### **Approach Machinehack analytics olympiad 2022**

Create a machine learning model to help an insurance company understand which claims are worth rejecting and the claims which should be accepted for reimbursement.

- Basic exploratory data analysis using pandas, matplotlib, seaborn packages.
- Data pre-processing
  - Column name lower casr
  - Feature Engineering
    - Create a binary feature if a person having child without a marriage.
    - o get a categorical columns percentage
    - numerical groupby numerical summary
- The final features for the model
  - 1\_age
  - o 2\_gender
  - 3\_driving\_experience
  - 4\_education
  - o 5\_income
  - 6\_credit\_score
  - 7\_vehicle\_ownership
  - o 8\_vehicle\_year
  - o 9\_married
  - o 10\_children

- 11\_postal\_code
- 12\_annual\_mileage
- 13\_speeding\_violations
- o 14\_duis
- 15\_past\_accidents
- o 16\_outcome
- 17\_type\_of\_vehicle
- o 18\_data
- 19\_not\_married\_hv\_child
- 20\_id\_age\_percentage
- 21\_id\_gender\_percentage
- 22\_id\_driving\_experience\_percentage
- 23\_id\_education\_percentage
- 24\_id\_income\_percentage
- o 25\_id\_vehicle\_ownership\_percentage
- 26\_id\_vehicle\_year\_percentage
- 27\_id\_married\_percentage
- 28\_id\_children\_percentage
- 29\_id\_type\_of\_vehicle\_percentage
- 30\_id\_not\_married\_hv\_child\_percentage
- 31\_id\_annual\_mileage\_percentage
- 32\_id\_speeding\_violations\_percentage
- 33\_id\_duis\_percentage
- 34\_id\_past\_accidents\_percentage
- o 35\_age\_credit\_score\_median

- 36\_age\_credit\_score\_mean
- 37\_age\_credit\_score\_max
- o 38\_age\_credit\_score\_min
- 39\_age\_annual\_mileage\_median
- 40\_age\_annual\_mileage\_mean
- 41\_age\_annual\_mileage\_max
- 42\_age\_annual\_mileage\_min
- 43\_age\_speeding\_violations\_median
- 44\_age\_speeding\_violations\_mean
- 45\_age\_speeding\_violations\_max
- 46\_age\_speeding\_violations\_min
- 47\_age\_duis\_median
- o 48\_age\_duis\_mean
- 49\_age\_duis\_max
- o 50\_age\_duis\_min
- 51\_age\_past\_accidents\_median
- 52\_age\_past\_accidents\_mean
- 53 age past accidents max
- 54\_age\_past\_accidents\_min
- 55\_gender\_credit\_score\_median
- 56\_gender\_credit\_score\_mean
- 57\_gender\_credit\_score\_max
- o 58\_gender\_credit\_score\_min
- 59\_gender\_annual\_mileage\_median
- o 60\_gender\_annual\_mileage\_mean

- 61\_gender\_annual\_mileage\_max
- 62\_gender\_annual\_mileage\_min
- 63\_gender\_speeding\_violations\_median
- 64\_gender\_speeding\_violations\_mean
- 65\_gender\_speeding\_violations\_max
- 66\_gender\_speeding\_violations\_min
- 67\_gender\_duis\_median
- 68\_gender\_duis\_mean
- 69\_gender\_duis\_max
- o 70\_gender\_duis\_min
- 71\_gender\_past\_accidents\_median
- 72\_gender\_past\_accidents\_mean
- 73\_gender\_past\_accidents\_max
- 74\_gender\_past\_accidents\_min
- 75\_driving\_experience\_credit\_score\_median
- 76\_driving\_experience\_credit\_score\_mean
- o 77\_driving\_experience\_credit\_score\_max
- 78\_driving\_experience\_credit\_score\_min
- 79\_driving\_experience\_annual\_mileage\_median
- 80\_driving\_experience\_annual\_mileage\_mean
- 81\_driving\_experience\_annual\_mileage\_max
- o 82\_driving\_experience\_annual\_mileage\_min
- o 83\_driving\_experience\_speeding\_violations\_median
- 84\_driving\_experience\_speeding\_violations\_mean
- 85\_driving\_experience\_speeding\_violations\_max

- 86\_driving\_experience\_speeding\_violations\_min
- 87\_driving\_experience\_duis\_median
- 88\_driving\_experience\_duis\_mean
- 89\_driving\_experience\_duis\_max
- 90\_driving\_experience\_duis\_min
- 91\_driving\_experience\_past\_accidents\_median
- 92\_driving\_experience\_past\_accidents\_mean
- 93\_driving\_experience\_past\_accidents\_max
- 94\_driving\_experience\_past\_accidents\_min
- o 95\_education\_credit\_score\_median
- 96\_education\_credit\_score\_mean
- 97\_education\_credit\_score\_max
- 98\_education\_credit\_score\_min
- 99\_education\_annual\_mileage\_median
- 100\_education\_annual\_mileage\_mean
- 101\_education\_annual\_mileage\_max
- 102\_education\_annual\_mileage\_min
- 103 education speeding violations median
- 104\_education\_speeding\_violations\_mean
- 105\_education\_speeding\_violations\_max
- 106\_education\_speeding\_violations\_min
- o 107\_education\_duis\_median
- o 108 education duis mean
- 109\_education\_duis\_max
- o 110\_education\_duis\_min

- 111\_education\_past\_accidents\_median
- 112\_education\_past\_accidents\_mean
- 113\_education\_past\_accidents\_max
- 114\_education\_past\_accidents\_min
- 115\_income\_credit\_score\_median
- 116\_income\_credit\_score\_mean
- 117\_income\_credit\_score\_max
- 118\_income\_credit\_score\_min
- o 119\_income\_annual\_mileage\_median
- 120\_income\_annual\_mileage\_mean
- 121\_income\_annual\_mileage\_max
- 122\_income\_annual\_mileage\_min
- 123\_income\_speeding\_violations\_median
- 124\_income\_speeding\_violations\_mean
- 125\_income\_speeding\_violations\_max
- 126\_income\_speeding\_violations\_min
- 127\_income\_duis\_median
- 128\_income\_duis\_mean
- 129\_income\_duis\_max
- 130\_income\_duis\_min
- 131\_income\_past\_accidents\_median
- 132\_income\_past\_accidents\_mean
- 133\_income\_past\_accidents\_max
- 134\_income\_past\_accidents\_min
- 135\_vehicle\_ownership\_credit\_score\_median

- 136\_vehicle\_ownership\_credit\_score\_mean
- 137\_vehicle\_ownership\_credit\_score\_max
- 138\_vehicle\_ownership\_credit\_score\_min
- 139\_vehicle\_ownership\_annual\_mileage\_median
- 140\_vehicle\_ownership\_annual\_mileage\_mean
- 141\_vehicle\_ownership\_annual\_mileage\_max
- 142\_vehicle\_ownership\_annual\_mileage\_min
- 143\_vehicle\_ownership\_speeding\_violations\_median
- 144\_vehicle\_ownership\_speeding\_violations\_mean
- 145\_vehicle\_ownership\_speeding\_violations\_max
- 146\_vehicle\_ownership\_speeding\_violations\_min
- 147\_vehicle\_ownership\_duis\_median
- 148\_vehicle\_ownership\_duis\_mean
- 149\_vehicle\_ownership\_duis\_max
- 150\_vehicle\_ownership\_duis\_min
- 151\_vehicle\_ownership\_past\_accidents\_median
- 152\_vehicle\_ownership\_past\_accidents\_mean
- 153\_vehicle\_ownership\_past\_accidents\_max
- 154\_vehicle\_ownership\_past\_accidents\_min
- 155\_vehicle\_year\_credit\_score\_median
- 156\_vehicle\_year\_credit\_score\_mean
- 157\_vehicle\_year\_credit\_score\_max
- 158\_vehicle\_year\_credit\_score\_min
- 159\_vehicle\_year\_annual\_mileage\_median
- o 160\_vehicle\_year\_annual\_mileage\_mean

- 161\_vehicle\_year\_annual\_mileage\_max
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- 163\_vehicle\_year\_speeding\_violations\_median
- 164\_vehicle\_year\_speeding\_violations\_mean
- 165\_vehicle\_year\_speeding\_violations\_max
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- 167\_vehicle\_year\_duis\_median
- 168\_vehicle\_year\_duis\_mean
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- 175\_married\_credit\_score\_median
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- o 180\_married\_annual\_mileage\_mean
- 181\_married\_annual\_mileage\_max
- 182\_married\_annual\_mileage\_min
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- 184\_married\_speeding\_violations\_mean
- 185\_married\_speeding\_violations\_max

- 186\_married\_speeding\_violations\_min
- 187\_married\_duis\_median
- 188\_married\_duis\_mean
- 189\_married\_duis\_max
- o 190 married duis min
- o 191\_married\_past\_accidents\_median
- 192\_married\_past\_accidents\_mean
- 193\_married\_past\_accidents\_max
- 194\_married\_past\_accidents\_min
- 195\_not\_married\_hv\_child\_credit\_score\_median
- 196\_not\_married\_hv\_child\_credit\_score\_mean
- 197\_not\_married\_hv\_child\_credit\_score\_max
- 198\_not\_married\_hv\_child\_credit\_score\_min
- 199\_not\_married\_hv\_child\_annual\_mileage\_median
- o 200\_not\_married\_hv\_child\_annual\_mileage\_mean
- 201\_not\_married\_hv\_child\_annual\_mileage\_max
- 202\_not\_married\_hv\_child\_annual\_mileage\_min
- 203\_not\_married\_hv\_child\_speeding\_violations\_median
- 204\_not\_married\_hv\_child\_speeding\_violations\_mean
- 205\_not\_married\_hv\_child\_speeding\_violations\_max
- 206\_not\_married\_hv\_child\_speeding\_violations\_min
- 207\_not\_married\_hv\_child\_duis\_median
- o 208\_not\_married\_hv\_child\_duis\_mean
- 209\_not\_married\_hv\_child\_duis\_max
- o 210\_not\_married\_hv\_child\_duis\_min

- 211\_not\_married\_hv\_child\_past\_accidents\_median
- 212\_not\_married\_hv\_child\_past\_accidents\_mean
- 213\_not\_married\_hv\_child\_past\_accidents\_max
- 214\_not\_married\_hv\_child\_past\_accidents\_min
- o 215 children credit score median
- 216\_children\_credit\_score\_mean
- 217\_children\_credit\_score\_max
- 218\_children\_credit\_score\_min
- o 219\_children\_annual\_mileage\_median
- 220\_children\_annual\_mileage\_mean
- 221\_children\_annual\_mileage\_max
- 222\_children\_annual\_mileage\_min
- 223\_children\_speeding\_violations\_median
- 224\_children\_speeding\_violations\_mean
- o 225\_children\_speeding\_violations\_max
- 226\_children\_speeding\_violations\_min
- 227\_children\_duis\_median
- 228\_children\_duis\_mean
- 229\_children\_duis\_max
- o 230\_children\_duis\_min
- 231\_children\_past\_accidents\_median
- o 232\_children\_past\_accidents\_mean
- 233\_children\_past\_accidents\_max
- 234\_children\_past\_accidents\_min
- o 235\_type\_of\_vehicle\_credit\_score\_median

- 236\_type\_of\_vehicle\_credit\_score\_mean
- 237\_type\_of\_vehicle\_credit\_score\_max
- 238\_type\_of\_vehicle\_credit\_score\_min
- 239\_type\_of\_vehicle\_annual\_mileage\_median
- 240\_type\_of\_vehicle\_annual\_mileage\_mean
- o 241\_type\_of\_vehicle\_annual\_mileage\_max
- o 242\_type\_of\_vehicle\_annual\_mileage\_min
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- 244\_type\_of\_vehicle\_speeding\_violations\_mean
- 245\_type\_of\_vehicle\_speeding\_violations\_max
- 246\_type\_of\_vehicle\_speeding\_violations\_min
- 247\_type\_of\_vehicle\_duis\_median
- 248\_type\_of\_vehicle\_duis\_mean
- 249\_type\_of\_vehicle\_duis\_max
- 250\_type\_of\_vehicle\_duis\_min
- 251\_type\_of\_vehicle\_past\_accidents\_median
- 252\_type\_of\_vehicle\_past\_accidents\_mean
- 253\_type\_of\_vehicle\_past\_accidents\_max
- 254\_type\_of\_vehicle\_past\_accidents\_min

- Created catboost classifier model and tuned hyperparameters by using optuna framework. Model evaluated with Logloss. After 100 trials,
  - The best score is 0.68106
  - The best hyperparemeters are,

{'reg\_lambda': 160,

'learning\_rate': 0.04010653349368823,

'n\_estimators': 221,

'max\_depth': 6,

'od\_type': 'IncToDec',

'random\_state': 1024,

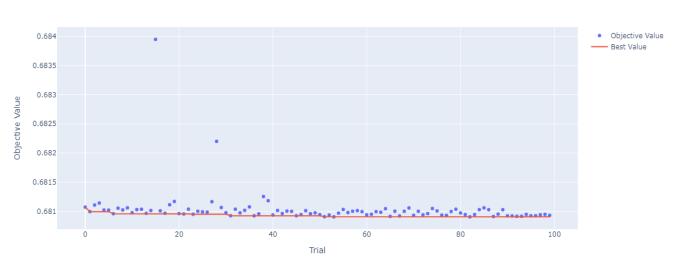
'boosting\_type': 'Plain',

'bootstrap\_type': 'Bayesian',

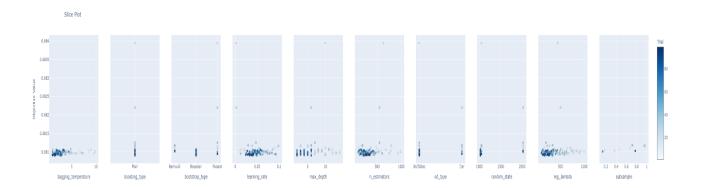
'bagging\_temperature': 2.7779687356027973}

 Visualizing the Optimization History - Explains the best score at each trials.

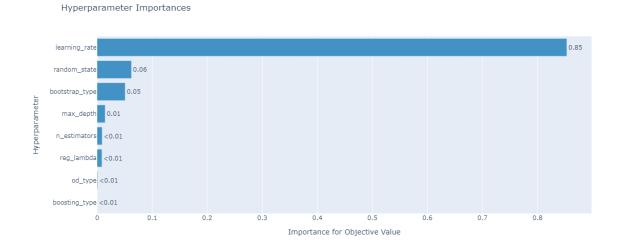




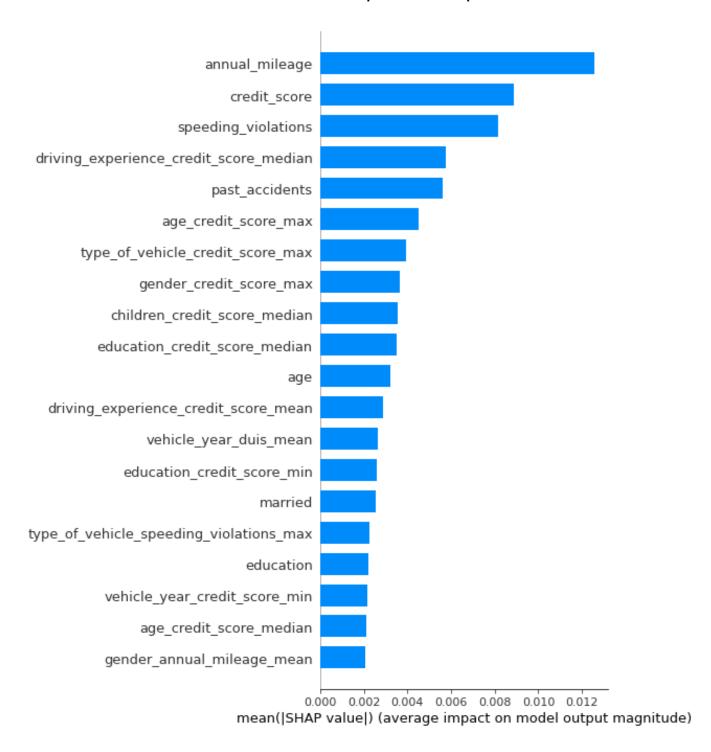
# • Visualizing High-dimensional Parameter Relationships



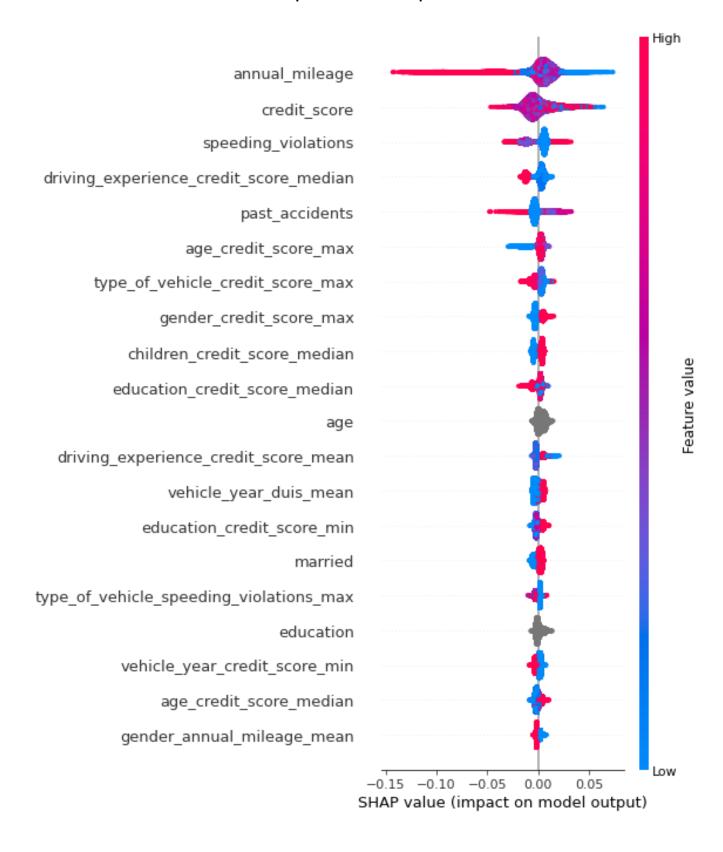
# Visualizing Parameter Importances



#### Catboost SHAP feature importances plot



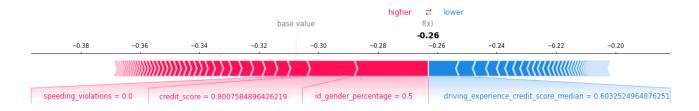
#### Catboost SHAP top features impact the model



## • Top feature influences for class 1

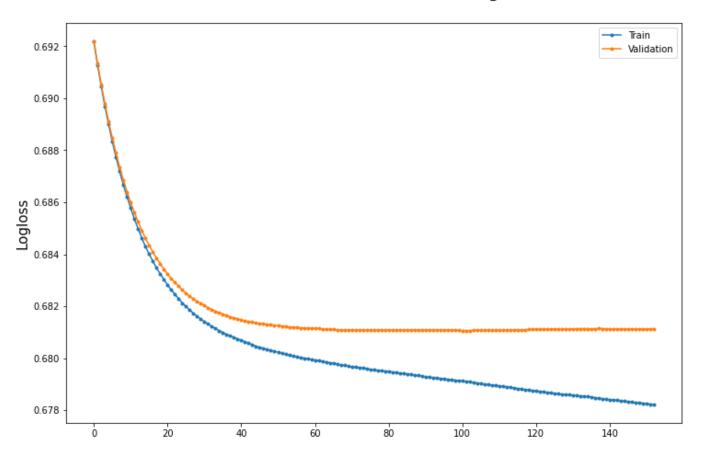


# • Top feature influences for class 0



## Overall Train and Validation Logloss

### Overall Train and Validation Logloss



- Train logloss: 0.67936, Validation logloss: 0.68106
- Final competition score is 0.68081