
- Tertiary education type customers are more likely to convert than secondary education type

#### Recommendations

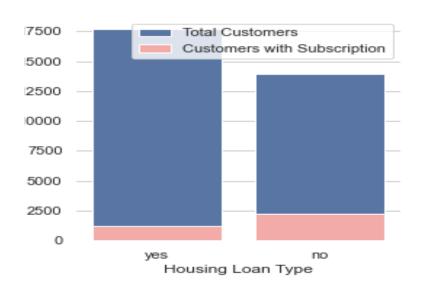
- More chances to increase the term deposit subscription if management people are focused more
- Top 3 recommendations in priority order will be Management, Technician and Blue Collar
- focusing more on tertiary education type customer as their ROI is more and they were not approached very much

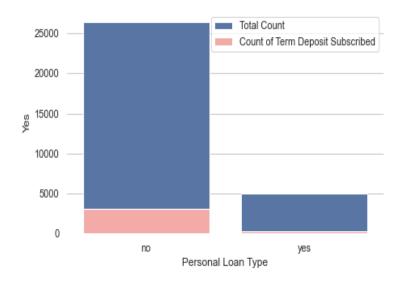


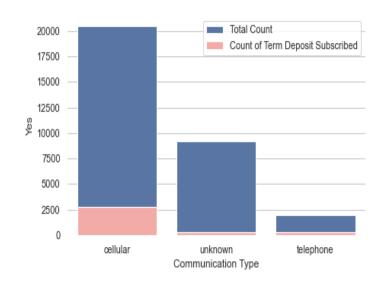


#### **Modeling**

#### Recommendation







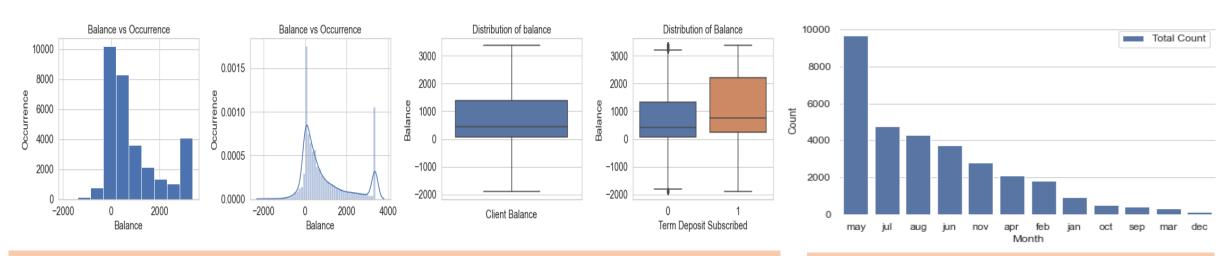
## INFERENCE

#### Inference

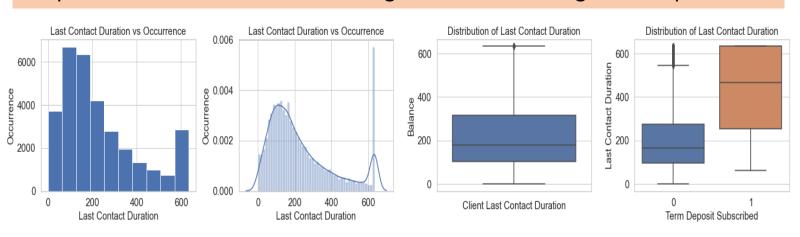
- Customers which have not taken housing loan are more likely to subscribe. Graph shows customers with housing loan were approached more, but focus should be changed to customers without Housing Loan
- 0 Missing Values. Unknown category accounts for 29% of the observations which is a very large number so we will consider it as a valid category in our analysis
- Communication done via cellular is more likely to engage customer and get term deposit subscription

#### **Modeling**

#### Recommendation

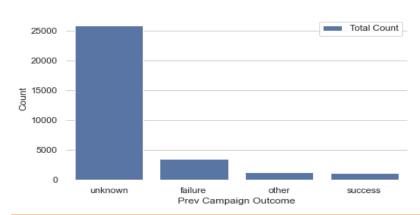


Graph-1 Balance column after treating outlier and missing value imputation



Graph-3 Last call duration column after outlier treatment and missing value imputation

Graph-2 Distribution of month column



Graph-4 Distribution of Previous campaign outcome



## Modeling on Imbalance

- Decision Tree, Bagging, Ada Boosting giving the highest accuracy
- These models will be biased towards the customers who do not have subscribed term deposit as there are 28154 customers who do not have subscribed term deposit
- There are only 3380 customers who have subscribed term deposit. So, these results can't be generalized



# Modeling on balance data

- After managing the imbalancing the target column and scaling the columns, we are getting the highest accuracy using Random Forest and Bagging Models
- These models will perform well as compared to imbalanced class models

#### Method Binary F1 Score

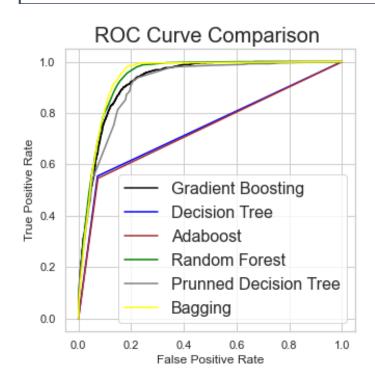
		200
1	Decision Tree	0.5123
2	Pruned Decision Tree	0.4965
3	Random Forest	0.4852
4	Bagging	0.5118
5	AdaBoosting	0.5180
6	GradientBoosting	0.4779
7	Ensemble	0.2837

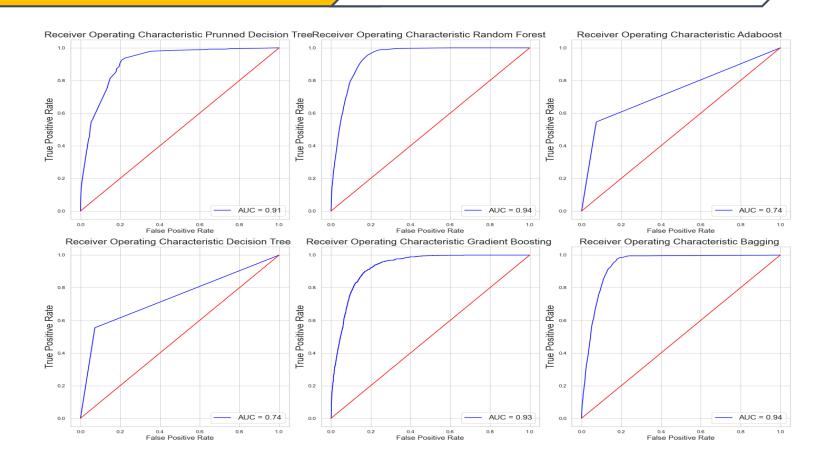
#### Method Binary F1 Score

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1	Decision Tree	0.5154
2	Pruned Decision Tree	0.5172
3	Random Forest	0.5659
4	Bagging	0.5970
5	AdaBoosting	0.5066
6	GradientBoosting	0.5847
7	Ensemble	0.5930

#### Modeling

#### Recommendation





- 1. Performance of Bagging and RandomForest is very close, which cover the maximum area under the curve.
- 2. AUC Bagging is 0.94 and F1-Binary score is 0.5970.

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- Company should focus on Management and technician more than blue collar and increase focus towards students.
- Increase focus on tertiary educated people as they give good ROI.
- Customers without housing loan should be prioritized over customer with housing loan



- customer\_age
- balance
- day\_of\_month
- last\_contact\_duration
- num\_contacts\_in\_campaign
- num\_contacts\_prev\_campaign
- job\_type\_admin.
- job\_type\_blue-collar
- job\_type\_entrepreneur
- job\_type\_housemaid
- job\_type\_management
- job\_type\_retired
- job\_type\_self-employed
- job\_type\_services
- job\_type\_student

