

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 case
 - Feature Engineering
 - Create a binary indicator to indicate if the policyholder has a child without marriage.
 - get a categorical columns percentage
 - numerical groupby numerical summary
- The final features for the model
 - 0_age
 - 1_gender
 - 2_driving_experience
 - 3_education
 - 4_income
 - 5_credit_score
 - 6_vehicle_ownership
 - 7_vehicle_year
 - 8_married
 - 9_children

10_annual_mileage
11_speeding_violations
12_duis
13_past_accidents
14_type_of_vehicle
15_not_married_hv_child
16_id_age_percentage
17_id_gender_percentage
18_id_driving_experience_percentage
19_id_education_percentage
20_id_income_percentage
21_id_vehicle_ownership_percentage
22_id_vehicle_year_percentage
23_id_married_percentage
24_id_children_percentage
25_id_type_of_vehicle_percentage
26_id_not_married_hv_child_percentage
27_id_annual_mileage_percentage
28_id_speeding_violations_percentage
29_id_duis_percentage
30_id_past_accidents_percentage
31_age_credit_score_median
32_age_credit_score_min
33_age_credit_score_mean
34_age_credit_score_max

35_age_annual_mileage_median
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38_age_annual_mileage_max
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42_age_speeding_violations_max
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44_age_duis_min
45_age_duis_mean
46_age_duis_max
47_age_past_accidents_median
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60_gender_speeding_violations_min
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248_type_of_vehicle_past_accidents_min
249_type_of_vehicle_past_accidents_mean
250_type_of_vehicle_past_accidents_max

- Created catboost classifier model and tuned hyperparameters by using optuna framework. Model evaluated with Logloss. After 100 trials,
 - The best score is 0.680893

- The best hyperparameters are,

`{'reg_lambda': 605,`

`'learning_rate': 0.04731571585972637,`

`'n_estimators': 772,`

`'max_depth': 6,`

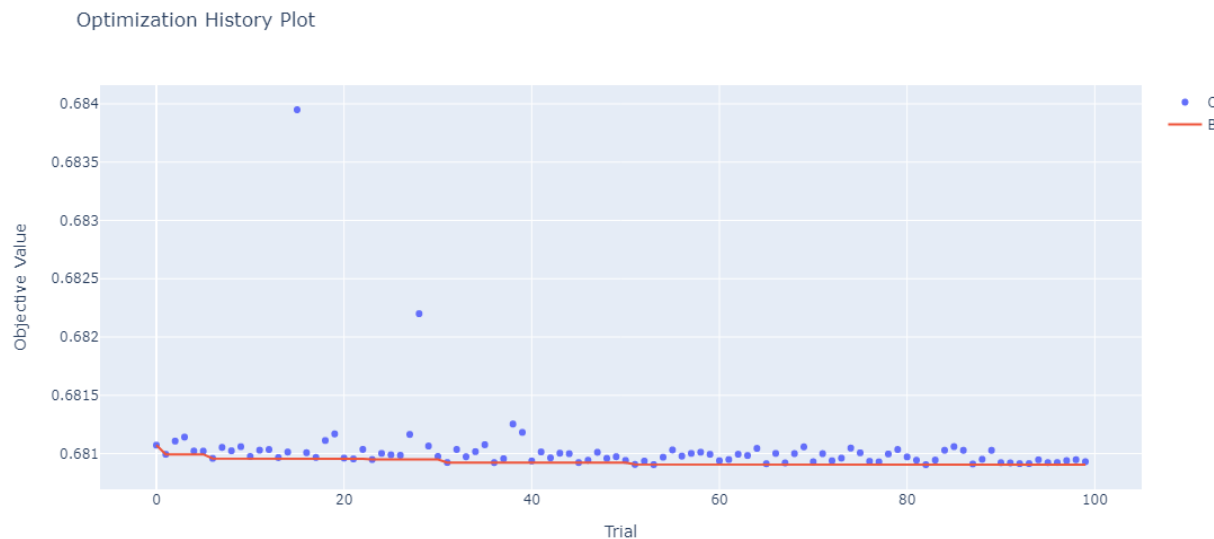
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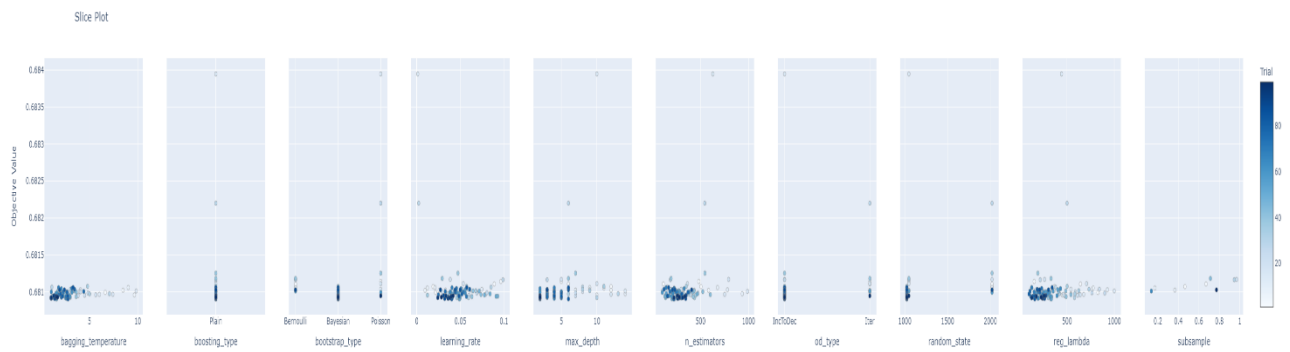
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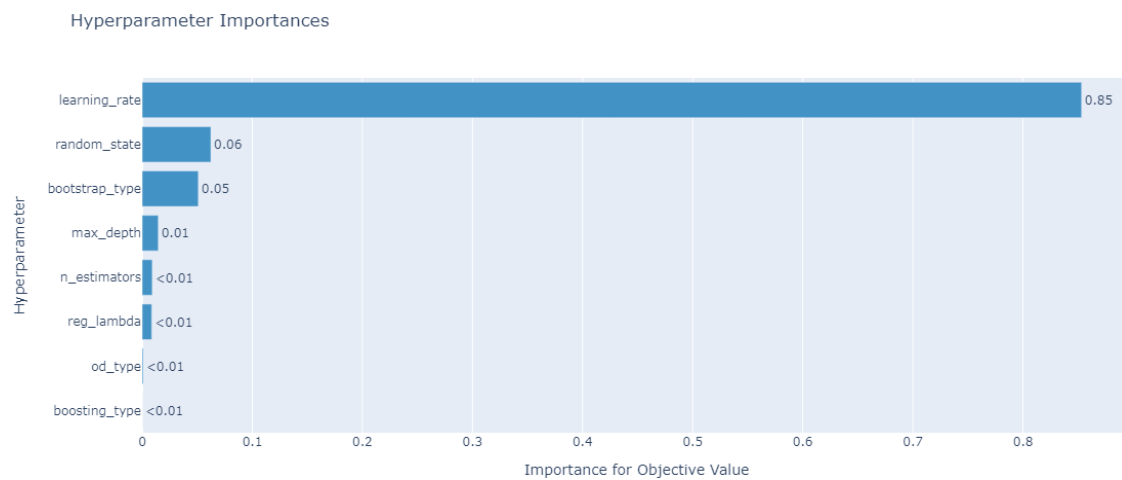
- Visualizing the Optimization History - Explains the best score at each trials.



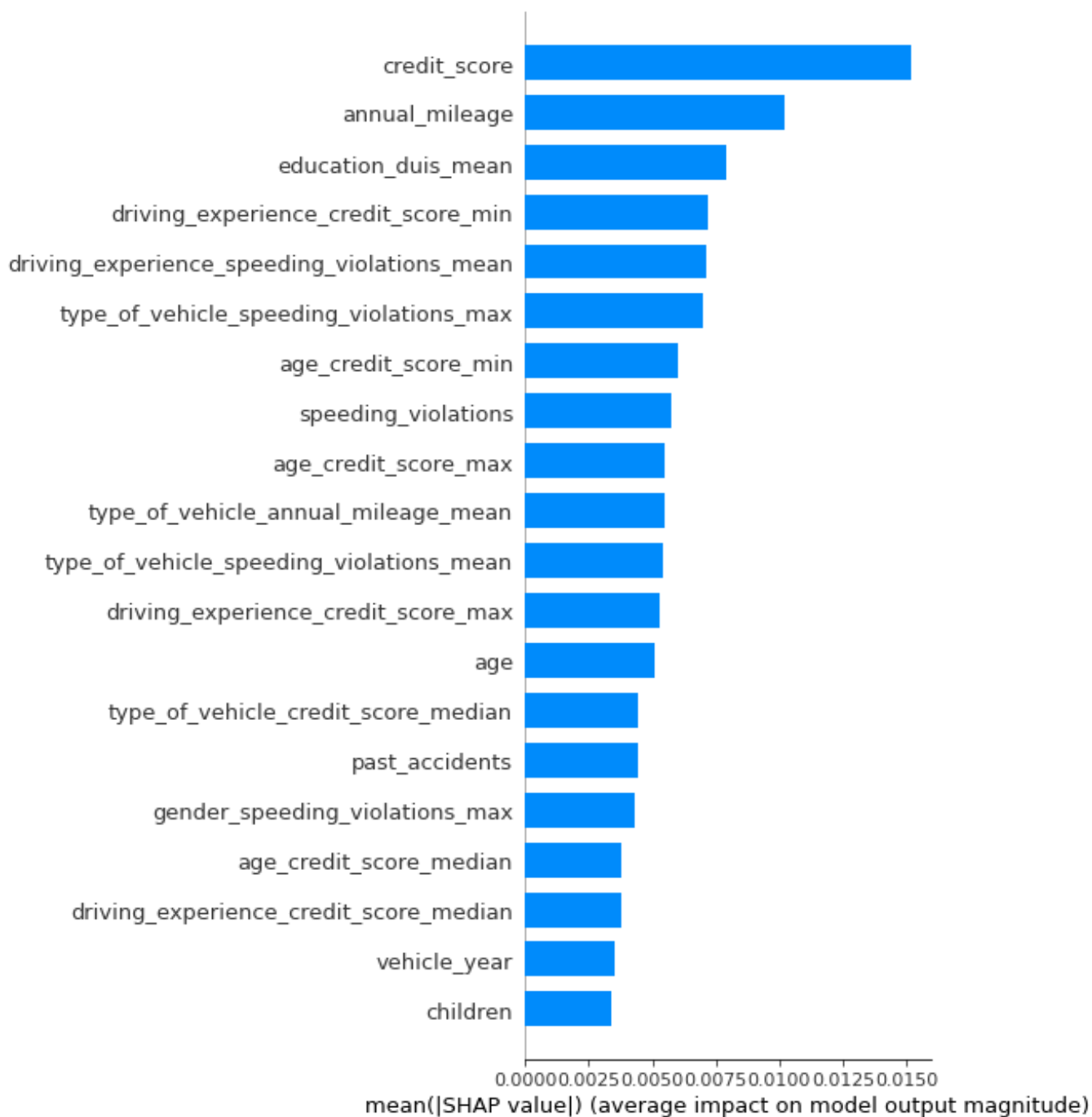
- Visualizing High-dimensional Parameter Relationships



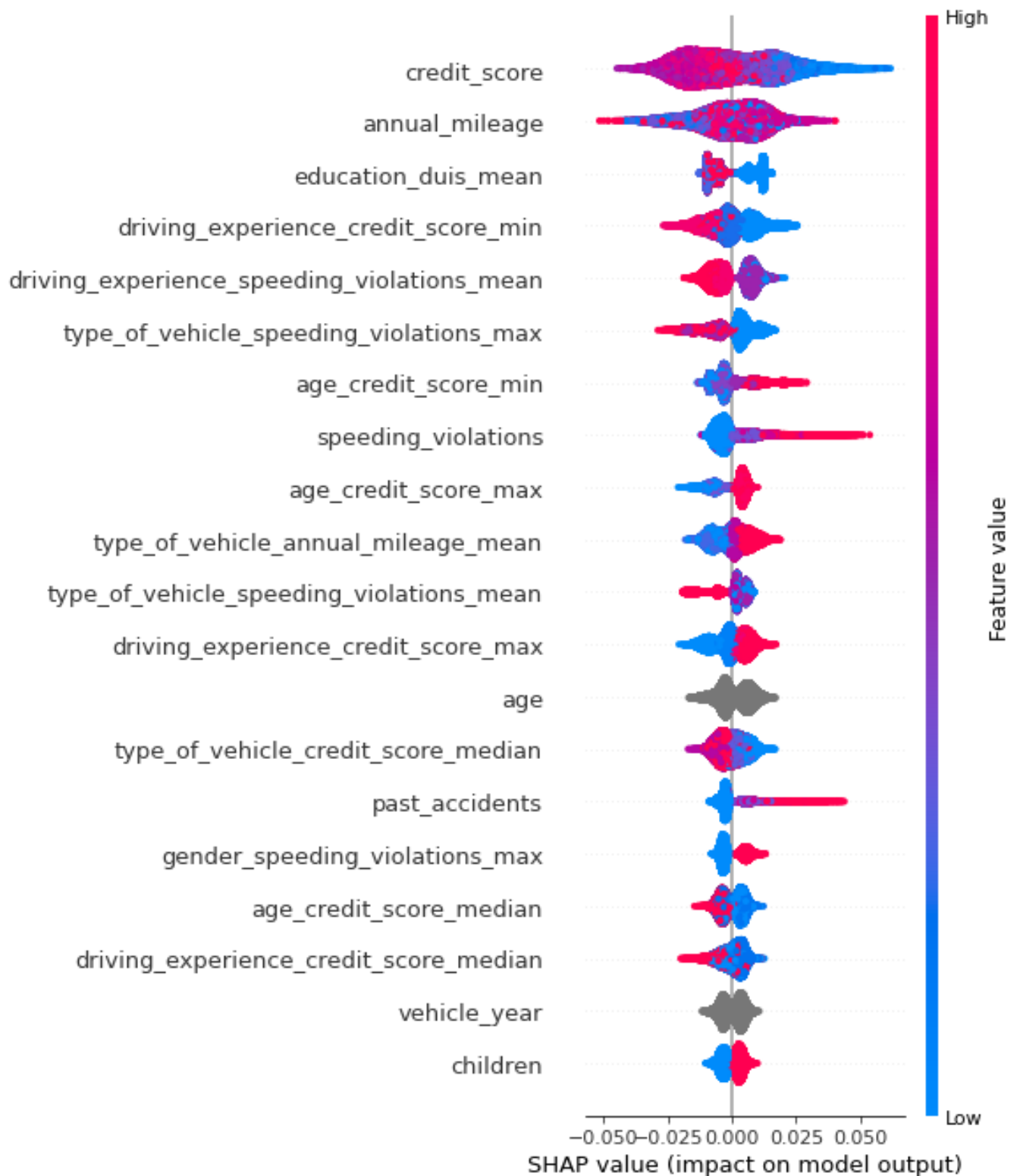
- Visualizing Parameter Importances



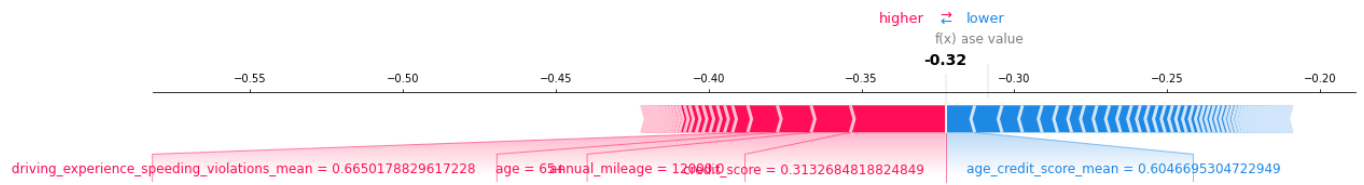
- Catboost SHAP feature importances plot



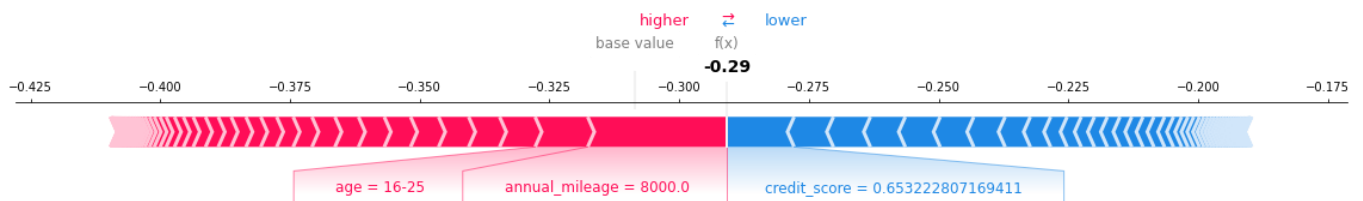
- Catboost SHAP top features impact the model



- Top feature influences for class 1

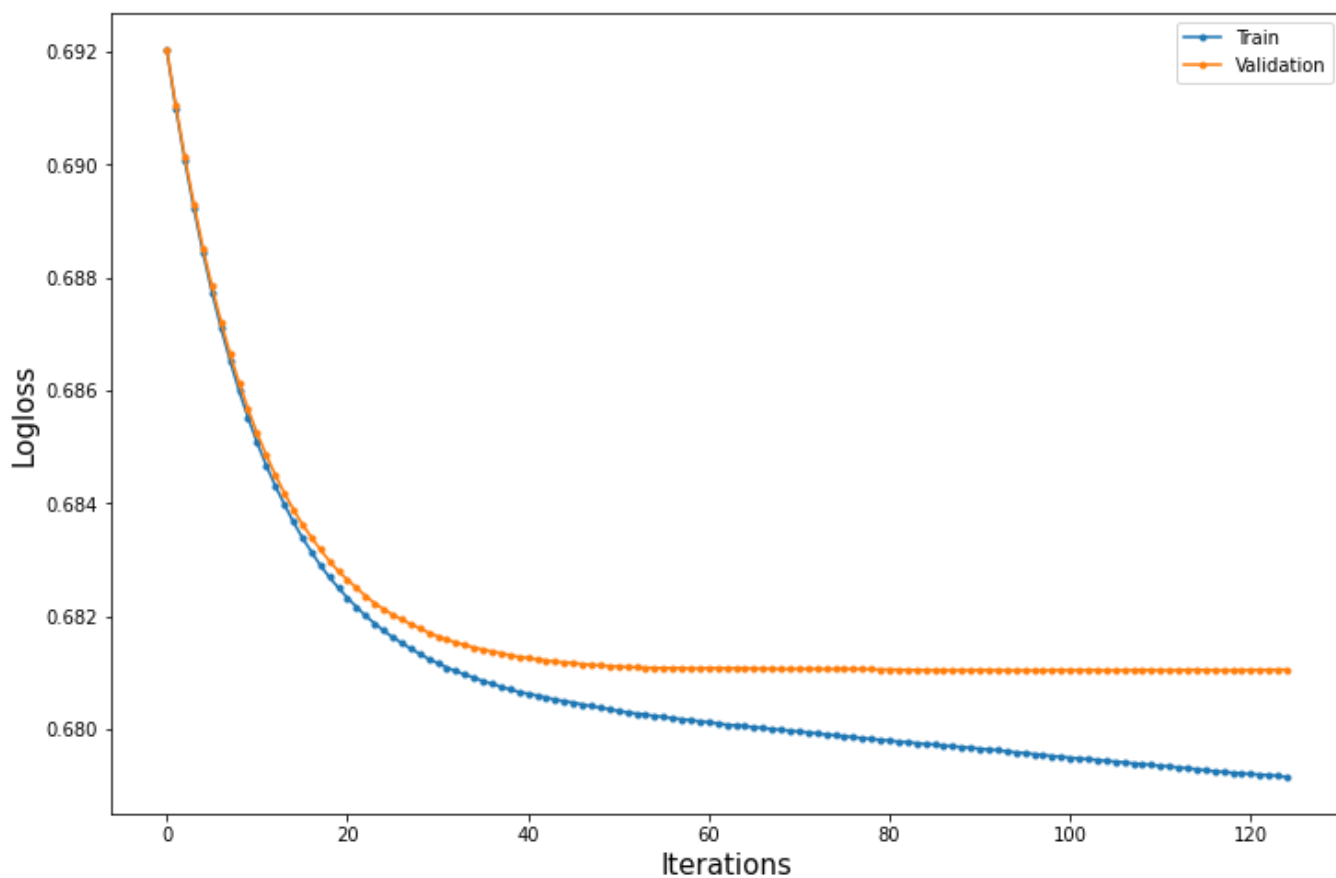


- Top feature influences for class 0



- Overall Train and Validation Logloss

Catboost Model Overall Train and Validation Logloss



- Train logloss: 0.67978 , Validation logloss: 0.68106
- Final competition score
 - Private LB: 0.68081
 - Public LB: 0.68037